

MRL 2025

**The 5th Workshop on Multilingual Representation Learning
(MRL 2025)**

Proceedings of the Workshop

November 8-9, 2025

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ISBN 979-8-89176-345-6

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No Language Data Left Behind: A Cross-Cultural Study of CJK Language Datasets in the Hugging Face Ecosystem

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Abstract

Recent advances in Natural Language Processing (NLP) have underscored the crucial role of high-quality datasets in building large language models (LLMs). However, while extensive resources and analyses exist for English, the landscape for East Asian languages, particularly Chinese, Japanese, and Korean (CJK), remains fragmented and underexplored, despite these languages serving over 1.6 billion speakers. To address this gap, we investigate the HuggingFace ecosystem from a cross-linguistic perspective, focusing on how cultural norms, research environments, and institutional practices shape dataset availability and quality. Drawing on more than 3,300 datasets, we employ quantitative and qualitative methods to examine how these factors drive distinct creation and curation patterns across Chinese, Japanese, and Korean NLP communities. Our findings highlight the large-scale and often institution-driven nature of Chinese datasets, grassroots community-led development in Korean NLP, and an entertainment and subculture-focused emphasis on Japanese collections. By uncovering these patterns, we reveal practical strategies for enhancing dataset documentation, licensing clarity, and cross-lingual resource sharing, guiding more effective and culturally attuned LLM development in East Asia. We conclude by discussing best practices for future dataset curation and collaboration, aiming to strengthen resource development across all three languages.

1 Introduction

With the emergence of Large Language Models (LLMs) transforming the field of Natural Language Processing (NLP) (Kenton and Toutanova, 2019; Brown et al., 2020; Achiam et al., 2023), the importance of high-quality datasets in model development has become increasingly critical. For datasets to be valuable in this context, they must meet both

quantitative requirements (sufficient size and coverage) and qualitative standards (reliability and representativeness). While English-language resources have been extensively studied, the landscape of datasets for East Asian languages—particularly Chinese, Japanese, and Korean (CJK)—remains comparatively underexplored (Joshi et al., 2020; Bender, 2019). This gap is especially noteworthy given that these languages collectively serve over 1.6 billion speakers and originate from major hubs of technological innovation.

In recent years, platforms such as HuggingFace have emerged as central repositories for distributing and accessing NLP datasets, making these resources widely accessible while introducing new challenges in dataset discovery, quality assessment, and cross-lingual collaboration (Hugging Face, 2023; Lhoest et al., 2021). These challenges are particularly pronounced for CJK languages due to their unique linguistic features, distinct cultural contexts, and varying approaches to data sharing and documentation.

While CJK languages play an increasingly important role in global NLP research, several critical issues need to be addressed. First, there is a limited understanding of how dataset creation patterns differ across these language communities—and how those differences reflect their respective NLP ecosystems. Second, although cultural and institutional factors evidently influence dataset generation, their specific impacts on dataset characteristics and quality have yet to be systematically investigated. Third, the potential for cross-lingual synergies among CJK languages remains largely untapped, despite their many shared cultural and linguistic foundations. For instance, while benchmarks like MMLU (Hendrycks et al., 2020) are being generated in multiple languages, insufficient comparative analysis exists regarding how these variants differ from traditional parallel corpora or how download patterns across regions reflect dis-

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†Corresponding author.

tinct cultural preferences. To address these challenges, this study investigates the HuggingFace ecosystem for Chinese, Japanese, and Korean NLP resources, focusing on dataset development and usage patterns. The specific objectives of this work are to:

- Examine the current landscape of CJK datasets on HuggingFace, including key meta-data such as domain, dataset size, documentation practices, and usage statistics.
- Analyze the cultural characteristics and development patterns underlying dataset creation in each language community, highlighting commonalities and differences in curation and documentation.
- Identify potential synergies and cross-lingual opportunities among the three languages, and propose strategies for more effective, collaborative dataset development.

2 Related Work

Documentation efforts for CJK language resources have expanded over time. For Chinese, [Tao et al. \(2009\)](#) introduce systematic approaches for constructing and evaluating linguistic data resources, while [Li et al. \(2023a\)](#) compile a comprehensive repository emphasizing accessibility and classification frameworks. In the Korean context, [Cho et al. \(2020\)](#) survey existing NLP resources, and [Cho et al. \(2023\)](#) examine how local research cultures influence resource development. However, these studies largely predate large generative models and rely on GitHub as the primary hub, while systematic analyses of CJK datasets within newer ecosystems like HuggingFace remain rare.

Major multilingual projects including BigScience([Le Scao et al., 2023](#)), CC100([Wenzek et al., 2019](#)), and LAION([Schuhmann et al., 2022](#)) expand non-English data availability, yet don’t investigate cultural factors affecting dataset usage within communities. The movement toward improved dataset documentation([Geburu et al., 2021](#)) highlights ethical considerations, though adoption varies across languages and platforms.

HuggingFace has emerged as a central repository for NLP resources, but studies flag challenges including inconsistent documentation([Yang et al., 2024](#)), limited transparency([Pepe et al., 2024](#)), and ambiguous licensing. These issues underscore the

need to examine dataset curation in cultural contexts([Lhoest et al., 2021](#)). Recent work by [Dargis et al. \(2024\)](#) offers insights for building evaluation frameworks for languages with particular traits, yet no study comprehensively analyzes how CJK dataset ecosystems are shaped by local research cultures, licensing preferences, and community-driven development.

Building on these perspectives, our research provides the first large-scale, comparative analysis of CJK datasets within the HuggingFace ecosystem, investigating how cultural contexts and documentation standards influence dataset usage patterns and resource quality.

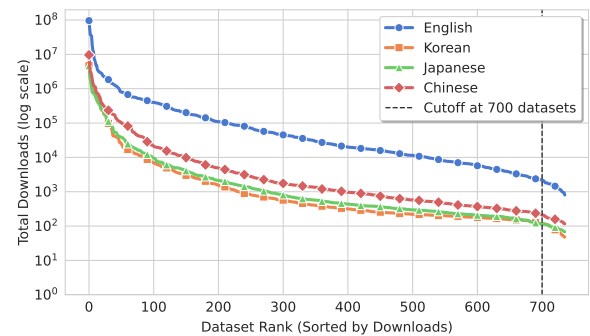


Figure 1: Datasets of each language sorted by number of downloads in descending order. Based on the decreasing pattern of downloads, we set the cutoff point at 700.

3 Method

3.1 Data Collection

We systematically collected dataset information from the HuggingFace platform using their Datasets API. Our data collection strategy focused on identifying actively used datasets for each target language (Chinese, Japanese, Korean, and English as a reference).

To determine a cutoff point for dataset inclusion, we analyzed the download frequency distribution for each language (Figure 1). The download counts follow a power-law distribution, with all languages showing consistent patterns. The distributions converge around the 700th dataset, where download counts fall below 100. Beyond this point, we observe minimal engagement and declining documentation quality. This natural boundary led us to set our cutoff at 700 datasets per language, ensuring both coverage and quality.

Datasets were retrieved from <https://huggingface.co/datasets> using language filters and download frequency sorting. All statistics were recorded on January 28, 2025.

Category	Evaluation Metrics
Scale & Composition	Dataset Size: Distribution across size categories (small, medium, large, extra-large) Language Makeup: Distribution of monolingual, English-paired, and multilingual datasets Task Types: Distribution of major NLP tasks (text generation, QA, classification, etc.)
Development Patterns	Ownership Structure: Proportions of corporate, institutional, and individual contributions License Types: Distribution of permissive, copyleft, unknown, and other licenses Community Activity: Dataset creation trends and instruction tuning development
Documentation Quality	Academic Validation: Presence of associated arXiv papers and research citations Documentation Standards: Adherence to HuggingFace dataset card templates Documentation Depth: Comprehensiveness of dataset descriptions and README files
Cultural Characteristics	Domain Focus: Specialized fields (e.g., medical, entertainment, content moderation) Resource Development: Approaches to dataset creation and curation Community Priorities: Language-specific preferences and development patterns

Table 1: Analysis framework for CJK datasets, organized by category.

For each dataset, we extracted metadata across four categories: **Scale & Composition** (dataset size, language combinations, task types, temporal patterns), **Development Patterns** (ownership, licensing, community metrics), **Documentation Quality** (dataset cards, citations, README files, metadata completeness), and **Cultural Characteristics** (domain focus, development approaches, community patterns).

In addition, we collected the complete dataset cards to analyze documentation practices and cultural characteristics in depth. We will release the full metadata and dataset card contents as a public resource upon publication.

3.2 Analysis Framework

Our analysis framework combines quantitative and qualitative approaches to examine CJK language datasets. Table 1 presents our analysis metrics across four main categories. For quantitative analysis, we focus on measuring dataset sizes, language distributions, task type proportions, ownership ratios, and documentation completeness. Our qualitative analysis examines domain preferences, resource development approaches, and community characteristics. This mixed-method approach helps us understand how dataset development patterns reflect each language community’s unique characteristics, particularly in terms of instruction tuning trends, domain preferences, and resource development strategies.

4 Results and Analysis

4.1 Overview of CJK Datasets

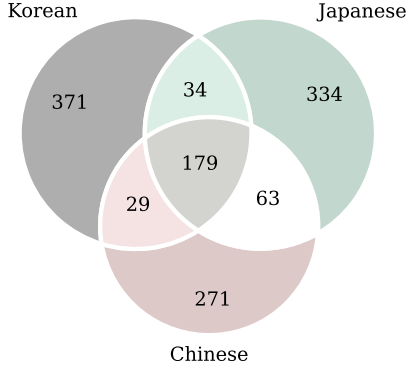
The stacked bar chart (Figure 2b) provides a view of the top 700 most downloaded datasets for each language, categorizing them into monolin-

gual, English-paired (bilingual with English), and multilingual (three or more languages) resources. In this broader analysis, Chinese datasets show the highest proportion of English-paired resources (148 datasets), notably higher than Korean (57) or Japanese (67), suggesting a greater emphasis on cross-lingual applications. The multilingual category shows substantial representation across all three languages, with similar proportions (Korean: 272, Japanese: 299, Chinese: 291), indicating active participation in multilingual resource development. While multilingual resources reflect diverse aspects of CJK datasets, we focus our subsequent analyses on *monolingual datasets* to better understand language-specific characteristics.

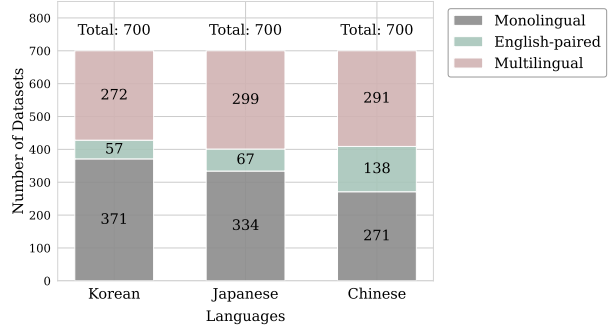
Dataset Size Distribution. Table 2 presents the size distribution of monolingual datasets across languages, categorized as Small (<10MB), Medium (10MB–100MB), Large (100MB–1GB), and Extra-Large (>1GB). Chinese datasets show a relatively balanced distribution across size categories, with a notable presence in large (10) and extra-large (12) categories. Japanese datasets demonstrate strong representation in small-scale resources (123) but notably lack extra-large datasets. Korean shows similar concentration in small datasets (137) and limited presence in medium and large categories, yet maintains a notable presence in the extra-large category (7). English datasets maintain the highest counts across all categories, providing a reference point for resource availability.

4.2 Comparative Characteristics of CJK Datasets

Task Distribution Figure 3 presents the distribution of task categories across languages through a



(a) Distribution of CJK Language Intersection



(b) Composition of Language Types in Datasets

Figure 2: Distribution and Composition Analysis of CJK Language Datasets. (a) Illustrates the intersections among CJK language datasets, showing unique and overlapping dataset counts. (b) Shows the composition of the top 700 downloaded datasets for each language, categorized into monolingual, English-paired, and multilingual resources.

Size	English	Chinese	Japanese	Korean
S (<10M)	258	144	123	137
M (10M–100M)	21	11	3	3
L (100M–1B)	14	10	4	3
XL (>1B)	22	12	-	7

Table 2: Dataset size distribution across languages.

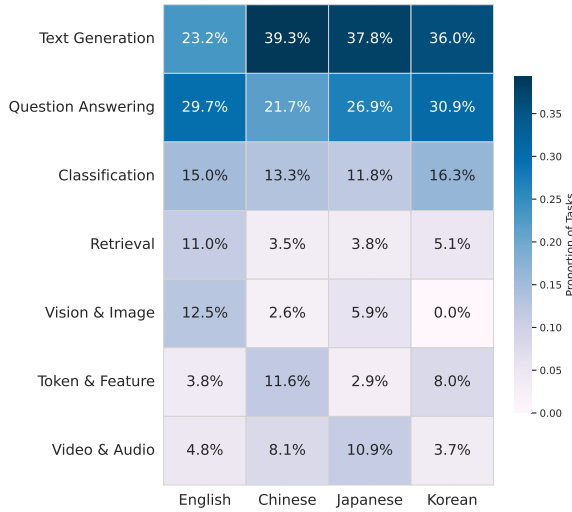


Figure 3: Task distribution across different languages. The heatmap illustrates the proportion of datasets belonging to the top 7 most frequent task categories across English, Chinese, Japanese, and Korean datasets.

heatmap visualization. *Text Generation* emerges as the dominant task across all languages, with particularly high proportions in Chinese (39.3%),

Task categories group related NLP tasks based on their functionality (e.g., Text Generation includes text-generation, language-modeling, fill-mask; Question Answering includes question-answering, multiple-choice, extractive-qa).

Japanese (37.8%), and Korean (36.0%) datasets compared to English (23.2%). *Question Answering* follows as the second most common task, with moderate variations: Korean (30.9%) and English (29.7%) show higher proportions than Chinese (21.7%) and Japanese (26.9%).

The analysis reveals distinctive task preferences across languages beyond these two categories. *Classification* tasks appear between 11.8% and 16.3% of datasets, with Korean (16.3%) having the highest ratio and Japanese (11.8%) the lowest. *Token & Feature* tasks are more prominent in Chinese (11.6%) and Korean (8.0%) than in English (3.8%) or Japanese (2.9%). *Video & Audio* tasks show varied representation, with Japanese leading at 10.9%, followed by Chinese (8.1%), English (4.8%), and Korean (3.7%). Lastly, *Vision & Image* tasks exhibit particularly striking differences: English leads at 12.5%, followed by Japanese (5.9%) and Chinese (2.6%), while Korean shows no representation (0.0%). *Retrieval* tasks also show notable variation, with English (11.0%) significantly ahead of other languages (3.5-5.1%).

These distinctive patterns reflect differing research priorities and technological needs across language communities. The Japanese emphasis on Video & Audio may correspond to its strong anime and entertainment industry, while Korean’s focus on Classification and Chinese’s on Token & Feature tasks suggest prioritization of fundamental NLP infrastructure development tailored to their respective linguistic complexities.

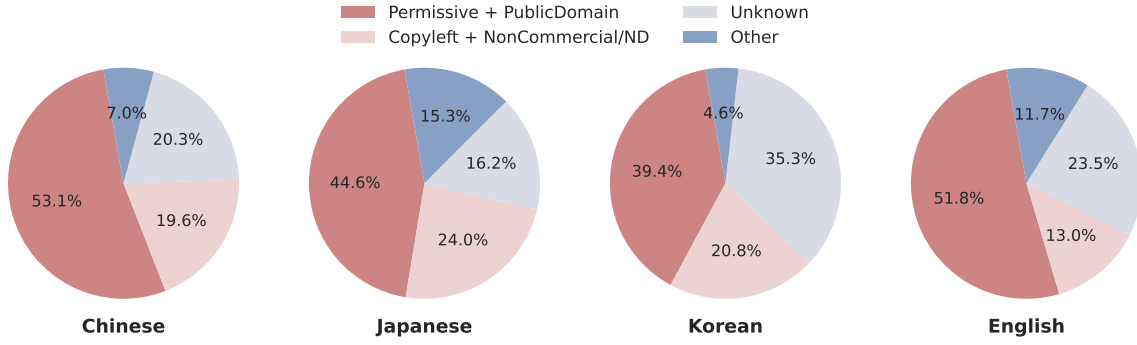


Figure 4: License distribution across CJK and English datasets, showing the proportion of *Permissive + PublicDomain*, *Copyright + NonCommercial/ND*, *Unknown*, and *Other* licenses for each language community.

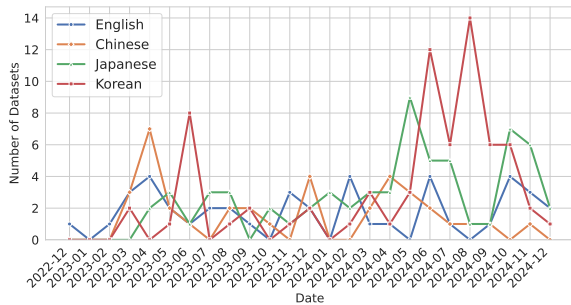


Figure 5: Instruction Datasets Over Time by Language (English and CJK), from late 2022 to 2024.

Evolution of Instruction Tuning Analysis of instruction-tuning datasets reveals distinct patterns across languages. Among the top 700 most downloaded datasets for each language, instruction-tuning datasets show notable presence: Korean (13.3%), Japanese (12.6%), Chinese (12.3%), and English (7.0%). This higher proportion in CJK languages compared to English suggests particularly active instruction-tuning development in these communities.

Analysis of temporal patterns (Figure 5) reveals distinct characteristics across languages. Chinese datasets show notable early activity in 2023, peaking around 7 releases. Korean datasets demonstrate dramatic fluctuations in 2024, reaching highest peaks of 12-14 releases mid-2024. Japanese datasets show moderate initial activity but increased activity during 2024, reaching peaks of 7-9 releases. English datasets maintain stable patterns throughout, typically with 1-4 releases monthly.

These patterns reflect different community approaches to instruction dataset development:

- **Chinese:** Early adoption with moderate peaks

We identify instruction datasets through ‘instruct’ keywords and common dataset names in metadata.

(around 7 releases) followed by decreased activity

- **Korean:** Shows the highest peaks (up to 14 releases) with considerable volatility
- **Japanese:** Late but substantial increase in development activity
- **English:** Consistent but moderate release patterns throughout

License Distribution Patterns Figure 4 shows how each language community approaches data licensing. Two major observations emerge. First, Chinese (53.1%) and English (51.8%) exhibit the highest proportions of *Permissive* or *Public Domain* licenses, indicating a shared culture of open access. Both also include moderate segments of *Unknown* (Chinese 20.3%, English 23.5%) and *Copyright/NonCommercial* (19.6% and 13.0% respectively), suggesting a balance between openness and controlled usage.

Second, Japanese (44.6%) and Korean (39.4%) have lower shares of *Permissive/Public Domain* compared to Chinese and English but differ substantially in other categories. Japanese devotes 24.0% to *Copyright/NonCommercial*—more than any other language—while also having a relatively high *Other* category (15.3%). In contrast, Korean stands out for its large *Unknown* portion (35.3%), underscoring possible gaps in documentation practices despite still having a notable *Copyright/NonCommercial* share (20.8%). Taken together,

Licenses were classified into five categories: *Permissive* (e.g., Apache, MIT, CC-BY), *Public Domain* (e.g., CC0, PDDL), *Copyright/ShareAlike* (e.g., GPL, CC-BY-SA), *Non-Commercial/ND* (CC-BY-NC, CC-BY-ND), and *Other*. For visualization, *Permissive* and *Public Domain* categories were combined, as were *Copyright/ShareAlike* and *Non-Commercial/ND*.

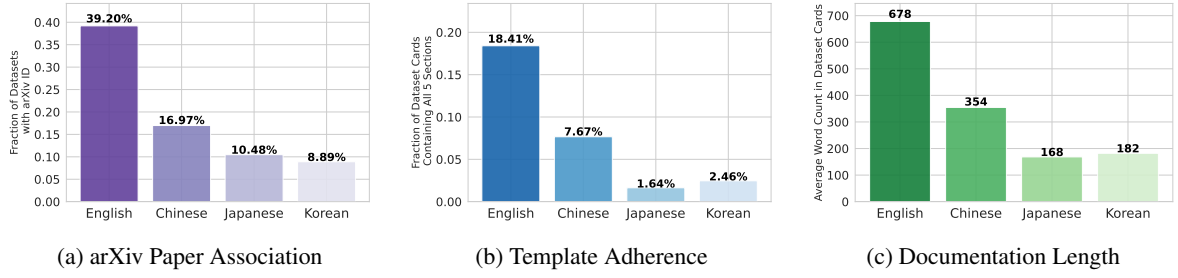


Figure 6: Comparison of Documentation Quality Across Languages. (a) Shows the percentage of datasets associated with academic publications, (b) presents the percentage of dataset cards containing all five structured sections, and (c) displays the average word count in dataset documentation.

these variations reflect distinct cultural, institutional, and legal factors influencing dataset license norms across CJK and English communities.

Documentation Quality Patterns Figure 6 illustrates three key metrics related to dataset documentation. For academic grounding, measured by the presence of associated arXiv papers, English datasets lead with 39.20%, followed by Chinese (16.97%), while Japanese (10.48%) and Korean (8.89%) trail behind. Regarding structural completeness, measured by the presence of all five recommended Hugging Face dataset card sections, English again leads (18.41%), with Chinese (7.67%), Japanese (1.64%), and Korean (2.46%) showing lower completeness. In terms of documentation depth, measured by average word count, English maintains the highest average (678 words), Chinese stands at 354, and Japanese and Korean remain lower at 168 and 182 respectively. Taken together, these figures indicate a consistent trend: English datasets demonstrate the most thorough and standardized documentation practices, Chinese resources show moderate completeness and Japanese and Korean documentation remains comparatively succinct or under-documented.

Dataset Ownership Patterns Figure 7 illustrates the proportions of datasets contributed by individual and community contributors, research institutes, and companies in the Korean, Chinese, and Japanese communities. Individual and community contributors dominate across all three languages: Korean datasets lead with 79.2%, followed by Japanese at 71.9% and Chinese at 61.6%. Research institutes play a stronger role in China (27.3%)

than in Korea (11.1%) or Japan (21.0%), suggesting more prominent institutional involvement in Chinese NLP resource development. Company contributions remain the smallest category across all three, though slightly higher in Chinese (11.1%) compared to Korean (9.7%) and Japanese (7.2%). This highlights the key role of grassroots efforts as primary drivers of dataset creation.

4.3 Language-Specific Characteristics

4.3.1 Chinese Dataset Ecosystem

Comprehensive Evaluation Frameworks Chinese NLP resources on Hugging Face frequently feature large-scale, well-structured evaluation suites. For example, *ceval/ceval-exam* (Huang et al., 2023) provides 13,948 multiple-choice questions across 52 domains, and *haonan-li/cmmlu* (Li et al., 2023b) covers 67 subject areas spanning elementary to advanced professional levels. These broad assessments facilitate detailed benchmarking of model performance across diverse knowledge domains.

Specialized Medical Domain Resources Chinese datasets also demonstrate significant depth in specialized fields. The *FreedomIntelligence/CM B* (Wang et al., 2023) collection features a hierarchical structure (6 main categories, 28 subcategories) spanning 11,200 medical questions, thus enabling targeted evaluations in clinical question-answering. Similarly, *TCMLM/TCM_Humanities* (Kang, 2024) focuses on Traditional Chinese Medicine, integrating resources from professional certification materials and historical texts.

Dialectal and Cultural Diversity In addition to specialized domains, Chinese datasets often emphasize linguistic diversity and cultural preservation. The *Nexdata/chinese_dialect* (Nexdata, 2025) corpus contains 25,000 hours of dialect

HuggingFace dataset card sections: *Description, Structure, Creation, Usage, and Additional Info*
Analysis limited to CJK datasets with verifiable institutional affiliations.

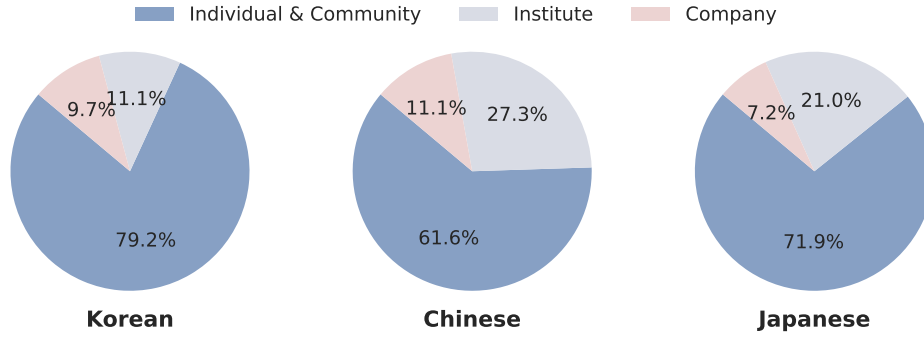


Figure 7: Dataset ownership across Korean, Chinese, and Japanese datasets, illustrating the proportions of individual and community contributors, research institutes, and companies.

speech data, facilitating fine-grained dialect modeling. Likewise, `raptorkwok/cantonese-traditional-chinese-parallel-corpus` ([raptorkwok, 2025](#)) offers over 130k aligned sentence pairs for Cantonese–Mandarin translation. Future efforts could enrich such dialectal resources by detailing speaker demographics, annotation workflows, and language-specific quirks—thereby promoting more equitable research coverage across China’s diverse linguistic communities.

4.3.2 Korean Dataset Ecosystem

Community-Driven Development and Its Impact Korean datasets on Hugging Face frequently emerge from grassroots, community-led efforts, rather than purely institutional or corporate projects. Prominent examples include contributions from open-source communities like HAERAE, which developed the widely-used HAERAE-HUB/KMMLU benchmark ([Son et al., 2024](#)), as well as individual developers such as `beomi`, `maywell`, and `taeminlee`, who have created highly-downloaded resources. Even widely-used benchmarks like `klue/klue` ([Park et al., 2021](#)) represent collaborative efforts between academia, industry, and individual researchers rather than single-entity projects. The broader ecosystem is dominated by individual and community contributors who account for 79.2% of Korean datasets. This community-driven approach has accelerated the proliferation of new resources but also contributed to inconsistencies in documentation and licensing. For instance, Korean has the highest proportion of “Unknown” licenses among CJK languages (35.3%), indicating gaps in legal clarity and potential challenges for commercial or cross-institutional usage. Moreover, only 8.89% of Korean datasets are linked to an arXiv publication—lower than both Chinese (16.97%)

and Japanese (10.48%). These factors may hinder collaborative research or reproducibility, underscoring the need for more standardized dataset cards ([Gebru et al., 2021](#)) and explicit licensing.

Content Moderation Focus A unique strength of the Korean dataset ecosystem is its emphasis on content moderation, encompassing hate-speech detection, toxicity filtering, and profanity masking. Popular resources such as `jeanlee/kmhas-korean-hate-speech` ([Lee et al., 2022](#)), `humane-lab/K-HATERS` ([Lab, 2025](#)) and `Dasool/KoMultiText` ([Choi et al., 2023](#)) reflect heightened community and research interest in combating harmful or discriminatory language online. However, these moderation-oriented resources raise broader ethical and regulatory questions, such as defining thresholds for *hate speech* or handling user privacy. Although the Hugging Face platform provides general community guidelines, more detailed policies—particularly for age-restricted or sensitive data—would help standardize safe usage of these potentially sensitive resources.

4.3.3 Japanese Dataset Ecosystem

Strong focus on subcultural content Japanese NLP datasets often integrate subcultural or entertainment-related material, an approach that distinguishes them from other CJK resources. For instance, `joujiboi/japanese-anime-speech` ([joujiboi, 2024](#)) targets automatic speech recognition in anime content, attracting high download counts and demonstrating direct utility for real-world applications such as subtitle generation. Additionally, `YANS-official/ogiri-test-with-references` ([YANS-official, 2023](#)) captures the distinctive *Ogiri* comedy tradition, illustrating

As of January 2025, based on Hugging Face’s publicly available platform policies and community guidelines.

Japan’s unique comedy culture through multimodal data (text and images). While such resources enrich models’ ability to handle colloquial or creative contexts, they also require careful documentation of stylistic nuances and potential copyright constraints. Many subcultural datasets involve fan works or licensed content, which often preclude fully open licenses. Researchers must therefore verify these constraints to avoid unintended usage restrictions or downstream complications.

Diverse Methods in Dataset Processing and Refinement Japanese datasets exhibit a reliance on translation-based pipelines and synthetic data generation rather than building new corpora from scratch. For example, the Magpie series (Xu et al., 2024) has been adapted into multiple Japanese resources—e.g., Aratako/Synthetic-JP-EN-Translation-Dataset-Magpie-Nemotron-4-20k and Aratako/Magpie-Tanuki-8B-annotated-96k (Aratako, 2024b,a)—highlighting how translations and AI-generated text can expand training data. While these strategies improve dataset availability, they raise concerns about translation errors, cultural misalignment, and potential biases introduced by synthetic text. Efforts such as neody/oscar-ja-cleaned (neody, 2023) and saillabalpaca-japanese-cleaned (Upadhayay and Behzadan, 2024) illustrate attempts to mitigate these issues through dataset cleaning and quality control. Systematic documentation of translation processes and validation protocols would help researchers assess dataset reliability. This localization approach may serve as a model for other languages seeking rapid resource expansion.

5 Discussion

Our analysis reveals distinct characteristics across CJK dataset ecosystems: Chinese datasets show strong institutional backing but inconsistent documentation; Korean datasets demonstrate community-driven development but face licensing gaps; and Japanese datasets emphasize subcultural content while dealing with copyright constraints.

Three practical issues warrant attention. First, licensing diversity (particularly "Unknown" licenses in Korean datasets and restricted licenses in Japanese resources) complicates collaborative projects. More consistent adherence to guidelines like "Datasheets for Datasets" (Geburu et al., 2021) could enhance reusability. Second, domain clustering (medical for Chinese, subcultural for Japanese,

and moderation for Korean) may underserve other areas needed for general-purpose LLM development. Third, culturally specific content requires transparent documentation, as simple translations miss nuanced cultural meanings.

Despite these differences, strong synergy potential exists. Joint benchmarks could facilitate cross-lingual comparisons, while unified documentation frameworks could standardize metadata and licensing. Our findings underscore both the richness and fragmentation of CJK resources, suggesting that clearer practices and cross-lingual collaboration can foster a robust ecosystem for East Asian LLM development.

6 Limitations

Our analysis primarily focused on datasets with relatively high download counts, which may have led us to overlook smaller or emerging resources that could shed light on niche trends or specialized applications. Furthermore, we limited our scope to the Hugging Face platform; investigating additional repositories (e.g., GitHub, Kaggle, or Papers with Code) could reveal a broader range of dataset characteristics and host factors. Although we manually requested permission to access certain private or restricted datasets, some ultimately remained inaccessible, thereby constraining the representativeness of our findings.

In addition, while Korean and Japanese datasets were examined with input from language experts, our review of Chinese data relied solely on documentation, potentially affecting the depth of our analysis. Finally, we chose to focus on three major East Asian languages, excluding many low-resource languages and dialects, whose inclusion could further expand and enrich our findings.

7 Conclusion

This study presents a comparative analysis of over 3,300 Chinese, Japanese, and Korean datasets on HuggingFace, revealing distinct ecosystem characteristics—Chinese datasets show strong institutional involvement, Korean resources are community-driven, and Japanese datasets emphasize subcultural content—highlighting that documentation, licensing, and ownership must be addressed in cultural context to guide inclusive East Asian language technologies.

Acknowledgements

This research was supported by Brian Impact, a non-profit organization dedicated to advancing science and technology.

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Cross-Document Cross-Lingual NLI via RST-Enhanced Graph Fusion and Interpretability Prediction

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Abstract

Natural Language Inference (NLI) is a fundamental task in natural language processing. While NLI has developed many subdirections such as sentence-level NLI, document-level NLI and cross-lingual NLI, Cross-Document Cross-Lingual NLI (CDCL-NLI) remains largely unexplored. In this paper, we propose a novel paradigm: CDCL-NLI, which extends traditional NLI capabilities to multi-document, multilingual scenarios. To support this task, we construct a high-quality CDCL-NLI dataset including 25,410 instances and spanning 26 languages. To address the limitations of previous methods on CDCL-NLI task, we further propose an innovative method that integrates RST-enhanced graph fusion with interpretability-aware prediction. Our approach leverages RST (Rhetorical Structure Theory) within heterogeneous graph neural networks for cross-document context modeling, and employs a structure-aware semantic alignment based on lexical chains for cross-lingual understanding. For NLI interpretability, we develop an EDU (Elementary Discourse Unit)-level attribution framework that produces extractive explanations. Extensive experiments demonstrate our approach’s superior performance, achieving significant improvements over both conventional NLI models as well as large language models. Our work sheds light on the study of NLI and will bring research interest on cross-document cross-lingual context understanding, hallucination elimination and interpretability inference. Our code and dataset are available at [CDCL-NLI-link](#).

1 Introduction

Natural Language Inference (NLI) is a fundamental task in natural language processing, aiming to determine the logical relationship between the

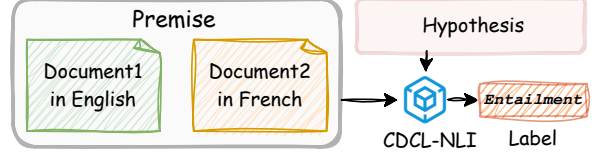


Figure 1: A CDCL-NLI example. Premise in **English** and **French**. The Entailment label requires combining information from both documents in premise.

Paradigm	Premise	Hypothesis	Language
Sentence-NLI	Sentence	Sentence	Mono/Multi
Document-NLI	Doc	Sent/Doc	Mono
CDCL-NLI	Multi Doc	Sentence	Multi

Table 1: Comparison of different NLI paradigms.

given premise and hypothesis pair (Dagan et al., 2005; MacCartney and Manning, 2009). While traditional NLI tasks primarily deal with single-language, short-text validations (Rodrigo et al., 2007), document-level NLI (Yin et al., 2021) expands the scope of NLI to longer contexts.

Table 1 compares different NLI paradigms systematically, highlighting the progressive evolution of NLI tasks. Sentence-NLI involves low-complexity reasoning on short sentence pairs, evolves from single-language approaches (Bowman et al., 2015; Herlihy and Rudinger, 2021) to multilingual settings (Conneau et al., 2018; Heredia et al., 2024), and is mainly used for fact verification (Wadden et al., 2020; Klemen et al., 2024). Document-level NLI extends NLI to reasoning over full-length documents within a single language (Wang et al., 2019; Yin et al., 2021), focusing on content comprehension (Yang et al., 2024).

However, the increasing globalization of information flow requires even more sophisticated inference capabilities across both language and document boundaries. In this paper, we introduce **Cross-Document Cross-Lingual Natural Language**

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Inference (CDCL-NLI), a novel paradigm extending traditional NLI to multi-document and multilingual settings. Figure 1 illustrates that CDCL-NLI jointly reasons over premise documents in English and French to verify the hypothesis. The correct Entailment prediction relies on integrating complementary information from both documents.

While CDCL-NLI addresses a real-world task with broad applications, it faces key challenges: **1) Lack of existing datasets**, which necessitates the construction of new resources to support research. **2) Multilingual Semantic Alignment**, requiring resolution of grammatical and conceptual differences across languages while preserving semantic consistency (Conneau et al., 2020). **3) Cross-Document Structure Alignment**, essential for capturing structural correspondences and implicit logical relations between documents of varying complexity (Wang et al., 2021); and **4) Interpretability**, demanding transparent reasoning processes and verifiable confidence in inference outcomes (Bereska and Gavves, 2024).

To address the first challenge, we curated a **CDCL-NLI dataset** through collecting diverse premise documents from GlobeSumm (Ye et al., 2024), generating hypotheses with GPT-4o (OpenAI, 2024) using customized prompts to ensure label diversity and balance and manually reviewing hypotheses and annotated explanations. The dataset contains 25,410 samples spanning 26 languages and 370 events.

To address the rest challenges, we proposed a novel method that comprises three key components. **1) Graph Construction Module:** This component promotes semantic alignment by fusing graphs based on lexical chains, effectively linking semantically related concepts across documents. **2) Graph Representation Module:** Utilizing an RST-enhanced Relation-aware Graph Attention Network (RGAT) (Mann and Thompson, 1988; Busbridge et al., 2019), this module supports structure alignment by capturing hierarchical discourse structures and cross-document dependencies through multi-head attention mechanisms. **3) Interpretability Attribution Module:** Leveraging Elementary Discourse Units (EDUs) (Mann and Thompson, 1988), this module generates extractive explanations that significantly enhance model interpretability and provide transparent insights into its decision-making process.

Extensive experiments on the CDCL-NLI and DocNLI datasets demonstrate that our method out-

performs conventional NLI approaches and three state-of-the-art large language models, surpassing the strongest baseline by 3.5% on our dataset. In the end, we highlight our main contributions as follows:

- We propose CDCL-NLI as a new task and construct a corresponding dataset covering 26 languages with 25,410 high-quality manually-annotated instances.
- We propose a novel method that leverages RST-enhanced graph fusion to align semantic concepts and discourse structures. The approach also enhances interpretability by generating extractive, EDU-level explanations.
- We conduct extensive experiments demonstrating our method’s effectiveness, outperforming all baselines by at least 3.5% and establishing a new benchmark for the CDCL-NLI task.

2 Related Work

2.1 Sentence-level NLI

Monolingual Methods. Sentence-level NLI benchmarks like SNLI (Bowman et al., 2015) and MultiNLI (Williams et al., 2018) have driven model evolution from ESIM (Chen et al., 2017) to transformer architectures (Devlin et al., 2018; Liu et al., 2019) and recent LLMs (OpenAI, 2023).

Cross-lingual Methods. Cross-lingual NLI relies on datasets like XNLI (Conneau et al., 2018) (15 languages) and XNLIeu (Heredia et al., 2024) (European languages). Multilingual models such as XLM-R (Conneau et al., 2020) and XLM-E (Chi et al., 2022) enable zero-shot transfer, while alignment methods like SoftMV (Hu et al., 2023) and prompt-based MPT (Qiu et al., 2024) improve cross-lingual semantic understanding.

Interpretability Mechanisms. Interpretability uses feature attribution methods like Integrated Gradients (Sundararajan et al., 2017) and (Huang et al., 2024) to highlight decision-driving features. Datasets such as e-SNLI (Camburu et al., 2018) provide human explanations, supporting explicit reasoning and interpretability benchmarks.

2.2 Document-level NLI

Datasets and Benchmarks. Document-level NLI benefits from datasets like DocNLI (Yin et al., 2021) with over one million instances. Domain-specific datasets such as ContractNLI (Koreeda and

Manning, 2021) focus on the challenges posed by long documents and specialized text genres.

Inference Methods. Recent approaches emphasize discourse structure and long-range dependencies (Chen et al., 2025). R2F (Wang et al., 2022) introduces explicit reasoning extraction, and DocInfer (Mathur et al., 2022) uses hierarchical encoding to model document structure, highlighting the need to capture document-level semantics.

Interpretability Mechanisms. Interpretability research focuses on evidence extraction and explanation generation. Systems like EvidenceNet (Chen et al., 2022) and R2F (Wang et al., 2022) automatically identify evidence to enhance reasoning transparency. LLM-based approaches like Chain-of-Thought (Wei et al., 2022) and Rethinking (Singh et al., 2024) further enable self-explanatory reasoning capabilities.

2.3 Graph-based Reasoning for NLI

Leveraging graph structures for semantic reasoning has emerged as a powerful paradigm. Discourse-aware graph networks model logical relationships within text for tasks like logical reasoning (Hou et al., 2022; Galitsky and Ilvovsky, 2025). Similarly, AMR-based graph reasoning uses Abstract Meaning Representation (AMR) to enhance question answering by providing a structured semantic representation (Huang and Zhang, 2025). Furthermore, prior work on graph merging and fusion has explored combining structures like AMR, RST, and CST for tasks such as multi-document summarization and inference (Banarescu et al., 2018; Liao et al., 2021; Shi et al., 2024).

Although prior studies have advanced sentence-level and document-level NLI, and graph-based methods have been applied to various reasoning tasks, the challenges in cross-document and cross-lingual NLI remain largely unaddressed. Our work fills this gap by introducing the CDCL-NLI dataset and proposing a systematic integration of an interpretable RST-enhanced graph fusion method to tackle these unique complexities.

3 CDCL-NLI Task Formulation and Dataset Construction

As shown in Figure 2, our CDCL-NLI dataset is constructed through a systematic pipeline involving stratified random sampling of premise documents across all topics, LLM-generated hypotheses, and

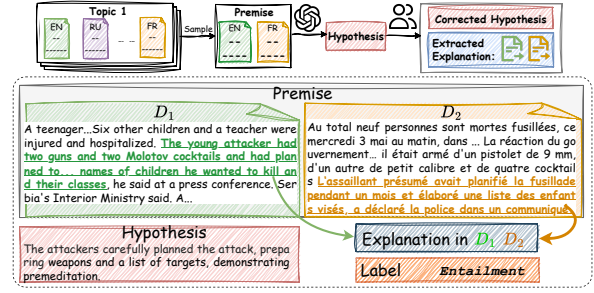


Figure 2: Overview of the CDCL-NLI dataset construction process and a data example. Premise contains D_1 and D_2 . Explanation is extracted from premise to enhance interpretability. Human annotation is based on language translated into English.

human verification to ensure data quality. In the dashed box, the figure shows a CDCL-NLI instance with a premise of two documents in different languages, an English hypothesis, a label, and EDU-based explanations for interpretability.

3.1 Task Formulation

Similar to the traditional NLI task, the goal of CDCL-NLI is to determine the inference label:

$$Label \in \{ "Entailment", "Neutral", "Contradiction" \},$$

between a given premise P and hypothesis H . Specifically, the premise P consists of two documents D_1 and D_2 , written in different languages but discussing the same topic. The hypothesis H is a sentence-level statement. The task requires reasoning over the combined information from P with H to determine their entailment relationship, involving both cross-document and cross-lingual premise integration.

3.2 Premise Data Collection

We collect our premises from GlobeSumm (Ye et al., 2024), a multi-document cross-lingual summarization dataset covering 370 topics across 26 languages. In GlobeSumm, documents for each topic span diverse media outlets, publication times, and languages, providing a rich foundation for cross-document and cross-lingual inference tasks. We curated CDCL-NLI dataset by stratified randomly selecting documents for each topic to form premise pairs. To enhance cross-lingual coverage, we strategically expanded our document collection through translation. **To address the cross-lingual aspect of the task, we used the DeepL API to translate the original English documents from

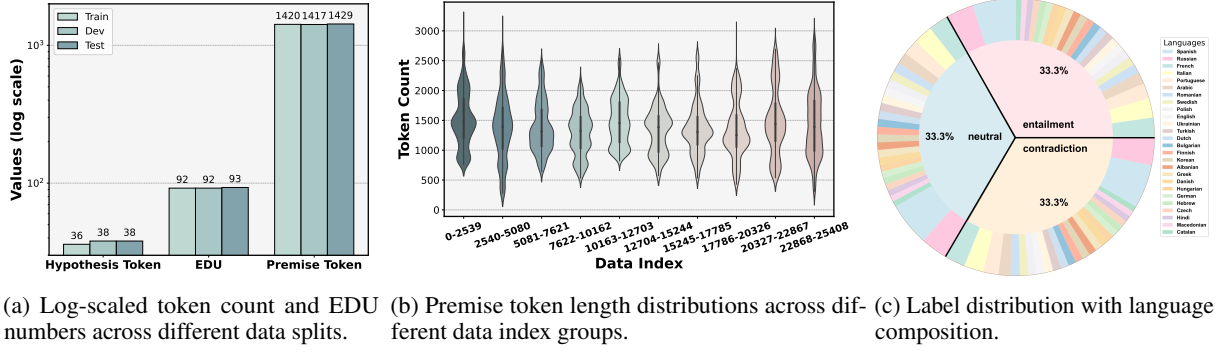


Figure 3: Statistic visualization of token length, EDU numbers, label distribution and language composition.

GlobeSumm into 25 target languages. This translation process ensures consistent, high-quality multilingual premises.** After rigorous quality filtering, our final dataset consists of high-quality inference instances covering 26 languages. Detailed premise establishment criteria and quality filtering standards are provided in Appendix A.1.

3.3 Hypothesis Generation and Label Specification

For each pair, we generate hypotheses across three NLI categories. Initial hypotheses are generated by GPT-4o (OpenAI, 2024) following specific guidelines (Wang et al., 2024) to ensure balanced label distribution and sufficient reasoning depth. Entailment hypotheses require joint or consistent support from the premise documents. Neutral hypotheses are plausible but neither supported nor contradicted. Contradiction hypotheses explicitly conflict, focusing on cross-document inconsistencies. To reduce hallucination, GPT-4o first generates explanations before finalizing hypotheses. Detailed prompts and protocols are included in Appendix A.2.

3.4 Manual Annotation and Quality Control

Our annotation involved two phases: hypothesis verification and EDU-based explanation (Figure 2). All human annotation was conducted on the original English versions of the premises and hypotheses. This design choice ensures that annotators did not require multilingual capabilities, and it minimizes the language gap during the critical verification process. To assess inter-annotator agreement, we randomly divided our training data into three equal parts. Each part was independently annotated by two of our three graduate students. This setup allowed us to calculate Cohen’s κ for each of the three annotator pairs, yielding an average κ of 0.71 across these pairs, which indicates strong

Dataset	CD	CL	Interp.	Avg.Tks	Labels
MultiNLI	×	×	×	33.7	3
XNLI	×	✓	×	50	3
e-SNLI	×	×	✓	45.1	3
DocNLI	✓	×	×	412	2
CDCL-NLI	✓	✓	✓	1,456	3

Table 2: Characteristics of NLI datasets showing cross-document (CD), cross-lingual (CL), and interpretability (Interp.) capabilities, along with average tokens per instance (Avg.Tks) and number of label classes.

agreement. For explanations, annotators selected minimal EDU sets supporting their decisions, with high agreement (Jaccard: 0.91; span overlap: 0.94; conclusion: 1.00). All annotations were reconciled through discussions to ensure quality (see Appendix A.3). The final dataset contains multilingual premise-hypothesis pairs, NLI labels, and EDU node indices for explanation, with clear meta-data indicating the source of each document.

3.5 Dataset Statistics

We summarize the key characteristics of different NLI datasets in Table 2, which shows substantial variations in their cross-document and cross-lingual capabilities. Our CDCL-NLI dataset consists of 25,410 cross-document, cross-lingual NLI instances spanning 26 languages and 370 events. We partitioned the dataset by event topics, yielding 22,200/1,605/1,605 train/dev/test instances with mutually exclusive event distributions. Figure 3a shows similar data characteristics across training, validation, and test sets; Figure 3b depicts token count variations across consecutive segments; and Figure 3c illustrates balanced label distributions (33.3% each) with roughly uniform language distribution within each label. We provide more information about our dataset in Appendix A.4.

4 Our Method: RST-enhanced Graph Fusion with EDU Level Interpretability

Our approach offers a robust solution for cross-document and cross-lingual NLI by leveraging RST-enhanced graph fusion and explanation prediction. As illustrated in Figure 4, the framework comprises three main components: RST graph construction and fusion module, graph representation generation module and interpretability and classification module.

We employ DM-RST (Liu et al., 2021) parser for discourse modeling as it offers an optimal balance between structural richness and computational feasibility. Compared to the locally-focused PDTB (Prasad et al., 2008), RST’s hierarchical structure effectively captures document-level organization essential for cross-document reasoning. While SDRT (Asher and Lascarides, 2003) is semantically richer, its $O(n^3)$ complexity is prohibitive for large-scale tasks. Our ablation study (Table 3) empirically validates the effectiveness of our RST parser, showing that including the RST graph module can significantly improve performance despite potential parsing errors.

4.1 RST Graph Construction and Fusion

RST Information Extraction. We employ DM-RST (Liu et al., 2021), a top-down multilingual document-level rhetorical structure parsing framework, to extract RST information from the premise documents. As shown in Figure 5, DM-RST generates two key features for document D : 1) EDU boundary indices and 2) RST tree parsing outputs. By processing these features, we get $D = \{EDU_1, EDU_2, \dots, EDU_n\}$ and rhetorical structure tree \mathcal{T} . EDU_i represents the i -th EDU’s textual content. \mathcal{T} is formally defined as:

$$\mathcal{T} = \left\{ (EDU_{[s \rightarrow t]}, EDU_{[t+1 \rightarrow u]}, r_{st}, r_{tu}) \mid \begin{array}{l} s, t, u \in [1, n], s \leq t < u, \\ r_{st}, r_{tu} \in \mathcal{R} \end{array} \right\},$$

where $EDU_{[s \rightarrow t]}$ denotes an EDU group that forms either a leaf node (when $s = t$) or a branch node (when $s < t$), and r_{st} represents the rhetorical relation. This tree structure captures both local EDU relationships and global discourse organization.

Embedding Model. To handle inconsistent cross-lingual encoding from premise documents in different languages, we use XLM-RoBERTa-Large (Conneau et al., 2020) as the base encoder, which supports over 100 languages and excels at

multilingual semantic representation. For each EDU_i in the RST structure, its initial vector is $\mathbf{h}_{EDU_i} = \phi(EDU_i) \in \mathbb{R}^d$, where ϕ denotes XLM-RoBERTa-Large and $d = 1024$. The hypothesis vector \mathbf{h}_{hypo} is computed similarly.

Single Graph Construction. Based on the RST tree \mathcal{T} , we construct graphs G_{D_1} and G_{D_2} for each document D_1 and D_2 respectively as shown in Figure 4. For graph $G(V, E, R)$, we define:

- **Node Set** $\mathcal{V} = \{v_i \mid EDU_{[s \rightarrow t]} \in \mathcal{T}\}$, where each v_i has features: Text_{v_i} , ϕ_{v_i} , and Type_{v_i} (e.g., nucleus or satellite).
- **Edge Set** $\mathcal{E} = \{(v_i, v_j) \mid v_i \neq v_j, (v_i, v_j, r) \in \mathcal{T}\}$, representing typed, bidirectional edges with rhetorical relations.
- **Relation Set** \mathcal{R} is from rhetorical relations in \mathcal{T} . For detailed relations and definitions of node features, please refer to the Appendix B.1, B.2.

Graph Fusion. After obtaining heterogeneous graphs $G_{D_1}(V_{D_1}, E_{D_1}, R)$ and $G_{D_2}(V_{D_2}, E_{D_2}, R)$ for the premise, we then merge them via lexical chains to enhance cross-document reasoning by:

- **Node Feature Fusion:** $V_P = V_{D_1} \cup V_{D_2}$, retaining all nodes and features.
- **Cross-document Edge:** Add bidirectional lexical edges between $v_i \in V_{D_1}$ and $v_j \in V_{D_2}$ if $\text{CosineSim}(v_i, v_j) > \delta$, and obtain E_P .¹
- **Adding Edge Types:** Extend R with a new "Lexical" relation R' to support lexical alignment.

The merged graph $G_P(V_P, E_P, R')$ preserves individual features while aligning semantics across documents, effectively supporting CDCL-NLI.

4.2 Graph Representation Generation

Node-level Representation. As shown in Figure 4, there are two layers of *RST-GAT* to process nodes’ features. *RST-GAT* builds upon the Relation-aware Graph Attention Network (RGAT) (Busbridge et al., 2019), which extends Graph Attention Network (GAT) (Velickovic et al., 2018) to handle relation-specific edge types in graphs.

Taking a graph $G(V, E, R)$ as an example, the initial node embeddings \mathbf{h}_V^0 are obtained as described in Section 4.1. Node representations are then updated through two layers of relation-aware multi-head attention as follows:

$$\mathbf{h}_{v_i}^{(l)} = \frac{1}{|R|} \sum_{r \in R} \alpha_r \cdot \frac{1}{K} \sum_{k=1}^K \sum_{v_j \in \mathcal{N}_r(v_i)} \beta_{ij,k}^{r,(l)} \mathbf{W}_{r,k} \mathbf{h}_{v_j}^{(l-1)} \quad (1)$$

¹Threshold δ is chosen empirically; see Appendix B.3 for detailed justification.

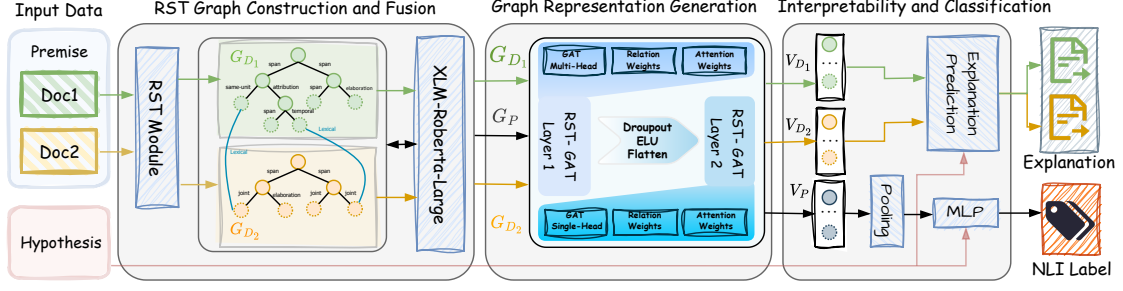


Figure 4: Our CDCL-NLI framework processes premise documents (D_1, D_2) and a hypothesis through a multi-stage process: 1) **RST Graph Construction**, where an RST parser generates initial discourse structures (G_{D_1} and G_{D_2}) which are then fused into a single premise graph (G_P) using semantic edges derived from XLM-RoBERTa embeddings; 2) **Graph Representation**, where the fused graph is processed by *RST-GAT* layers; and 3) **Interpretability and Classification**, which extracts node-level explanations and uses the graph representations (\mathbf{h}_{G_P}) and hypothesis representation (\mathbf{h}_{hypo}) to predict the final NLI label.

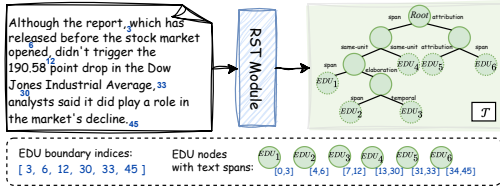


Figure 5: RST graph construction. The RST module first segments text into EDUs (EDU₁-EDU₆), with boundaries in blue, and then organizes an RST tree \mathcal{T} showing discourse relations.

where $l = 1, 2$. Here, α_r denotes the softmax-normalized weight of relation r , capturing the relative importance among relations, while $\beta_{ij,k}^{r,(l)}$ represents the attention coefficient over neighboring nodes, indexed by node pairs (v_i, v_j) , attention head k , relation r , and layer l . After two layers of message passing, the resulting node embeddings are denoted as $\mathbf{h}_V = \{\mathbf{h}_{v_i}^{(2)}\}$. The same update procedure is applied independently to G_{D_1} , G_{D_2} , and G_P , producing embeddings $\mathbf{h}_{V_{D_1}}$, $\mathbf{h}_{V_{D_2}}$, and \mathbf{h}_{V_P} , respectively. Detailed formulations of the attention weights and parameter configurations are provided in Appendix B.4.

Graph-level Representation. The global representation (\mathbf{h}_{G_P}) of the merged graph G_P is obtained by averaging node features after two *RST-GAT* layers. This pooling captures discourse-level semantics while preserving local rhetorical relations, enabling effective classification.

Classification Loss. Given the concatenated graph representation \mathbf{h}_{G_P} and hypothesis features

\mathbf{h}_{hypo} , the classification loss is computed using the standard cross-entropy (CE) formulation:

$$\mathcal{L}_{cls} = \text{CE}(\mathbf{y}, \text{Softmax}(\text{MLP}(\mathbf{h}_{G_P} \oplus \mathbf{h}_{hypo})) \in \mathbb{R}^3), \quad (2)$$

where \mathbf{y} denotes the ground-truth label and \mathbf{p} denotes the predicted probability distribution.

Enhanced Triplet Loss. Triplet loss (Weinberger and Saul, 2006; Schroff et al., 2015) is a metric learning method that encourages the anchor-positive distance to be smaller than the anchor-negative distance. Leveraging the structure of our CDCL-NLI dataset, where each premise aligns with three hypotheses (entailment, neutral, contradiction), we propose a neutral-constrained triplet loss:

$$\mathcal{L}_{\text{triplet}} = \max(0, d(a, p) - d(a, n) + \sigma) + \max(0, d(a, \text{neu}) - d(a, n) + \theta), \quad (3)$$

where $d(x, y)$ is the Euclidean distance, and a, p, neu, n denote the premise paired with entailment, neutral, and contradiction hypotheses, respectively. Margins σ and θ enforce the semantic order: entailment $<$ neutral $<$ contradiction.

4.3 EDU-level Explanation Prediction

For interpretability, we propose an attention-based method to extract explanation nodes.

Node Importance. Using multi-head attention weights from the first *RST-GAT* layer, the importance score I_i of node v_i in G_{D_1}, G_{D_2} is

$$I_i = \frac{1}{K} \sum_{k=1}^K \sum_{r \in R} \sum_{v_j \in \mathcal{N}_r^{\text{in}}(v_i)} \beta_{ji,k}^{r,(1)}. \quad (4)$$

Let $\mathbf{H} = [\mathbf{h}_{v_0}; \dots; \mathbf{h}_{v_n}]$ be node features and $\mathbf{I} = [I_0, \dots, I_n]^\top$ importance scores. Weighted

features are $H' = I \odot H$, where \odot denotes element-wise product with broadcasting.

Hypothesis-aware Interaction. Given hypothesis embedding $h_{hypo} \in \mathbb{R}^{d^{out}}$, attention over weighted features $H' \in \mathbb{R}^{n \times d^{out}}$ produces interaction features:

$$O = \text{Attention} \left(\frac{h_{hypo} H'^T}{\sqrt{d^{out}}} \right) H'. \quad (5)$$

Feature Fusion and Classification. The model is optimized by Binary Cross-Entropy (BCE) loss:

$$\mathcal{L}_{exp} = \frac{1}{N} \sum_{i=1}^N \text{BCE}(y_i, \text{Sigmoid}(\text{MLP}([h'_i \oplus o_i]))) \quad (6)$$

where $y_i \in \{0, 1\}$ is ground truth label of node i , h'_i and o_i are the weighted and interaction features for node i respectively.

The total loss combines all components:

$$\mathcal{L}_{total} = \gamma \mathcal{L}_{exp} + \lambda (\mathcal{L}_{cls} + \mathcal{L}_{triplet}), \quad (7)$$

where γ and λ are balancing hyperparameters set as 0.2 and 0.8 respectively through grid search on the validation set.

5 Experiments

5.1 Experiment Settings

Metrics. Model evaluation considers classification and explanation quality. For classification on DocNLI (imbalanced), we report **Micro F1** and **Weighted F1**. On CDCL-NLI dataset, we use **Macro Precision**, **Macro Recall**, and **Macro F1** for balanced class performance. Explanation quality is assessed using **BLEU** (1-4), **ROUGE-1/2/L**, and **METEOR**.

Baselines.

- **Conventional NLI Models:** We compare two well-established models, both trained on our dataset: **DocNLI** (Yin et al., 2021), a document-level NLI model tailored for long texts, and **R2F** (Wang et al., 2022), a retrieval-based framework for document-level NLI. All conventional baselines and our proposed method are built upon the same underlying pretrained language model to ensure fair comparison. Training details are provided in Appendix C.1.
- **Large Language Models:** We evaluate three LLMs: **Llama3-8B-Instruct** (Meta AI, 2024), **Qwen-3-8B** (Qwen, 2025) and **GPT-4o** (OpenAI, 2024), where the LLaMA and Qwen model is further fine-tuned with LoRA adapters. All models are tested in a few-shot setting, with fine-tuning configurations in Appendix C.2.

5.2 Experiment Results and Analysis

Main Results and Ablation Study. Table 3 presents a performance comparison of our proposed method against several competitive baselines on two test sets. TestSet1 is a cross-lingual test set (the original test set of the CDCL-NLI dataset). TestSet2 is an English-translated version of TestSet1, designed to evaluate model robustness in a cross-document scenario without language barriers, and to quantify the performance degradation caused by cross-lingual factors. This dual evaluation framework enables a clearer analysis of the impact of language variation on NLI performance.²

Our model consistently achieves the best results on both test sets, with macro F1 scores of **68.95%** on the cross-lingual set and **70.68%** on the English-translated set, surpassing strong baselines such as DocNLI and R2F by notable margins. The generally higher scores on the English test set highlight the relative ease of reasoning within a single, well-resourced language, in contrast to the added challenges of cross-lingual understanding, which requires effective language transfer and alignment. The hypothesis-only baseline, which trains solely on the hypothesis, attains near-random performance (36% F1), indicating minimal dataset artifacts in the hypothesis statements.

Among the large language models evaluated in the few-shot setting, Qwen3-8B achieves the best performance, with F1 scores of 59.86% on the cross-lingual set and 67.34% on the English set, outperforming both GPT-4o and Llama3-8B. Nevertheless, our approach surpasses Qwen3-8B by 9.09% on the cross-lingual set and 3.34% on the English set, highlighting the effectiveness of our method. Detailed prompts and zero-shot results and reported in Appendix D.1, Appendix D.2.

The ablation study highlights the importance of each component: removing the explanation module (- Exp) results in a moderate performance drop of 1.89% on both cross-lingual and English test sets; removing the graph module (- Graph) causes a more pronounced decline of 17.58% and 8.97%, respectively. When both components are removed (- Exp & Graph), performance sharply decreases on both test sets, demonstrating that these modules jointly contribute to the model’s robustness under different language conditions.

²Unless noted, all reported test results refer to TestSet1.

Model Type	Model	TestSet1:Cross-Lingual			TestSet2:English			Trained
		Precision	Recall	F1 Macro	Precision	Recall	F1 Macro	
Conventional Model	Hypothesis-only	35.78	36.02	35.84	35.89	35.97	35.91	✓
	DocNLI	64.75	64.30	64.46	69.29	68.39	68.70	✓
	R2F	65.04	65.42	65.42	67.18	68.47	67.13	✓
Large Language Model	Llama-3-8B	45.94	52.62	48.07	51.69	57.98	53.03	✓
	GPT-4o	52.50	56.30	54.00	62.50	65.00	64.50	×
	Qwen3-8B	60.34	56.29	59.86	71.71	67.62	67.34	✓
CDCL-NLI Model	Ours	71.09	70.84	68.95	72.65	72.46	70.68	✓
	- Exp	65.99	67.29	65.86	69.01	69.97	68.79	✓
	- Graph	53.07	57.38	51.37	68.64	64.55	61.71	✓
	- Exp & Graph	49.15	52.71	48.70	49.15	52.71	50.67	✓

Table 3: NLI model performance on cross-lingual (TestSet1) and English (TestSet2) sets. Our full model achieves the highest F1 scores, showing clear gains from explanation and graph components. Large language models perform well but are generally outperformed. ✓ indicates training on target data; × means no training. Explanation - Exp.

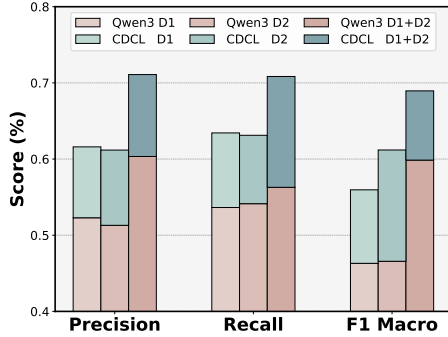


Figure 6: NLI performance using single documents ($D1$, $D2$) versus combined ($D1 + D2$). The F1 gain confirms the need for cross-document reasoning, with both documents contributing similarly.

Single-Document vs Cross-Document. To validate the cross-document nature of our dataset, we compare the performance of models using only a single document ($D1$ or $D2$) against those using the $D1 + D2$, as illustrated in Figure 6. The substantial performance gap—at least a 7% F1 improvement—demonstrates that effective inference requires integrating information from both documents. Additionally, the similar F1 scores for $Document_1$ (63.2%) and $Document_2$ (62.8%) indicate that both documents provide equally important information, underscoring the necessity of synthesizing evidence from both sources rather than relying on either alone. Additional results are presented in Appendix D.3.

Cross-Lingual Generalization. To further assess the robustness and generalization of our approach, we conduct cross-lingual transfer experiments in a challenging scenario where the training

F1 Scores on Target Language (Ours vs. R2F)			
ES →RU	ES →FR	ES →IT	ES →EN
55.53/25.03	58.28/27.31	54.68/29.31	57.94/34.21
RU →ES	RU →FR	RU →IT	RU →EN
52.83/46.26	46.67/35.50	50.89/39.77	49.67/47.78
FR →ES	FR →RU	FR →IT	FR →EN
50.31/43.25	56.6/22.24	58.65/39.32	49.67/47.22
IT →ES	IT →RU	IT →FR	IT →EN
53.72/36.01	57.19/36.21	53.17/37.22	56.67/47.21
EN →ES	EN →RU	EN →FR	EN →IT
60.31/49.94	51.27/32.46	60.28/30.80	55.11/38.33

Table 4: Cross-lingual performances (macro F1 scores) of our method and R2F. Source languages are colored. Spanish (ES), Russian (RU), French (FR), Italian (IT) and English (EN). Our method demonstrates superior generalization across languages compared to baselines.

and testing languages are distinct. Specifically, we select five typologically and geographically diverse languages—Spanish, Russian, French, Italian, and English—to ensure comprehensive coverage and to reflect real-world multilingual settings. For each source language, we translate the data into all target languages, resulting in 20 transfer directions. Models are trained on one language and evaluated on a different target language, with no overlap between training and test languages. As shown in Table 4, our method consistently outperforms the R2F baseline across most transfer directions, often by substantial margins. R2F is chosen as it improves upon DocNLI for cross-document reasoning. These results demonstrate the effectiveness of our approach in synthesizing information from cross-lingual document pairs and its strong transferability to diverse language pairs, validating the

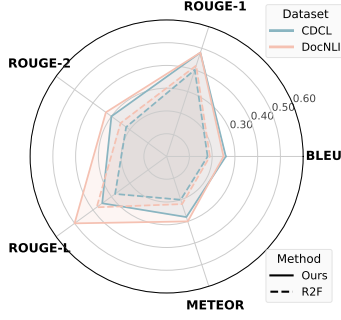


Figure 7: Explainability comparison between our method and R2F on CDCL-NLI and DocNLI datasets using BLEU, ROUGE (1/2/L), and METEOR metrics. Our method consistently outperforms R2F across all metrics and datasets.

Method	Dev		Test	
	W. F1	Mi. F1	W. F1	Mi. F1
DocNLI	88.05	86.25*	87.09	85.06*
R2F	90.18*	89.15	89.16*	87.86
Ours	91.58	88.61	90.30	88.47

Table 5: Performance comparison on the document-level DocNLI. Results marked with * are from our reproduction. Weighted F1 -W. F1, Micro F1 - Mi. F1

design of our experimental setup and the broad applicability of our method in multilingual cross-document NLI tasks.

Interpretability Study. To evaluate our method’s effectiveness, we compared it against the R2F baseline using five standard metrics (ROUGE-1/2/L, BLEU, METEOR) on both CDCL and DocNLI datasets. As shown in Figure 7, our method (solid line) consistently outperforms r2f (dashed line) across all metrics on both datasets. The improvements are particularly pronounced in ROUGE-L, where our method achieves 0.34 versus 0.30 on CDCL-NLI and 0.50 versus 0.37 on DocNLI, demonstrating enhanced capability in preserving structural coherence. It is worth noting that the interpretability data for DocNLI was provided by R2F.

Comparison on DocNLI Dataset. We evaluate the generalization of our method on the DocNLI dataset using weighted and micro F1 metrics. As shown in Table 5, our approach achieves state-of-the-art weighted F1, outperforming both the DocNLI baseline and R2F, but slightly underperforms R2F on micro F1. This is mainly due to class imbalance between training and evaluation sets, and R2F’s advantage on the simpler reasoning tasks

common in DocNLI, while our method is optimized for more complex reasoning. These results suggest that balanced sampling or improved adaptability could further boost performance.

6 Conclusion

This work systematically investigates CDCL-NLI, addressing key challenges in cross-document reasoning and multilingual understanding. We introduce a novel CDCL-NLI dataset spanning 26 languages and comprising 25,410 meticulously annotated instances. And we propose an RST-enhanced graph fusion mechanism with explanation prediction. Through extensive experiments and analyses, we demonstrate that our method effectively captures both structural and semantic information across documents and languages. Specifically, the RST-enhanced graph fusion mechanism and explanation prediction component not only improve model interpretability but also enhance performance, as validated by our ablation studies.

Acknowledgments

This work is supported by the National Key Research and Development Program of China (No. 2022YFB3103602), the National Natural Science Foundation of China (No. 62176187, No. 62202210). This work is also supported by the open project of Sichuan Provincial Key Laboratory of Philosophy and Social Science for Language Intelligence in Special Education (No. YYZN-2023-1).

Limitations

Our current framework is constrained to reasoning between pairs of documents, while real-world scenarios often involve multiple documents across diverse topics. This limitation points to valuable directions for future research in multi-document multi-lingual inference.

Ethics Statement

All data in our proposed dataset are collected from publicly available sources with respect for privacy and copyright. We have removed any personally identifiable information during preprocessing. The dataset is intended for research purposes only, and we advise users to be aware of potential biases present in the original data.

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A Dataset Details

A.1 Premise Establishment Criteria

To ensure the quality and reliability of our CDCL-NLI dataset, we establish the following criteria for premise selection:

- **Content Parallelism:** The document pairs must discuss the same topic while being naturally written in their respective languages, rather than being translations of each other. This ensures authentic cross-lingual reasoning scenarios.
- **Information Complementarity:** While maintaining topic consistency, documents in different languages should present complementary perspectives or details, enabling meaningful cross-document inference tasks.
- **Language Distribution:** Premise document pairs are randomly sampled from different languages to reflect real-world cross-lingual scenarios. Each pair must consist of documents in two distinct languages, ensuring the dataset captures authentic cross-lingual reasoning challenges.

These criteria ensure that our dataset captures genuine cross-lingual reasoning challenges while maintaining natural language expression across different languages.

A.2 CDCL-NLI Label Definitions and Hypothesis Generation

Label Definitions. We define three inference labels for CDCL-NLI, considering various evidence distribution scenarios across documents:

- **Entailment:** The hypothesis is supported when either:
 - Evidence from both documents jointly supports the hypothesis through cross-document reasoning, or
 - One document provides sufficient supporting evidence while the other document contains no contradicting information

In both cases, the conclusion must be logically derivable without requiring external knowledge.

- **Contradiction:** The hypothesis is contradicted when either:
 - Information from either document directly contradicts the hypothesis, or
 - The combined information from both documents leads to a logical conclusion that contradicts the hypothesis, or
 - The two documents present mutually contradictory evidence regarding the hypothesis
- **Neutral:** The relationship is neutral when:
 - Neither document alone nor their combination provides sufficient evidence to support or contradict the hypothesis, or
 - The documents contain only partially relevant information that doesn’t allow for a definitive conclusion, or
 - The hypothesis introduces new information or claims that go beyond what can be verified from the documents

These definitions account for the complex nature of cross-document reasoning, where evidence may be distributed asymmetrically across documents and require different levels of information integration for reaching conclusions.

Hypothesis Creation. To generate high-quality hypotheses for our CDCL-NLI dataset, we designed a structured prompt for GPT-4o that specified detailed requirements for each label. The complete prompt template is reproduced in Figure 12. This prompt design requires GPT-4o to generate evidence explaining the reasoning behind each hypothesis, which significantly reduces hallucination and improves alignment with the source documents. The structured output format facilitates automated processing while ensuring that each hypothesis is accompanied by clear justification of its entailment category. The generated hypotheses were subsequently reviewed by human annotators to ensure quality and adherence to the specified criteria.

A.3 Data Quality Assessment

Explanation Annotation Guidelines. We establish the following principles for EDU-based explanation annotation:

1. **Minimal Sufficiency:** Annotators should select the minimal set of EDUs that are necessary and sufficient to support the inference conclusion, avoiding redundant or irrelevant units.
2. **Cross-document Coverage:** Selected EDUs

must include evidence from both premise documents when the inference requires cross-document reasoning, ensuring the explanation captures cross-lingual interactions.

3. **Logical Completeness:** The selected EDUs should form a complete logical chain that clearly demonstrates how the inference conclusion is reached.

Quality Metrics. We measured CDCL-NLI dataset using multiple metrics as shown in Table 6

The explanation component of our annotations was evaluated using three complementary metrics, all showing exceptional improvement after reconciliation:

- EDU Selection achieved 76% Jaccard similarity, indicating strong consensus on evidence selection
- Span Coverage reached 81% overlap ratio, demonstrating precise identification of relevant text spans
- Explanation Consistency achieved 85%, ensuring logical coherence in reasoning

Our annotation quality assessment demonstrated strong reliability across all NLI categories. Our initial inter-annotator agreement score is 0.71 and annotation quality is further improved through adjudication.

Through our rigorous quality control and filtering process, we refined our dataset from an initial collection of 27,750 potential instances to 25,410 high-quality inference pairs. This 8.4% reduction reflects our commitment to maintaining high standards in both label accuracy and explanation quality, ensuring the dataset’s reliability for both classification and interpretability research.

A.4 Data Information

Language Distribution. Figure 8 illustrates the language distribution of our dataset, where Spanish (15.3%), Russian (10.4%), and French (8.4%) represent the top three most frequent languages, while languages like Hebrew, Czech, and Hindi each accounts for approximately 1-2% of the data. This distribution not only reflects the imbalanced nature of multilingual usage in real-world scenarios but also ensures broad coverage of linguistic phenomena, enabling the study of diverse cross-lingual inference patterns.

Language Pair Distribution. As shown in Figure 9a, the dataset exhibits diverse language combinations across 24 languages. Spanish demonstrates

Category	Description (Metric)	Score
NLI Label	Entailment (Cohen’s κ)	0.72
	Neutral (Cohen’s κ)	0.71
	Contradiction (Cohen’s κ)	0.71
Explanation	EDU Selection (Jaccard Sim.)	0.76
	Span Coverage (Overlap Ratio)	0.81
	Explanation Consistency (Align.)	0.85

Table 6: Dataset quality assessment results.

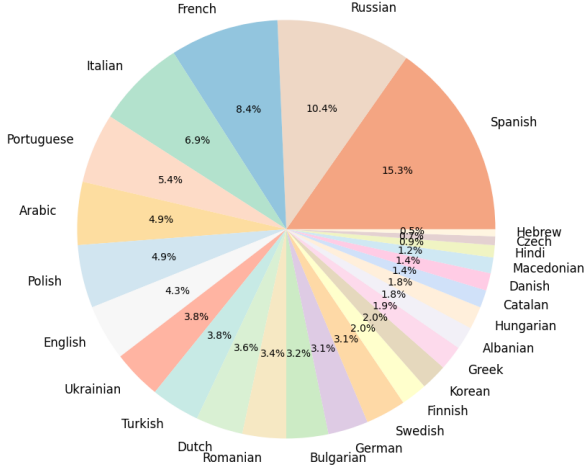


Figure 8: Language distribution of CDCL-NLI dataset.

the highest interaction frequency with other languages, particularly evident in Spanish-Russian (224 instances) and Spanish-Portuguese (178 instances) pairs. The heat map reveals several interesting patterns:

- Most language pairs maintain a balanced bidirectional relationship, with similar instance counts in both directions
- Romance languages (Spanish, French, Portuguese, Italian) show stronger interconnections
- Less-resourced languages like Albanian and Macedonian have fewer cross-lingual pairs
- Russian and Spanish serve as central hub languages, connecting with most other languages in the dataset

EDU Count Distribution by Language Pair.

The violin plot in Figure 9b illustrates the distribution of Elementary Discourse Units (EDUs) across the top language pairs. Several key observations emerge:

- Most language pairs show a median EDU count between 80 and 120 units
- The distributions are generally symmetric, indicating consistent EDU patterns regardless of the

source language

- Romance language pairs (Romanian-Spanish, Portuguese-Spanish, Italian-Spanish) exhibit similar EDU distribution patterns
- Some pairs, particularly those involving Spanish as one of the languages, show wider distributions, suggesting more diverse discourse structures
- The violin shapes indicate that extreme EDU counts (very low or very high) are relatively rare across all language pairs

This analysis suggests that while the dataset maintains diverse language coverage, it also preserves consistent discourse complexity across different language combinations.

B Graph Construction Details

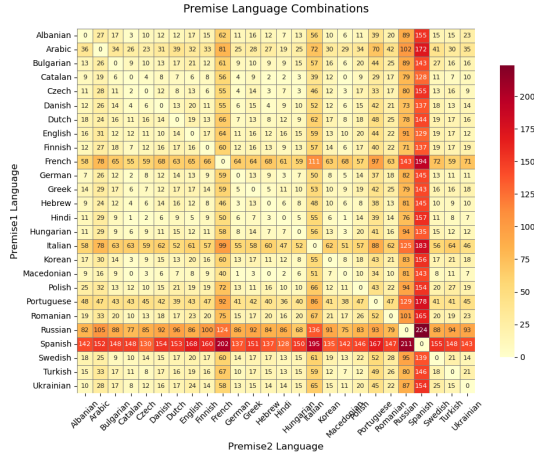
B.1 Relation Types

RST Graph Construction with Selected Relation Types.

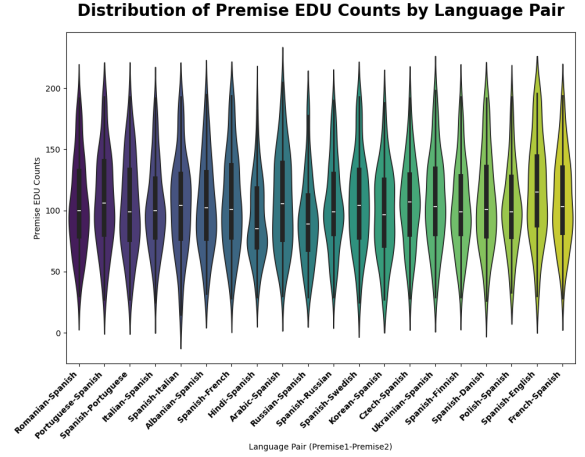
In constructing individual RST graphs for each document, we select a subset of relation types to focus on the most salient discourse and semantic connections. Specifically, we use the following relation types: Temporal, Summary, Condition, Contrast, Cause, Background, Elaboration, Explanation, and lexical chains. This selection balances coverage and complexity, ensuring that the resulting graph captures essential discourse relations and key semantic links without introducing excessive sparsity or noise. The inclusion of lexical chains further strengthens semantic cohesion by linking related words and expressions across different segments.

Graph Fusion with Extended Relation Types.

During the fusion of RST graphs from multiple documents, we expand the set of relation types to include a broader range of discourse and organizational structures. The extended set comprises: Temporal, TextualOrganization, Joint, Topic-Comment, Comparison, Condition, Contrast,



(a) Heat map of premise language combinations across the dataset.



(b) Distributions of EDU counts across top-20 language pairs.

Figure 9: Statistic visualization of language pair distributions and their EDU characteristics.

Evaluation, Topic-Change, Summary, Manner-Means, Attribution, Cause, Background, Enablement, Explanation, Same-Unit, Elaboration, and Lexical chains. This comprehensive set allows for richer cross-document alignment by capturing diverse forms of rhetorical and semantic relationships. Both in single-document and fused graphs, these relations serve as edge types in the construction of the Relation-aware Graph Attention Network (RGAT), enabling the model to effectively encode complex discourse and semantic structures.

B.2 Node Feature Definition

Specifically, for leaf nodes, we define:

$$\phi(v_i) = \phi(\text{EDU}_s), \text{Text}_{v_i} = \text{EDU}_s, \text{Type}_{v_i} = 1.$$

For branch nodes, we define:

$$\phi(v_i) = \frac{1}{2}(\phi(v_j) + \phi(v_k)),$$

$$\text{Text}_{v_i} = \text{Text}_{v_j} \oplus \text{Text}_{v_k}, \text{Type}_{v_i} = 0,$$

where v_j, v_k are the children of v_i , and \oplus denotes concatenation. For completeness, we provide the detailed formulas for the relation-level and node-level attention mechanisms used in updating node embeddings.

B.3 Justification of the Cross-Document Edge Threshold δ

The threshold δ for adding cross-document lexical edges is set to 0.8 based on empirical analysis balancing sparsity and relevance of edges. We evaluated different threshold values on a validation set using the following metrics:

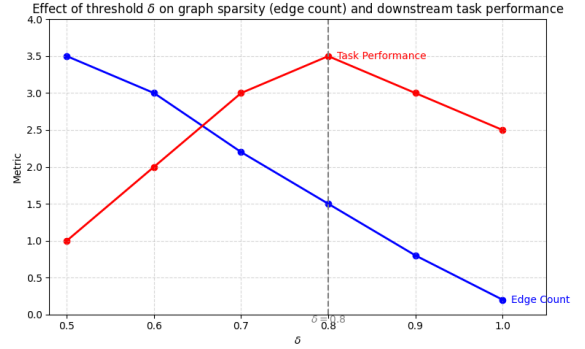


Figure 10: Effect of threshold δ on graph sparsity and task performance. Edge count (blue) decreases as δ increases, while task performance (red) peaks at $\delta = 0.8$ (dashed line), providing optimal balance between relevant connections and noise reduction.

- **Edge Sparsity:** Higher thresholds reduce the number of edges, leading to sparser graphs that help avoid noise.
- **Semantic Relevance:** Lower thresholds introduce more edges but may include irrelevant or weakly related node pairs.
- **Downstream Task Performance:** We observed that $\delta = 0.8$ achieves the best trade-off, maximizing performance on the target task (e.g., accuracy or F1 score).

Figure 10 shows the impact of varying δ on edge count and task performance, confirming the choice of 0.8 as a reasonable and effective threshold.

B.4 Graph Attention Formulas

Relation Weight. The relation importance weights α_r are learnable parameters normalized by

Baseline	Base Model	Optimizer	LR	Batch Size	Max Length	Epochs
Hypothesis-only	XLM-R Large	AdamW	3×10^{-6}	16	512	20
DocNLI	XLM-R Large	AdamW	3×10^{-6}	16	512	20
R2F	XLM-R Large	AdamW	1×10^{-6}	16	512	20
Ours	XLM-R Large	AdamW	1×10^{-5}	16	512(per EDU)	20

Table 7: Training hyperparameters for conventional baseline models and our model. These configurations, including the consistent use of the XLM-RoBERTa-Large base model and AdamW optimizer, were utilized to ensure reproducibility and fair comparison.

softmax:

$$\alpha_r = \frac{\exp(w_r)}{\sum_{r' \in R} \exp(w_{r'})},$$

where w_r is a trainable scalar parameter for rhetorical relation r .

Hyperparameters. For the model defined in Equation 1, the following settings are used: The first layer uses $K = 4$ attention heads. The second layer uses $K = 1$ attention head. Residual connections and dropout with rate 0.1 are applied after each layer.

Node-level Attention Coefficients. The attention coefficients $\beta_{ij,k}^{r,(l)}$ measure the importance of neighbor node v_j to node v_i under relation r , head k , and layer l . They are computed as:

$$\beta_{ij,k}^{r,(l)} = \frac{\exp\left(\psi\left(a_{r,k}^{(l)\top} \left[\mathbf{W}_{r,k} \mathbf{h}_{v_i}^{(l-1)} \parallel \mathbf{W}_{r,k} \mathbf{h}_{v_j}^{(l-1)}\right]\right)\right)}{\sum_{v_m \in \mathcal{N}_r(v_i)} \exp\left(\psi\left(a_{r,k}^{(l)\top} \left[\mathbf{W}_{r,k} \mathbf{h}_{v_i}^{(l-1)} \parallel \mathbf{W}_{r,k} \mathbf{h}_{v_m}^{(l-1)}\right]\right)\right)}, \quad (8)$$

where $\mathbf{W}_{r,k}$ is the trainable linear transformation matrix for relation r and head k , $a_{r,k}^{(l)}$ is the learnable attention vector for relation r , head k , and layer l , $[\cdot \parallel \cdot]$ denotes vector concatenation, $\psi(\cdot)$ is the ELU activation function.

Additional Details. Each layer uses residual connections and dropout with a rate of 0.1 to improve training stability. The first layer uses $K = 4$ attention heads, while the second layer uses $K = 1$.

C Training Details

C.1 Model Training Hyperparameters

All the models are implemented in PyTorch and trained on an NVIDIA A100 GPU. To ensure fair comparison and reproducibility of results, all conventional baseline models and our model were fine-tuned under consistent experimental settings. As

detailed in Table 7, each baseline utilizes the **XLM-RoBERTa-large** pretrained model as the base architecture and the **AdamW** optimizer for training. The learning rates are carefully selected for each model variant to optimize performance, while maintaining a uniform batch size of 16, a maximum input sequence length of 512 tokens, and training for 20 epochs. These standardized hyperparameters guarantee that performance differences stem from model design rather than training discrepancies, thereby supporting the validity and reproducibility of our comparative evaluation. Specially, for our model, as we split the documents into EDUs, so the maximum length is for one single EDU. By processing shorter EDUs instead of full documents, our model in long-text scenarios minimizes information loss, leading to improved performance.

C.2 LLM Fine-tuning Hyperparameters

For fine-tuning the Llama3-8B-instruct and Qwen3-8B model, we employed LoRA (Low-Rank Adaptation) to efficiently adapt the large-scale pretrained model with limited computational resources. The key hyperparameters for LoRA tuning included a rank of 16, which balances adaptation capacity and parameter efficiency, and a dropout rate of 0.1 to mitigate overfitting. The learning rate was set to 2×10^{-4} with a linear warmup over the first 500 steps, followed by a constant decay. We used a batch size of 64 sequences and capped the maximum input length at 1024 tokens to fully leverage the model’s context window. Training was conducted for 10 epochs, which empirically provided a good trade-off between convergence and training cost. These hyperparameters were chosen based on prior LoRA tuning best practices and preliminary experiments to ensure stable and effective adaptation of the Llama3-8B-instruct and Qwen3-8B model. The prompt is shown in Figure 11.

Fine-tuning Prompt

You are skilled in the NLI task. Given a premise consisting of two documents and a hypothesis, each with its specified language, your task is to determine the natural language inference (NLI) relationship between the hypothesis and the premise. Note that the premise and hypothesis may be in different languages. The output should be one of three labels: Entailment, Contradiction, or Neutral.

Input format:

Premise 1 (Language: <Lang1>): <Premise1 text>

Premise 2 (Language: <Lang2>): <Premise2 text>

Hypothesis: <Hypothesis text>

Output format:

One of the labels: Entailment, Contradiction, or Neutral

Example:

Premise 1 (Language: English): The cat is sitting on the mat.

Premise 2 (Language: French): Le chat est assis sur le tapis.

Hypothesis: The animal is resting on a rug.

Output: Entailment

Now, given the input premises and hypothesis, provide the NLI label.

Figure 11: Llama3-8B-Instruct and Qwen3-8B Finetuning Prompt.

Model	TestSet1: Cross-Lingual			TestSet2: English		
	Precision	Recall	F1 Macro	Precision	Recall	F1 Macro
Llama-3-8B	44.00	50.00	46.00	49.00	55.00	50.00
GPT-4o	50.00	54.00	52.00	59.00	62.00	61.00
Qwen3-8B	58.00	54.00	57.00	68.00	64.00	63.00

Table 8: Zero-shot performance of large language models on the CDCL-NLI dataset.

D Additional Experiments

D.1 LLM Few-shot Prompt

As shown in Figure 13, one example is provided to demonstrate how to determine the logical relationship between the premise and the hypothesis. The model is instructed to output exactly one of three labels: *entailment*, *contradiction*, or *neutral*. This prompt effectively guides the model to understand the task objective and output format, thereby enhancing its reasoning capability across multiple languages and documents during the few-shot validation stage (Chen et al., 2024).

D.2 LLM in Zero-shot Scenario

The zero-shot results reported in Table 8 are obtained using the same prompt design as the few-shot experiments, differing only in the absence of

in-context examples. As expected, all models perform worse under the zero-shot setting compared to their few-shot counterparts, demonstrating the effectiveness and necessity of providing exemplars in the prompt for this task. Despite the overall performance drop, the relative ranking of the three models remains consistent with the few-shot scenario, with Qwen3-8B achieving the highest scores, followed by GPT-4o, and then Llama-3-8B. This consistency indicates that these models’ capabilities in handling the CDCL-NLI task are stable across different prompting strategies. Moreover, the results highlight the challenge of zero-shot cross-document and cross-lingual natural language inference, emphasizing the importance of prompt engineering and in-context learning to boost model performance on complex multilingual and multi-document reasoning tasks.

Model	Single Document1	Single Document2	Combined Documents
DocNLI	54.22	54.95	64.46
R2F	57.09	57.12	65.42

Table 9: F1 Macro scores for different methods across premises with varying numbers of documents.

EDU	Text	EDU	Text
1	7. května	22	řekl prokurátor Giovanni Matos místní televizní stanici Canal N.
4	Společnost okamžitě nereagovala na žádost o komentář.	24	jsou 27 obětí,“
7	(Reuters) -	25	„Informace jsou správné,
11 ①	Úředníci uvedli v neděli, že nehoda v malé zlaté dolině na jihu Peru odnesla život 27 pracovníků.	26	potvrdila je policie v Yanaquihuě,
12	Jedná se o jeden z nejmrtnějších důležitých událostí v těžebním průmyslu v tomto jihoamerickém státě.	27	„Jedná se o formální dolinu (...),
15 ②	Nehoda se stala v sobotu ráno v těžební společnosti Yanaquihua, která se nachází v provincii Condesuyos v departementu Arequipa.	30	dodal.
17	Zdá se, že došlo ke zkratu, která způsobila požár uvnitř tunelu,	33	musíme jít
18	vedla regionální vláda.	34	a zjistit, kde jsou mrtví, jestli je tam bezpečné,
37 ③	Regionální vláda Arequipy a ministerstvo vnitra mobilizovaly policie, zdravotníky a sanitky, aby pomohly při péči o oběti a jejich záchraně.	35	aby se tam mohli dostat policisté a soudní pracovníci
39	Podle statistik peruánského ministerstva těžeb a energie je toto nejvyšší počet obětí v jediném těžebním nehodě	36	a provést procedury,“
40	nejméně od roku 2000.		

Table 10: Elementary Discourse Units (EDUs) from *Document*₁ with their corresponding Spanish text. Segments highlighted in green represent evidence supporting the Entailment classification. EDU indexes with circled numbers ① indicate cross-document "Lexical" chains linking to corresponding EDUs in *Document*₂.

D.3 Baseline Evaluation in Single Document Scenario

To further demonstrate the cross-document characteristic of our dataset, we add this extra experiment to evaluate the performance using either a single document (*Document*₁ or *Document*₂) as the premise compared to using the full combined premise, as summarized in Table 9. The noticeable improvement in F1 score when both documents are combined indicates that effective inference relies on integrating information from multiple sources. Additionally, the similar results observed between **Single Document 1** (54.22% and 57.09% F1) and **Single Document 2** (54.95% and 57.12% F1) imply that each document provides valuable and roughly equal contributions. This further supports the notion that reasoning in this task benefits from synthesizing evidence across documents rather than focusing on a single source.

E Case Study

E.1 Our Method Case

Our approach employs a multi-stage framework for analyzing complex multi-document multi-lingual NLI scenarios. Take the given example in Figure 13, the Yanaquihua gold mine incident in Condesuyos, Peru, where a short circuit-induced fire resulted in 27 fatalities among workers trapped within a tunnel, prompting mobilization of local authorities and rescue teams. We begin by parsing the premise documents using Rhetorical Structure Theory (RST), which generates hierarchical discourse trees wherein each node represents an Elementary Discourse Unit (EDU). These nodes are assigned unique indices, with their textual content comprehensively documented in Tables 10 and 11.

Following RST parsing, we construct individual discourse graphs for each premise document. These discrete graphs are subsequently integrated into a unified premise graph through the establish-

ment of "Lexical" chains that leverage semantic information and discourse relations to facilitate enhanced inference. As illustrated in Tables 10 and 11, EDU nodes sharing identical uppercase character designations indicate the presence of cross-document "Lexical" chains. This consolidated graph representation effectively captures the comprehensive discourse context across the premises, enabling more robust and coherent semantic modeling.

The classification module processes this unified graph in conjunction with the hypothesis to predict the appropriate NLI label. Concurrently, the explanation extraction module identifies a salient subset of nodes within the premise graph that substantiate the classification decision. These explanation nodes are visually distinguished through green font highlighting in Tables 10 and 11, explicitly denoting their explanatory significance.

Our integrated methodology capitalizes on the hierarchical discourse structure inherent in RST parsing and the semantic connectivity across documents, ensuring that the model’s inference is both accurate and interpretable. The explicit identification of explanation nodes within the discourse structure facilitates transparent, human-comprehensible rationales grounded in the premise texts, thereby advancing the explainability of NLI systems in complex multi-document, multi-lingual scenarios. This approach proves particularly valuable when analyzing intricate real-world situations such as the Yanaquihua mine disaster, where understanding the causal relationships and contextual factors is crucial for proper inference.

E.2 LLM Answer Case

As shown in Table 3, Qwen3-8B achieves higher scores compared to Llama3-8B-instruct and the closed-source GPT-4o. One key reason is that we evaluate Qwen3-8B using its thinking (chain-of-thought) mode, as illustrated in Figure 14. We still take the case in validation prompt (Table 13) as an example, the model systematically parses each premise, accurately extracts key facts, and performs detailed cross-checking between the articles and the hypothesis. It also demonstrates the ability to handle subtle differences in wording (such as distinguishing between deaths and rescues) and to resolve potential ambiguities in translation (e.g., the meaning of "oběti" in Czech).

Nevertheless, our proposed approach still outperforms Qwen3-8B, primarily due to its ability to

explicitly capture document structure through RST parsing and cross-document, cross-lingual semantic integration via "Lexical" chains. Moreover, our method demonstrates superior efficiency with significantly lower computational requirements and faster inference time, making it more practical for real-world applications while maintaining state-of-the-art performance.

EDU	Text	EDU	Text
14	informó el Ministerio Público de ese país.	53	[Al menos siete muertos en Texas
15 ^①	Al menos 27 personas murieron en Perú	54	tras atropellamiento en una parada de autobús cerca de un refugio para inmigrantes]
17	y otras dos fueron rescatadas	56	lo que impidió que los mineros pudieran escapar.
18	luego de un incendio el sábado en una mina de oro en la sureña provincia de Condesuyos,	57	Se informó que
21	Según las primeras investigaciones, la tragedia tuvo lugar	59	el fuego se propagó de manera muy rápida por las estructuras de madera que sostienen el yacimiento,
23 ^②	tras producirse un cortocircuito a 100 metros de la entrada de la mina Yanaquihua,	60	dedicado a la extracción de oro,
24	conocida como Esperanza I.	61	Medios locales peruanos indicaron que
28	informó el Gobierno regional de Arequipa.	63	27 trabajadores quedaron atrapados en la mina
29	“Se habría producido un cortocircuito	64	tras un incendio.
31	que provocó un incendio en el interior del socavón,	65	Getty Images
32	que habría puesto en riesgo la vida de los trabajadores”,	71	James Casquino, alcalde de Yanaquihua, dijo que
33	Medios locales indicaron que	73	el dueño de la mina fue a la comisaría de ese distrito
34	27 trabajadores atrapados habían fallecido por asfixia.	75	para pedir ayuda en el rescate de las personas
35	La noche del sábado, el Ministerio del Interior confirmó en su cuenta de Twitter el accidente.	76	que se encontraban atrapadas.
38	indicó el tuit.	78	[Mueren varios migrantes en un accidente de auto en Nuevo México cerca de la frontera]
39	“Personal policial se encuentra en el distrito de Yanaquihua	79	Las autoridades indicaron que
41	para apoyar en las labores de rescate de los cuerpos de mineros	80 ^③	hacia la zona se habían movilizado rescatistas.
42	que fallecieron dentro de un socavón en la provincia de Condesuyos”,	81	Familiares de las víctimas se reunieron frente a la comisaría de Yanaquihua
49	Imágenes difundidas en redes sociales mostraban una gran columna de humo negro proveniente de la mina,	83	para recabar información sobre la suerte de sus seres queridos
51	y medios locales indicaron que	84	y exigir a las autoridades que agilizaran las labores de rescate de los cuerpos.
52	en el momento del cortocircuito había personal trabajando a unos 80 metros de profundidad.	85	El fiscal Giovanni Matos indicó a un medio local que
87	las tareas en la mina podían demorar	89	porque no se sabía si los equipos de rescatistas podían ingresar a la mina
23	para retirar los cadáveres.	90	para retirar los cadáveres.
91	[Una tormenta de polvo en Illinois causa múltiples muertes y decenas de hospitalizados tras choque masivo]	94	indica la compañía en su página web.
95	La mina pertenece a Yanaquihua S. A. C., una empresa	96	que reúne a pequeños productores mineros dedicados a la explotación del oro y otros metales,

Table 11: Elementary Discourse Units (EDUs) from *Document₂* with their corresponding Spanish text. Segments highlighted in green represent evidence supporting the Entailment classification. EDU indexes with circled numbers ① indicate cross-document "Lexical" chains linking to corresponding EDUs in *Document₁*.

Hypothesis Generation Prompt

[Hypothesis Generation Prompt] We are creating a cross-document cross-lingual NLI dataset. Below are two documents under the event topic: [CATEGORY], treated as one premise in this NLI task. Based on them, generate hypotheses in three labels. You must **strictly follow** the instructions:

1. Hypothesis: The hypothesis should be a factual statement based on the content of the articles. It must be a simple statement and **should not contain any explanation or analysis like “this contradicts” or “this agrees with” or “this is inconsistent with.”**

2. Evidence: The evidence section should explain how the hypothesis relates to the articles, including any contradictions or confirmations, using specific quotes from the articles.

Document Details:

- **Document 1:** Date: [DATE_1]; Article: [ARTICLE_1]
- **Document 2:** Date: [DATE_2]; Article: [ARTICLE_2]

[Task 1: Entailment Generation] Generate an Entailment Hypothesis and evidence.

The hypothesis is supported if evidence from both documents together or from one document alone (without contradiction in the other) logically supports it.

Guidelines:

- Ensure each detail is verifiable by premise
- Include specific facts (dates, names, etc.)
- No speculation—strictly based on facts

Evidence:

- Quote relevant parts from both articles and explain how they jointly support the hypothesis

[Task 2: Neutral Generation] Generate a Neutral Hypothesis and evidence.

One hypothesis is neutral if there is insufficient or only partial evidence in the premise to confirm or deny it, or if it contains information beyond what the premise verify.

Guidelines:

- Reasonable speculation or expanded related aspects in a reasonable way
- Propose middle ground if there's conflicting information

Evidence:

- Show partial support from one or both articles without full confirmation
- Explain how the hypothesis goes beyond but stays consistent with the Document content

Remember, A neutral hypothesis should not be directly confirmed by the premise (which would make it entailed), nor should it contradict the articles (which would make it conflicting).

[Task 3: Conflicting Generation] Generate a Conflicting Hypothesis and evidence.

One hypothesis is contradicted if either document or their combined information directly opposes it, or if the documents conflict with each other regarding the hypothesis.

Guidelines:

- Negate or reverse key information in premise
- Complex and multi-faceted hypothesis with multiple contradictions
- Try to combine multiple points of contradiction
- Ensure the hypothesis appears reasonable but actually conflicts clearly

Evidence:

- Show which document(s) the hypothesis contradicts and explain specific points
- If applicable, explain why this hypothesis cannot coexist with the premise content

Output in JSON format:

```
{ "entail_evidence": "...",
  "entail_hypothesis": "...",
  "neutral_evidence": "...",
  "neutral_hypothesis": "...",
  "conflict_evidence": "...",
  "conflict_hypothesis": "..."}
}
```

Figure 12: Hypotheses Generation Prompt.

Validation Prompt

You are tasked with a cross-document and cross-language Natural Language Inference (NLI) task. Your goal is to determine the relationship between the "premise" and the "hypothesis". The premise consists of two documents presented in different languages. Here is one example:

Premise(Document1 in Spanish)

Al menos 27 personas murieron y dos fueron rescatadas tras un incendio en la mina de oro Yanaquihua, en Condesuyos, Perú. Las investigaciones apuntan a un cortocircuito ocurrido a unos 100 metros de la entrada, que provocó un fuego que se expandió rápidamente por las estructuras de madera del socavón, dificultando la salida de los trabajadores. Autoridades regionales señalaron que la mayoría de los mineros fallecieron por asfixia. El Ministerio del Interior confirmó el accidente la noche del sábado y la policía trabaja en el rescate de los cuerpos. Imágenes difundidas mostraron una densa columna de humo, mientras que medios locales informaron que había personal laborando a 80 metros de profundidad. El alcalde de Yanaquihua indicó que el dueño de la mina acudió a la comisaría para solicitar apoyo en el rescate.

Premise(Document2 in Czech)

7. května (Reuters) - Úředníci uvedli v neděli, že nehoda v malé zlaté dolině na jihu Peru odnesla život 27 pracovníků. Jedná se o jeden z nejúmrtnějších důležitých událostí v těžebním průmyslu v tomto jihoamerickém státě. Nehoda se stala v sobotu ráno v těžební společnosti Yanaquihua, která se nachází v provincii Condesuyos v departementu Arequipa. Zdá se, že došlo ke zkratu, která způsobila požár uvnitř tunelu, uvedla regionální vláda. „Informace jsou správné, potvrdila je policie v Yanaquihu, jsou 27 obětí,“ řekl prokurátor Giovanni Matos místní televizní stanici Canal N. Regionální vláda Arequipy a ministerstvo vnitra mobilizovaly policii, zdravotníky a sanitky, aby pomohly při péči o oběti a jejich záchraně. Podle statistik peruánského ministerstva těžeb a energie je toto nejvyšší počet obětí v jediném těžebním nehodě nejméně od roku 2000. Společnost okamžitě nereagovala na žádost o komentář.

Hypothesis and Label

Hypothesis: "The Yanaquihua gold mine in the province of Condesuyos, Peru, experienced a fatal incident on a Saturday morning due to a short circuit that caused a fire, leading to the death of 27 workers trapped inside the tunnel, with local authorities and rescue teams being mobilized to the site."

Output: entailment

Now, given the following input, output exactly one word indicating the NLI label: neutral, entailment, or contradiction.

Premise:[Premise]

Hypothesis: [Hypothesis]

Output the NLI label (neutral/entailment/contradiction):

Figure 13: LLM Validation Prompt.

Qwen3-8B Reasoning Output

Okay, let's tackle this NLI task. So, the premise has two articles in Spanish and Czech, and the hypothesis is in English. I need to determine if the hypothesis is entailed, contradicted, or neutral based on the premises. First, I'll read through the Spanish article. It mentions that on Saturday, there was a fire in a gold mine in Condesuyos province, caused by a short circuit 100 meters from the entrance. The mine is called Yanaquihua, known as Esperanza I. They say 27 people died, two were rescued. The regional government of Arequipa mentioned the short circuit caused the fire, risking workers' lives. Local media said 27 trapped workers died of asphyxia. The Ministry of Interior confirmed the accident on Saturday, and police were there for rescue. The fire spread quickly through wooden structures, preventing escape. The mine belongs to Yanaquihua S.A.C., a company with small miners.

Now the Czech article: Officials said the accident in the small gold mine in southern Peru resulted in 27 deaths. It happened on Saturday morning at the Yanaquihua mine in Condesuyos province, Arequipa department. A short circuit caused a fire inside the tunnel. The regional government confirmed 27 victims. The prosecutor Giovanni Matos said the information is correct, and police are there to find the dead, check safety for rescue teams. Regional government and interior ministry mobilized police, medics, and ambulances. It's the highest number of deaths in a single mining accident since 2000. The company didn't respond to a comment request.

Hypothesis: The Yanaquihua gold mine in Condesuyos, Peru, had a fatal incident on Saturday morning due to a short circuit causing a fire, leading to 27 workers' deaths trapped inside the tunnel, with local authorities and rescue teams mobilized. Check each part. The Spanish article says the fire was caused by a short circuit, leading to 27 deaths. The Czech article confirms the same: short circuit causing fire, 27 deaths. Both mention Saturday morning (the Spanish says "sábado" which is Saturday, and the Czech says "v sobotu ráno" which is Saturday morning). The mine is Yanaquihua in Condesuyos, Peru. The death count is 27, and both mention authorities and rescue teams being mobilized. The hypothesis states all these points. The Spanish article also mentions the mine's name and the company, which the Czech article doesn't, but that's not conflicting. The hypothesis doesn't mention the company, so that's okay.

Are there any contradictions? The Spanish article mentions two people rescued, but the hypothesis says 27 died. Wait, the hypothesis says "leading to the death of 27 workers trapped inside the tunnel." The Spanish article says 27 died and two were rescued. The Czech article says 27 victims, which could include the two rescued? Wait, maybe not. If two were rescued, then the deaths would be 27, and the two rescued are alive. So the hypothesis says 27 workers died, which matches the Spanish article's 27 deaths. The Czech article says "27 oběť" which is victims, which could be the 27 who died, but maybe the two rescued are not counted as victims? Or maybe the Czech article is using "oběť" as victims, which could include those who died and those rescued? Wait, in Czech, "oběť" is victims, usually meaning those who died. But the Spanish article says 27 died and two rescued. The Czech article says 27 victims, which might be the same 27, but the two rescued might not be considered victims. So the hypothesis says 27 workers died, which aligns with both articles. The Czech article says "27 oběť" which is victims, so that's consistent.

Also, the hypothesis mentions the fire caused by a short circuit, which both articles confirm. The mobilization of authorities and rescue teams is mentioned in both. The time is Saturday morning in both. The mine's name and location are correct.

Therefore, the hypothesis is fully supported by both articles. So the label should be entailed.

Figure 14: Illustration of Qwen3-8B's chain-of-thought reasoning process. The model systematically analyzes premise documents by extracting key facts, performing cross-document verification, and resolving translation ambiguities (e.g., Czech term "oběť"). While this reasoning approach enables Qwen3-8B to outperform other LLMs like Llama3-8B-instruct and GPT-4o, our RST-based method achieves superior performance through more intuitive explanations, explicit discourse structure modeling, and cross-lingual semantic integration, all while requiring significantly lower computational resources and faster processing times.

Universal Patterns of Grammatical Gender in Multilingual Large Language Models

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Abstract

Grammatical gender is a fundamental linguistic feature that varies across languages, and its cross-linguistic correspondence has been a central question in disciplines such as cognitive science and linguistic typology. This study takes an information-theoretic approach to investigate the extent to which variational usable information about grammatical gender encoded by a large language model generalizes across languages belonging to different language families. Using mBERT as a case study, we analyze how grammatical gender is encoded and transferred across languages based on the usable information of the intermediate representations. The empirical results provide evidence that gender mechanisms are driven by abstract semantic features largely shared across languages, and that the information becomes more accessible at the higher layers of the language model.

1 Introduction

Grammatical gender is a nominal category (e.g., masculine, feminine, and neuter) that continues to challenge linguists due to the complexity of gender systems across languages and the rules governing its assignment to nouns (Corbett, 1991; Varlokosta, 2011). These rules vary cross-linguistically and cannot always be inferred from a noun’s surface form. For instance, the German *das Mädchen* ‘the_{NEUT} girl’ is grammatically neuter despite denoting a female entity, and common concepts such as *sun* differ in gender across languages, masculine in French (*le soleil*) but feminine in German (*die Sonne*).

In addition to its linguistic implications, the study of grammatical gender provides insights into cognitive science (Lucy, 1996; Bender et al., 2011; Kemmerer, 2017; Kann, 2019), assists second language learners in navigating the seemingly arbitrary rules of gender assignment (Sahai and Sharma, 2021), and helps reducing gender bias in language models (Zhou et al., 2019).

Examining grammatical gender from a typological perspective can further illuminate shared linguistic principles contributing to the assignment of grammatical gender across languages. Recent studies in computational linguistics provide clues, based on static multilingual embeddings, about the existence of universal patterns in the assignment of grammatical genders, transferable across several languages (Veeman et al., 2020). However, the linguistic depth and extent of the universal patterns of grammatical gender have remained unexplored, primarily because the multilingual word embeddings do not provide a clear mechanism in distinguishing between formal and semantic features. In particular, it is still unclear whether the linguistic patterns that drive such universalities emerge at the morphological or semantic levels and how the gender system across languages might be related at these levels (Basirat et al., 2021).

On the other hand, previous studies have shown large language models (LLMs) normally encode linguistic information in a more transparent and structured way, allowing for an access into distinct linguistic levels (Peters et al., 2018; Jawahar et al., 2019; Hewitt and Manning, 2019; Tenney et al., 2018; de Vries et al., 2020). Lower layers primarily encode surface-level and morphological features, middle layers capture syntactic structure, and higher layers represent semantic properties and more abstract linguistic features (Jawahar et al., 2019; Tenney et al., 2018). Additionally, later studies show that multilingual LLMs are capable at capturing the universal aspects of languages at their intermediate representations (Pires et al., 2019; Chi et al., 2020), including the grammatical abstractions such as gender (Sukumaran et al., 2024).

Building upon these studies, we employ mBERT (Devlin et al., 2019) to investigate the universal and language-specific aspects of grammatical gender across different linguistic levels, such as morphology and semantics. mBERT, a multilingual

encoder-only language model trained on a diverse set of languages, provides a structured distribution of linguistic information across its intermediate representations. This allows us to systematically examine grammatical gender at multiple linguistic levels. Moreover, its shared feature space across languages facilitates universal analyses.

Taking an information theoretic strategy, we investigate universal aspects of grammatical gender based on the amount of information transferable (generalizable) across gender systems of languages. Specifically, we extend the concept of variational-usable (\mathcal{V} -usable) information (Xu et al., 2020) to measure the extent to which the gender information from a source language is generalizable to a target language. A high amount of generalizable information is interpreted as evidence of structural similarities between the gender systems of the source and target languages. In addition to the cross-lingual analysis, the application of \mathcal{V} -usable information is also motivated as it allows us to effectively measure the intra-lingual complexity of gender systems.

Our experiments on a typologically diverse set of languages provide empirical evidence that linguistic information about gender is largely generalizable across languages with similar gender categories, while their genealogical relationship plays a secondary role. Additionally, we show that linguistically driven complexities of gender systems are reflected in the hidden representations of the language model, leading to variations in usable information in our intra-lingual analysis. Furthermore, our layer-wise analysis of usable information highlights the varying contributions of intermediate representations to gender encoding, both within and across languages. Finally, further examination of intermediate representations confirms the role of both morphology and semantics in gender representation, with semantic aspects proving to be more generalizable across languages.

Overall, this study adopts a computational approach to explore the relationships between different systems of grammatical gender based on their encoding in the intermediate representations of a large language model. Specifically, the contributions of this study include:

- Systematically evaluating how well grammatical gender information generalizes across languages with different gender systems in a multilingual large language model.
- Introducing a novel approach based on the

variational usable information to investigate the generalizability of the intermediate representations of a language model for encoding grammatical gender across languages.

- Probing the intermediate representations to disentangle the roles of morphology and semantics in gender prediction.

2 Grammatical Gender

Grammatical gender is an abstract system of noun classification found in many languages, often overlapping with, or considered as subset of, noun class systems (Comrie, 1999). It is generally considered an inherent property of the noun itself (Spencer, 2002; Cucerzan and Yarowsky, 2003), with determiners, adjectives, and sometimes verbs agreeing with the noun in gender. Although grammatical gender is frequently correlated with biological sex, it is distinct from it, as evidenced by instances of gender-sex mismatches—for example, in German, *das Mädchen* ('the_{NEUT} girl') is grammatically neuter despite referring to a female entity. Furthermore, grammatical gender should not be conflated with nominal declension classes (Comrie, 1999).

Common gender categories include masculine, feminine, neuter, and common, with Indo-European languages typically featuring masculine/feminine/neuter (e.g., German, Russian), neuter/common (e.g., Danish, Dutch), and masculine/feminine (e.g. French, Italian) gender systems. In contrast, two-gender systems are common in Afro-Asiatic languages (Corbett, 1991). The function of grammatical gender is still debated: some researchers suggest it aids in referent identification or categorization for cognitive processes such as storage and retrieval (Allasonnière-Tang and Kilarski, 2020; Contini-Morava and Kilarski, 2013; Senft, 2000; Lakoff and Johnson, 2008), while others dismiss it as 'historical junk' (Trudgill, 2011).

2.1 Gender Assignment Theories

Grammatical gender assignment can be influenced by formal features (such as morphology, phonology, or orthography) and semantics (Corbett, 1991; Sahai and Sharma, 2021) (e.g. assignment based on biological sex), or it may be entirely arbitrary (Andersson, 1992). However, the rules for gender assignment are far from clear, given their complexity and the exceptions that exist in many languages, further complicated by declension classes, inflectional morphology, and agreement involving num-

ber, case, and gender (Garbo, 2016). This continues to puzzle researchers (Fedden and Corbett, 2019), although several hypotheses have emerged.

Corbett and Fraser (2000) ascribe semantic factors a higher contribution in gender assignment, whereas Rice (2006) argue that formal and semantic features are equally important. Basirat et al. (2021) tested these theories by using character-based embeddings (formal features), context-based embeddings (semantic features), and their combination to predict grammatical gender in Russian, French, and German. Their findings revealed that formal features outperformed semantic ones as predictors of gender, and combining both did not yield significant improvements, challenging both the semantic-dominance and equality hypotheses. Similar results were reported by Sahai and Sharma (2021) who demonstrated that training a classifier using orthographic and semantic features for French results in high accuracy with orthographic features alone, but performance is further enhanced when semantic features are included.

2.2 Gender Systems Across Selected Languages

This study is based on a detailed investigation of gender transfer across seven languages from the Indo-European and Afro-Asiatic language families: Arabic, Beja, Danish, German, Greek, Italian, and Russian. In this section, we briefly overview the gender system of these languages to motivate our discussions in the following sections.

Arabic has a two-gender system (masculine/feminine) and a rich morphology, with verbs, nouns, pronouns, and adjectives agreeing in gender. Gender assignment is based on both semantic (i.e. natural gender) and morphological criteria, although the gender of inanimate nouns is often semantically arbitrary, e.g. *baab* ‘door.MASC’. At the morphology level, masculine nouns are unmarked, while feminine nouns are overtly marked by suffixes, e.g., *shajar-ah* ‘tree-FEM’ (Alkohlani, 2016).

Beja, an Afro-Asiatic language of the Cushitic branch, classifies nouns into masculine and feminine. Gender is primarily marked on nouns through prefixes and suffixes, which agree with adjectives, pronouns, and other modifiers within the noun phrase (NP) in terms of case, number, and gender. For example, the prefix *ʔuu* agrees in case, number, and gender with the noun *gáw*: *ʔuu-gáw* ‘MASC.NOM.SG.DEF-house’ (Appleyard, 2007).

Danish has a two-gender system of com-

mon/neuter, with common historically formed by merging masculine and feminine. Gender is not overtly marked on the noun itself, but appears in definite NPs through determiner suffixes that agree with the noun’s gender (e.g., *hus-et* ‘house-NEUT.DEF.SG’, *bil-en* ‘car-COM.DEF.SG’) or with indefinite determiners (e.g., *et hus* ‘a_{NEUT} house’, *en bil* ‘a_{COM} car’). Adjectives also show gender agreement with the noun, but there is no gender marking in the plural (Gegersen et al., 2021).

German has three grammatical genders (masculine/feminine/neuter), and determiners and adjectives agree with the noun in gender (e.g., *ein-e schön-e Frau* ‘a-FEM beautiful-FEM woman’). However, the language also has a complex case system that interacts with gender marking. Gender assignment in German is considered complex, influenced by both semantic factors or clusters (e.g., all fruits are feminine) and morphological features (e.g. all nouns with the suffix *-heit* are feminine) (Bender et al., 2011; Fedden and Corbett, 2019). Despite these patterns, gender assignment in German is often perceived as arbitrary, with many exceptions (Fedden and Corbett, 2019).

Greek uses a three-gender system of masculine/feminine/neuter in which gender assignment is predominantly based on formal features (Varlokosta, 2011; Corbett, 1991), although semantic rules exist, e.g. fruits and vegetables are often assigned neuter case. Gender is often overtly marked on the noun: for instance, masculine nouns frequently end in *-as* (e.g., *ándras*, ‘man’), *-os*, or *-is*; feminine nouns often end in *-í* (e.g., *psychí*, ‘soul’) or *-a*; and neuter nouns tend to end in *-o* (e.g., *moró*, ‘baby’), *-í*, or *-ma*, although exceptions exist, such as the neuter noun *kréas*, ‘meat’. Greek is morphologically rich, with adjectives and determiners requiring agreement in gender, number, and case, complicating the prediction of gender.

In Italian, nouns are categorized into masculine and feminine gender, where masculine nouns typically have an *o*-suffix (*il naso* ‘the_{MASC.SG} nose’), and feminine nouns end in *-a* (*la mela* ‘the_{FEM.SG} apple’), with few exceptions, e.g. *il pianeta* ‘the planet’ and *la mano* ‘the hand’. However, nouns with *e*-suffixes can be either masculine or feminine. Gender is considered to be based on both formal and semantic features (Bianchi, 2013).

Russian has a three-gender system (masculine, feminine, neuter). The language’s rich morphology and complex inflection system (Parker and Sims, 2020) require adjectives and numerals

to agree with nouns in case, gender, and number. Gender is overtly marked on the noun, as seen in *zhenshchin-a* ('woman-FEM.SG.NOM') and *zhenshchin-u* ('woman-FEM.SG.ACC'). Gender assignment follows both morphological and semantic rules, such as the features [+male] and [+female] (Fraser and Corbett, 1994). However, exceptions exist, like *mužčina* ('man'), a masculine noun ending in *-a*. In the absence of semantic features, gender is assigned according to the declension class (Nikunlassi, 2000). Additionally, animacy plays a role in accusative marking for masculine, animate nouns. In such cases, the accusative form coincides with the genitive, marked by the *-a* suffix (e.g., *Ya vizhu student-a* 'I see student-MASC.SG.ACC.ANIM'), further complicating the distinction between gender classes.

3 Related Work

Veeman et al. (2020) investigate universal patterns in grammatical gender using a set of static multilingual word embeddings. Their study primarily employs a neural transfer learning approach, where the accuracy of gender classification from a source training language to a target test language serves as an indicator of similarity between their gender systems. Their findings suggest that while some factors influencing gender assignment are universal, as evidenced by successful cross-lingual transfer, others are idiosyncratic to specific language families. Similarly, Veeman and Basirat (2020) explored how different types of multilingual word embeddings capture information about grammatical gender and how well this information is transferable between languages. Their findings reveal an overlap in the encoding of gender in Swedish, Danish, and Dutch.

We extend the investigations of Veeman et al. (2020) in two key ways. First, instead of accuracy as a transferability metric, we adopt variational usable information (Xu et al., 2020), allowing for a comparative analysis of gender system complexity across languages (Ethayarajh et al., 2022). Second, we investigate gender universalities at a deeper linguistic level by analyzing the generalizability of usable information across different layers of a multilingual LLM, instead of static word embeddings.

Several studies have addressed the encoding of grammatical gender in word embeddings. For instance, Basirat and Tang (2018, 2019) study how a set of static word embeddings encode grammatical gender of Swedish nouns and Basirat et al. (2021)

investigate the contribution of the formal and semantic features encoded in word embeddings into the assignment of grammatical gender. Additional approaches, including surrogate models and decision trees (Sahai and Sharma, 2021), have further illuminated the mechanisms behind gender prediction. For instance, Sukumaran et al. (2024) found that transformer models can generalize grammatical gender from minimal examples, albeit with a masculine bias.

4 Method

Our investigation of gender transfer spans both layers of a language model and languages. Specifically, we assess gender transferability across languages by measuring the information each intermediate layer provides for gender prediction. For this purpose, we adopt \mathcal{V} -usable information (Xu et al., 2020), an extension of Shannon mutual information (Shannon, 1948) that accounts for computational constraints. The \mathcal{V} -usable information in a random variable X for predicting a category Y is defined as the difference in conditional entropy between predictions based on X and a baseline prediction with no input features (denoted as Φ):

$$I_{\mathcal{V}}(Y; X) = H(Y | \Phi) - H(Y | X) \quad (1)$$

A higher value of $I_{\mathcal{V}}(Y; X)$ indicates that X significantly reduces uncertainty in predicting Y .

In our setting, X is a random vector in an embedding space formed by a hidden layer of a language model while processing nouns in a given language, and Y represents a probability vector of grammatical genders. To quantify the amount of information encoded in the embedding space of a source language i , denoted as X_i , for predicting grammatical genders in a target language j , denoted as Y_j , we extend Equation 1 as:

$$I_{\mathcal{V}}(Y_j; X_i) = H_{\mathcal{V}}(Y_j | \Phi) - H_{\mathcal{V}}(Y_j | X_i) \quad (2)$$

Intuitively, $I_{\mathcal{V}}(Y_j; X_i)$ measures the usable information that the embeddings from the source language provide for predicting gender in the target language. A high value of $I_{\mathcal{V}}(Y_j; X_i)$ suggests a strong similarity between the gender systems of the source and target languages.

In some cases that the gender systems are highly different from each other, for example when a gender category is seen in a language but not in the other (e.g., common is in Danish but not in Arabic), $I_{\mathcal{V}}(Y_j; X_i)$ can be negative or an invalid number.

We set the negative values and invalid numbers to zero to satisfy the non-negativity constraint of usable information and manage the NaN exceptions.

For a given language pair and hidden layer, we calculate the marginal entropy $H_V(Y_j | \Phi)$ in Equation 2 based on the gender distribution of the target language and approximate the conditional entropy $H_V(Y_j | X_i)$ using a light classifier trained on embedding-gender pairs from the source language i . The cross-entropy loss on a test sample from the target language j is then used as an estimate of $H_V(Y_j | X_i)$. To address class imbalance, cross-entropy loss is weighted by the gender distribution in the source language.

5 Experiment Setup

We investigate transfer learning of grammatical gender across a typologically diverse set of languages with different grammatical gender systems and minimal lexical similarity, as outlined in Table 1. Except for Danish-German, where Danish is included to broaden gender systems, this design choice helps minimize reliance on surface-level lexical overlap. The data is sourced from Universal Dependencies (v. 2.14) (Nivre et al., 2016), where nominal gender annotations are included as part of the inflectional features. For each language, we concatenate all treebanks that include gender annotations.

Language	Family	M	F	N	C
Arabic	AA-Semitic	67	33	0	0
Beja	AA-Cushitic	75	25	0	0
Danish	IE-Germanic	0	0	31	69
German	IE-Germanic	37	41	22	0
Greek	IE-Hellenic	19	52	29	0
Italian	IE-Romance	55	45	0	0
Russian	IE-Slavic	45	35	20	0

Table 1: Gender distribution (%) in the test languages. M: masculine. F: feminine. N: neuter. C: common. AA: Afro-Asiatic. IE: Indo-European.

The experiments are based on the multilingual BERT model (mBERT) (Devlin et al., 2019) consisting of 12 layers plus an initial embedding layer each with 768 features. The model is trained on a data set including text from an extensive range of 104 languages, including all our test languages except Beja, which we have intentionally selected to assess the degree of cross-lingual transfer beyond mBERT’s training languages.

Following Veeman et al. (2020), we extract embeddings from the formal representations of nouns provided in the FORM column of the Universal Dependencies treebanks. In cases where tokens are divided into subtokens, we average their embeddings. Since the experiments are based on cross-lingual transfer, morphosyntactic gender indicators from the source language are absent in the target language input. This design helps ensure that model performance reflects genuine cross-linguistic generalization rather than reliance on surface-level lexical cues in the target language.

For each sentence in a language, we construct a dictionary that maps the contextual embeddings of its nouns to their grammatical gender. The embeddings are extracted from all layers of mBERT, resulting in an embedding matrix of 768×13 for each occurrence of a noun in a language.

A known limitation of using mBERT in multilingual settings is that model performance can vary across languages due to differences in their representation in the pretraining data (Wu and Dredze, 2020). To mitigate this imbalance and ensure cross-linguistic comparability, we downsample the total number of nouns per language to match the smallest sample size in Arabic (5,151 nouns). For Beja, a total of 555 nouns are included.

We estimate the usable information based on 7×13 logistic regression models, corresponding to the number of languages and hidden layers. Each classifier is trained for 30 epochs with early stopping (patience of 5 epochs). We use AdamW as the optimizer with a manually tuned learning rate of 5×10^{-5} , and a learning rate scheduler that reduces the learning rate every 10 epochs by a factor of 0.1.

The train-validation-test split for all languages is 80-10-10. Training is performed on the training (80%) and validation (10%) splits, while cross-lingual entropy is estimated using the test split (10%). For each source-target language pair, $H_V(Y_j | X_i)$ in Equation 2 is estimated as the average cross-entropy loss over five random seeds.

6 Results

In this section, we present and analyze the results of our experiments through 1) intra-lingual analysis of the usable information, 2) their transferability across languages, and 3) their variations across layers and languages.

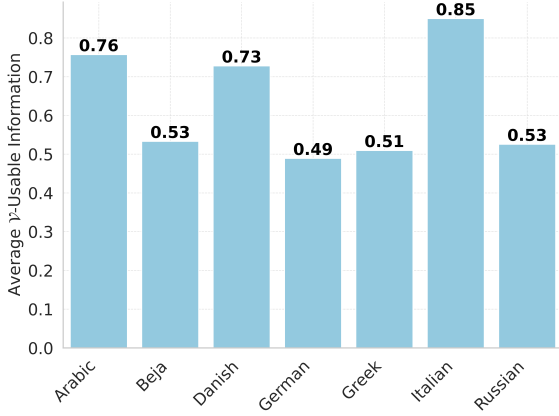


Figure 1: Averaged intra-lingual usable information.

6.1 Intra-lingual Analysis

We begin by examining the intra-lingual results of usable information for predicting gender (i.e., when the source and target languages are the same). [Figure 1](#) presents the average usable information for predicting gender within languages across all layers of mBERT. The differences in the results can be explained by two factors: the complexity of the gender system and the quality of the intermediate representations for each of the test languages.

In general, the differences in usable information can be interpreted as variations in the complexity of a target task ([Ethayarajh et al., 2022](#)). Specifically, in the case of languages seen in the mBERT’s training data, it indicates that the intermediate representations are significantly more informative about grammatical gender in Arabic, Danish, and Italian than in German, Greek, and Russian. This observation aligns with linguistic evidence, as the latter group of languages has more complex gender systems in different ways. Firstly, Arabic, Danish, and Italian have only two grammatical genders, whereas German, Greek, and Russian have three. Additionally, the former group has relatively predictable gender assignment patterns, often rooted in morphological inflections and syntactic agreements. In contrast, languages such as German, Greek, and Russian have more intricate agreement systems with numerous inflectional irregularities, making gender prediction more challenging. More details about the gender systems of the languages can be seen in [Section 2.2](#).

Given Beja’s absence from mBERT’s training data, we speculate that the moderate information for its gender prediction originates from typologically related languages in pretraining, such as Ara-

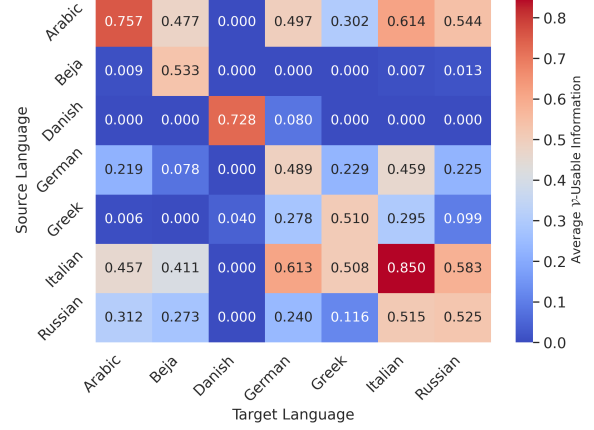


Figure 2: Averaged cross-lingual usable information.

bic, which also has a two-gender system (masculine/feminine).

Beyond linguistic factors, variations in intra-lingual usable information may also be influenced by the quality of intermediate representations, which are, in turn, affected by the distribution of training data for each language in mBERT’s pre-training corpus. However, this remains difficult to analyze, as the exact composition of mBERT’s training data has not been publicly disclosed.

6.2 Cross-lingual Analysis

[Figure 2](#) summarizes the usable information for predicting gender in a target language based on the information gained from a source language. The results, averaged over the intermediate layers of mBERT, provide clear evidence about the varying transferability of gender across languages. Danish and Beja have the least generalizable systems, while Arabic and Italian demonstrate the highest.

The poor cross-lingual performance of Danish can be attributed to its unique common/neuter gender system, the only such system in our study. However, transfer to Beja appears more feasible despite its absence from mBERT’s training data. Notably, Arabic \rightarrow Beja achieves relatively strong transfer, followed by Italian. This pattern likely reflects the structural similarity of their gender systems, with Arabic benefiting additionally from genetic relatedness and language contact with Beja ([Vanhove, 2012](#)). Moreover, the limited orthographic overlap between Beja and other test languages indicates that this successful transfer cannot be attributed to surface formal features at the tokenization level; rather, it is likely due to deeper cross-linguistic representations in mBERT that capture

universal patterns of gender assignment (Veeman et al., 2020). This effect may also be strengthened by indirect transfer from typologically related languages present in mBERT’s training data and by loanwords from Arabic.

The cross-lingual results in Figure 2 indicate that gender information generalizes more effectively from Arabic and Italian to other languages, except for Danish, which has entirely different gender categories. Arabic transfers best to Italian, as both languages share the same gender categories (i.e., masculine and feminine), and moderately well to languages that also include a neuter gender. Similarly, Italian transfers well to languages with both masculine and feminine genders. This suggests a strong alignment between the masculine and feminine genders in Arabic and Italian and their counterparts in other languages. Still further investigation is needed to explain special cases, such as Italian → German, where cross-lingual transfer is more informative than mono-lingual.

Surprisingly, both German and Russian provide nearly the same amount of information for predicting gender in Italian as they do in their own monolingual settings. This indicates strong structural similarities between these languages, which is likely the result of partially similar morphosyntactic gender agreement in these languages, as discussed in Section 2.2 and their alignment in the masculine and feminine categories, as discussed earlier in this section. A deep investigation of this phenomenon falls outside the scope of this paper.

For Greek as a source language, moderate transfer is achieved to German and Italian, with an average score of 0.3, and fairly low results on other languages. The low transfer to Arabic and Beja can be due to the differences in the number of grammatical genders and the distant genealogical relationship between these languages and Greek. The near-zero transfer to Russian is likely due to differences in declension systems, agreement rules, and the higher number of exceptions and irregularities in Russian, which is also reflected in the transfer from Russian to Greek.

6.3 Layer-wise Analysis

In this section, we provide detailed analyses of usable information in the intermediate representations for predicting gender across languages. The results across layers and languages are represented in Figure 3. The unnormalized results, including the negative usable information and standard devi-

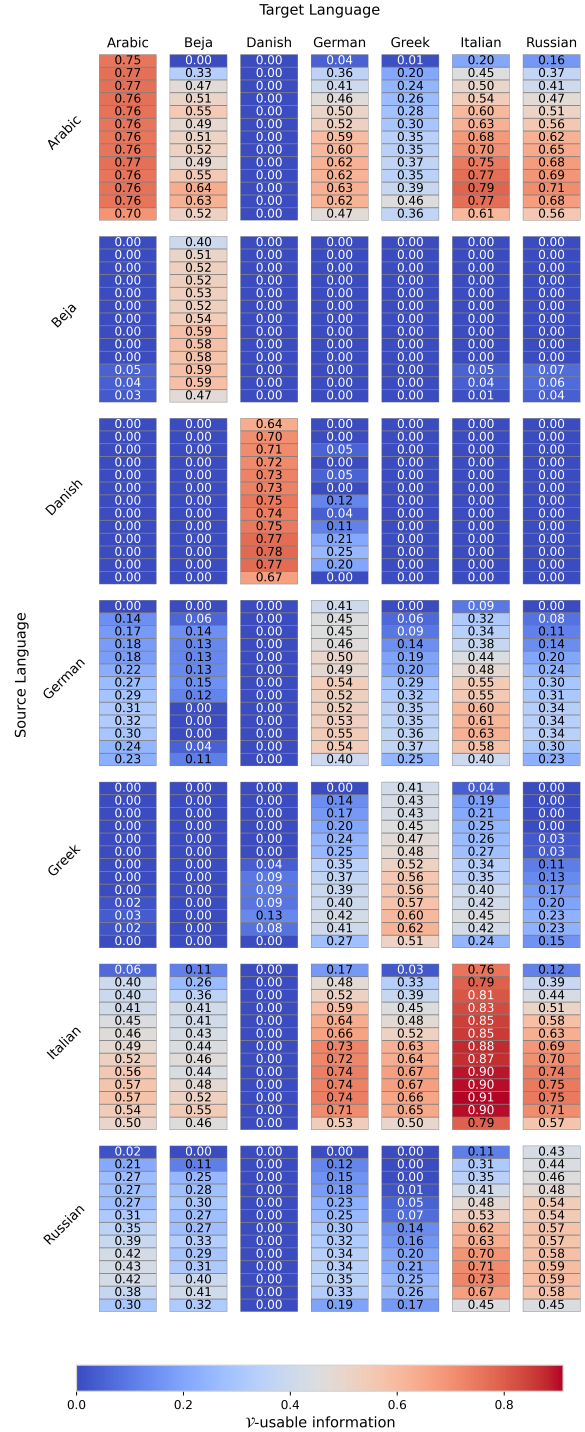


Figure 3: Mean usable information across language pairs and layers. Layers are ordered top-down, from the embedding layer to layer 12.

ations, are also visualized in Appendix A.

The usable information for gender prediction increases from the initial layer, peaks between Layers 9-11, and slightly decreases at the final layer. This trend is visible in both monolingual and cross-lingual settings. One exception, however, is German → Beja, where the trend experiences a

drop after Layer 6. Further distinct visualizations of the trends by each language are in Appendix B.

The increasing trend in usable information highlights the importance of the number of transformer layers in encoding gender information generalizable across languages. To further assess the significance of higher contribution of top layers to cross-lingual gender transfer, we group the model’s layers into two groups: (1) the lower layers, including the embedding layer (0) and Layers 1–6, and (2) the upper layers (6–12). For each source-target language pair, we compute the mean performance of these two groups and test whether the top layers are significantly more informative than the lower layers. We conduct a paired t-test and a Wilcoxon signed-rank test, comparing the mean performance of the lower and upper layers, for settings with a positive sum of usable information across layers.

Both statistical tests show that the usable information scores are significantly higher in the upper layers compared to the lower layers (paired t-test: $t = -7.93$, $p = 1.12 \times 10^{-9} < 0.001$; Wilcoxon: $W = 11.00$, $p = 4.22 \times 10^{-7} < 0.001$). These results suggest that cross-lingual gender transfer is primarily driven by linguistic features encoded in the middle to late layers, indicating that semantic features contribute more to gender assignment than formal features encoded in lower layers (Corbett and Fraser, 2000; Tenney et al., 2018).

The increasing trend in the usable information persists even in the monolingual setting, where the classifier is trained and tested on the same language (paired t-test: $t = -3.52$, $p = 0.006 < 0.01$; Wilcoxon: $W = 1.0$, $p = 0.03 < 0.05$). This pattern is also observed in languages where gender is explicitly marked morphologically on nouns through their formal features. One example is Italian, with few exceptions in the marking of feminine and masculine nouns, as mentioned in Section 2.2 (mean lower layer score = 0.82, mean upper layer score = 0.88). These results support the semantic-dominance hypothesis proposed by Corbett and Fraser (2000) and are consistent with the findings of Sahai and Sharma (2021) for French, which suggest that while orthographic and formal features alone yield high accuracy, performance improves further when semantic features are incorporated.

Notably, we observe a consistent performance drop in the final layer (see Figure 3). A possible explanation is that the last layer of mBERT encodes more abstract linguistic knowledge and long-range dependencies, which may be less rel-

evant for gender prediction (Puccetti et al., 2021; Peters et al., 2018). Similar declines in the final layers’ performance are also reported in general for higher-level linguistic probing tasks (Kunz and Kuhlmann, 2022).

7 Conclusions

This study explores the cross-linguistic transferability of grammatical gender in multilingual language models, focusing on the extent to which gender information generalizes across languages with different gender systems. Using variational-usable (\mathcal{V} -usable) information, we quantify how grammatical gender is encoded within and across languages in mBERT. Our findings reveal that gender information is more transferable between languages that share similar gender categories, whereas genealogical relationships play a secondary role.

Through intra-lingual analysis, we demonstrate that the complexity of a language’s gender system is reflected in the amount of usable information available in the intermediate representation of mBERT. Our cross-lingual results highlight that languages with two-gender systems, such as Arabic and Italian, exhibit the highest transferability, particularly to languages with similar gender distinctions. In contrast, languages with more complex gender systems, such as German and Russian, show reduced transfer due to the added complexity of declension systems and irregularities in gender assignment.

A layer-wise analysis further reveals that intermediate representations in mBERT play a critical role in encoding gender information. Gender distinctions are captured more effectively in the middle-to-upper layers, supporting the idea that semantic information is more generalizable across languages than purely morphological features.

Overall, our findings contribute to a deeper understanding of how grammatical gender is represented in multilingual LLMs and offer insights into universal aspects of grammatical gender. Future research could extend this analysis to other multilingual models (e.g., mGPT, BLOOM) and investigate additional factors influencing gender transfer, such as word frequency effects, training data composition, and finer-grained linguistic features. Expanding the study to a broader range of languages beyond Indo-European and Afro-Asiatic families would further enhance our understanding of cross-linguistic gender representation.

Limitations

A limitation of this study is the relatively small selection of languages analyzed. To better generalize cross-linguistic patterns in grammatical gender assignment, it is crucial to evaluate transfer learning across a more diverse set of languages, particularly from underrepresented language families. Additionally, our analysis is based solely on mBERT, an encoder-only model, which may limit the scope of the findings. Expanding the study to include additional multilingual language models, such as mT5, BLOOM, or mGPT, could provide more reliable and comprehensive insights into the transferability of grammatical gender. Another potential limitation is the uneven distribution of training data across languages in mBERT, which may influence gender transferability. Low-resource languages likely have weaker representations, affecting gender predictability. A broader investigation of training data composition and its impact on gender encoding would help disentangle model-specific biases from linguistic typology.

Acknowledgments

We thank the anonymous reviewers for their valuable feedback on this paper. We also acknowledge the Danish e-Infrastructure Consortium (DeiC) for providing computational resources through UCloud, supported under the Linguistic Universals in Language Models project.

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A Appendix

Original results for the averaged \mathcal{V} -usable information across layers for cross-lingual transfer between language pairs. Negative values were converted to zero to respect the boundaries of \mathcal{V} -usable information (see Section 6).

B Appendix

Averaged \mathcal{V} -usable information across layers for each source language, illustrating transfer scores to all target languages in the study.

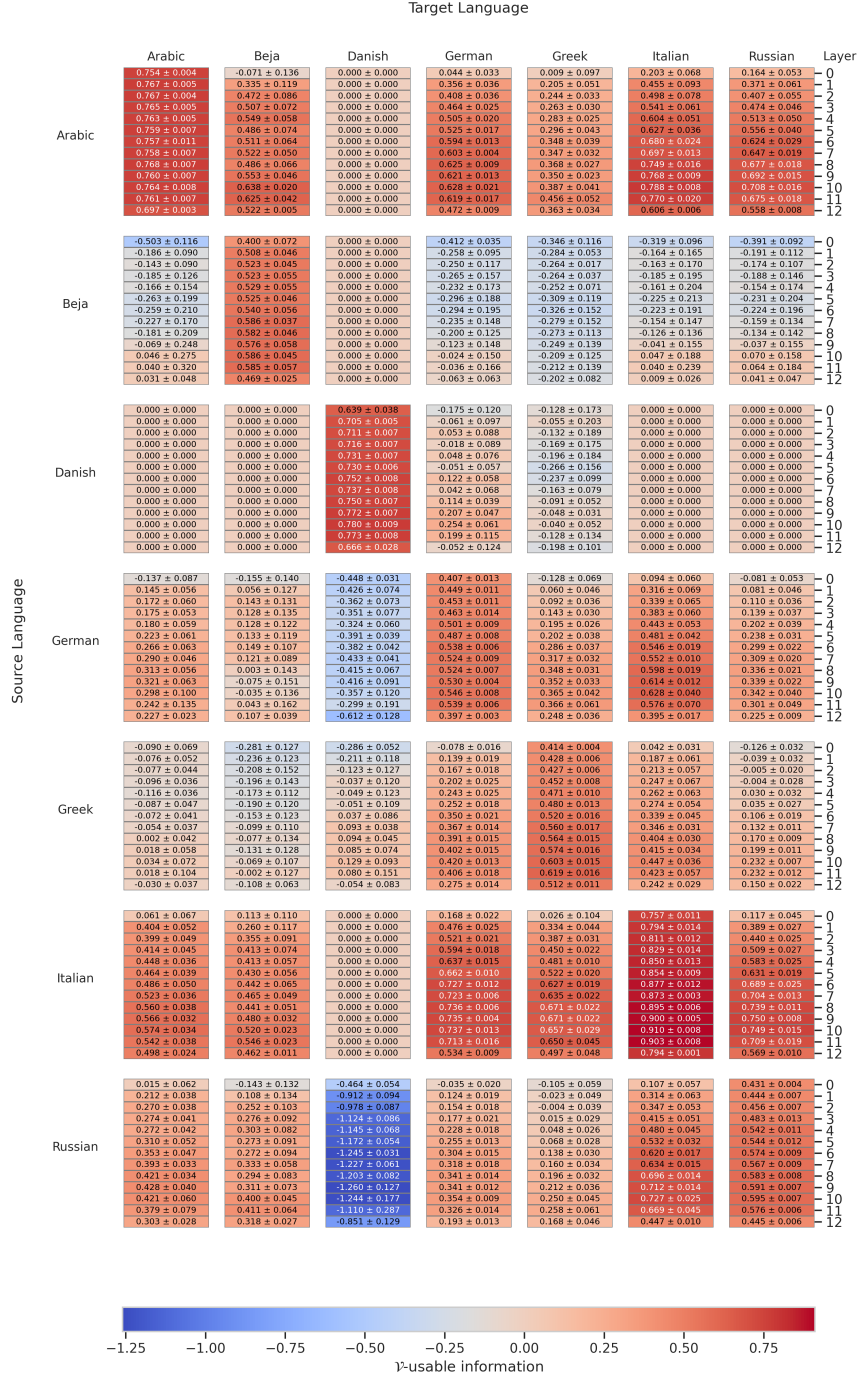


Figure 4: Mean usable information across language pairs and mBERT layers.

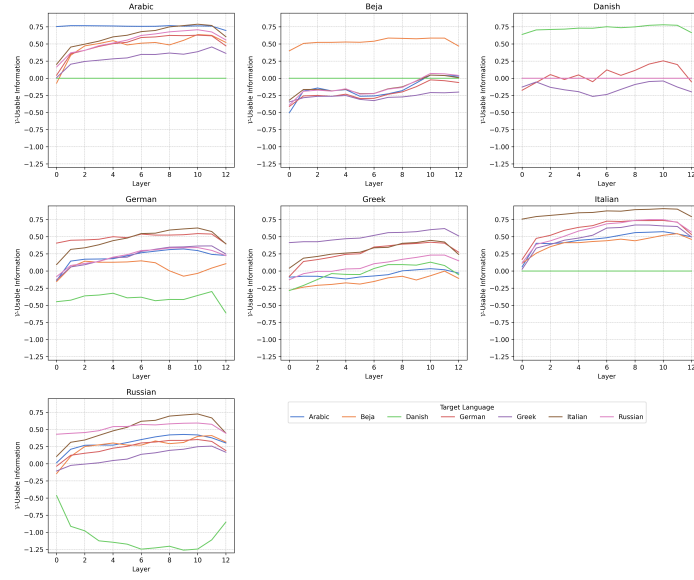


Figure 5: Averaged \mathcal{V} -usable information across mBERT layers for each source language, with transfer scores to all target languages.

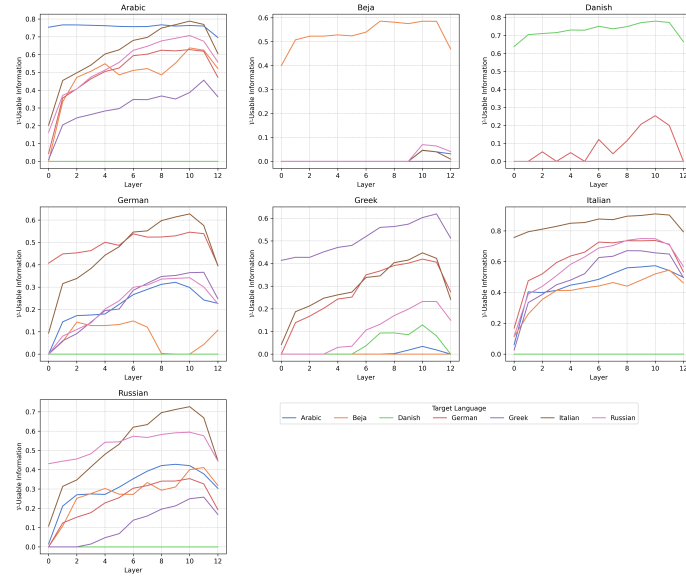


Figure 6: Averaged \mathcal{V} -usable information across mBERT layers for each source language, with transfer scores to all target languages, after setting negative values to zero.

Cross-lingual Transfer Dynamics in BLOOMZ: Insights into Multilingual Generalization

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Abstract

Multilingual large language models have emerged as a promising solution for resource-constrained settings, with significant efforts aimed towards improving multilingual capabilities of English-centric pretrained models. However, the broader cross-lingual implications of fine-tuning interventions remain understudied. This work examines instruction tuning (IT) over the BLOOMZ model for Question Answering (QA) in low-resource settings, with special emphasis on transfer dynamics across several languages. Our findings reveal two critical insights: first, IT on the target language can negatively impact its own performance in constrained short-span generation tasks due to overgeneration tendencies; second, in QA tasks, IT appears to suppress performance in some interfering languages, thereby enhancing capabilities in some target Indic languages by *more than doubling* QA performance. These results highlight important trade-offs in multilingual LLM adaptation and enhance our understanding of cross-lingual transfer mechanisms.

1 Introduction

Large language models (LLMs) excel in tasks like classification, text generation, and information extraction. Recently, cross-lingual alignment has been widely studied to enhance the multilingual capabilities of LLMs (Zhu et al., 2024; Zhang et al., 2024; Hu et al., 2021). Since most of the world’s languages can be deemed low-resource owing to the limited amounts of high-quality data (Asai et al., 2024; Razumovskaia et al., 2024), cross-lingual alignment is an important problem to tackle.

Prior work on multilinguality has largely focused on cross-lingual dynamics within English-centric models and pretrained decoder-only models (Zhao et al., 2024; Xu et al., 2023; Wendler et al., 2024). In this work, we study the cross-lingual abilities of

BLOOMZ, a multilingual, multi-task instruction-tuned model (Muennighoff et al., 2023; Scao et al., 2022). We focus on a constrained generation task, closed question answering (QA), that can be objectively evaluated (unlike open-ended generation tasks like machine translation) while still being vulnerable to generation-related artefacts (unlike classification tasks). We examine the impact of instruction tuning (IT) on QA on several Indic and non-Indic languages. Surprisingly, we find significant performance improvements using languages that transcend language family relatedness and surface-level script similarities, indicating that BLOOMZ exhibits cross-lingual generalization beyond typological proximity (Ifergan et al., 2024). We also present a new multilingual logit lens-based analysis to provide more insights into cross-lingual dynamics that result in performance improvements or degradations. Our analysis reveals two key phenomena: 1) Suppression of the target language and 2) a tendency to over-generate in the target language, both of which significantly affect the model’s output as illustrated in Figure 1.

Alignment with prior work. A growing consensus from recent work (Zhao et al., 2024; Wendler et al., 2024) is that English-centric models like Llama (Touvron et al., 2023) and Mistral (Jiang et al., 2023) process multilingual prompts by internally mapping to an English “thinking space” in intermediate layers, while the initial and final layers are multilingual in nature. Concurrent work explores language-specific neurons in the multilingual LLMs and reveals their significant roles in the outer layers (Tang et al., 2024; Zhu et al., 2024). Kargaran et al. (2024) argues that stronger alignment between English and non-English middle layer embeddings correlate with better cross-lingual transfer.

While current LLMs and adaptation methods demonstrate promising surface-level cross-lingual

	BASE	de-MT-IT
<p>ଟେସଲା ତାଙ୍କ କୃତିତ୍ୱ ଓ ଏବଂ ଗୋଟିଏ ପାଇଁ ପ୍ରସିଦ୍ଧ ଥିଲେ, ପରିଶେଷରେ ଏହା ତାଙ୍କୁ ଏକ ଆବିଷ୍କାରୀ "ପାଗଳ ବୈଜ୍ଞାନିକ" ...</p> <p>Q: ତାଙ୍କର ବୈଜ୍ଞାନିକ ସଫଳତା ଉପରେ ଟେସଲା କ'ଣ ପାଇଁ ପ୍ରସିଦ୍ଧ ଥିଲେ?</p> <p>[(Odia Sample) Translation: Apart from his scientific achievements, what was Tesla famous for?]</p>	<p>ଅଂଶେଷିତ ✗</p> <p>(Contains bengali characters)</p>	<p>ଗୋଟିଏ ✕</p> <p>(Showmanship)</p>
<p>ਦੱਖਣੀ କੈਲିଫର୍ନିଆ ਵਿੱਚ ਇੱਕ ମୁଖ୍ୟ ଅଂଶ ସଂସ୍କୃତି, ଅନ୍ତ ମହାନଗରୀ ଅଂଶ ସଂସ୍କୃତି, ਇੱକ ...</p> <p>Q: ਅଲ ସੈଣ୍ଟର ମହାନଗରୀ ଅଂଶ ଅਤੇ ସੈନ ଡିଏଗୋ-କାରଲସସିଡ-ସੈନ ମାରକୋସ ମହାନଗରୀ ଅଂଶ କି ସଂସ୍କୃତି ହେବ?</p> <p>[(Punjabi Sample) Translation: What makes up the El Centro metropolitan area and the San Diego-Carlsbad-San Marcos metropolitan area?]</p>	<p>ଦକ୍ଷିଣୀ ସରହੱਦି ਇਲାକା ✗</p> <p>(Contains hindi characters)</p>	<p>ਦੱਖਣୀ ସରହੱଦି ਇਲାକା ✕</p> <p>(Southern Border Region)</p>
<p>Einige moderne Gelehrte, wie Fielding H. Garrison, sind der Meinung, dass die Ursprünge der ...</p> <p>Q: Fielding H. Garrison glaubt, wohin lässt sich die Wissenschaft der Geologie zurückverfolgen?</p> <p>[(German Sample) Translation: Fielding H. Garrison believes that the science of geology can be traced to where?]</p>	<p>Persien ✕</p> <p>(Persia)</p>	<p>Persien, nach Ende der muslimischen Eroberung ✗</p> <p>(Persia, after the end of muslim conquest)</p>

Figure 1: Examples demonstrating that Instruction tuning on a small German-QA train set (generated via NLLB-MT) improves Odia and Punjabi performance by suppressing interference from Bengali and Hindi, respectively, but leads to overgeneration on German. Complete passages omitted for brevity.

abilities (on tasks like style transfer), they struggle with deeper cross-lingual reasoning and knowledge transfer. This limitation suggests the presence of a cross-lingual knowledge barrier, as noted by Chua et al. (2024). Towards addressing this gap, it has been observed that fine-tuning on certain languages can improve the performance of others, indicating the presence of cross-lingual bridging mechanisms (Singh et al., 2024b; Bai et al., 2024; Ifergan et al., 2024; Wang et al., 2024; Bai et al., 2023). Our experiments also support this possibility of cross-lingual bridging mechanisms. Our findings align with Ifergan et al. (2024) who documented BLOOM’s unique ability to facilitate factual recall across languages with different scripts.

2 Methodology

2.1 Logit Lens

Understanding how knowledge propagates through the layers of a model is critical for gaining insights into the internal workings of multilingual LLMs. One such interpretive tool is the Logit Lens, introduced by nostalgebraist (2020). This technique provides a mechanism to probe the latent representations in intermediate layers by mapping them directly to vocabulary probabilities using the last layer’s linear language modeling head. In prior work, Zhao et al. (2024) used logit lens to investigate the multilingual alignment of intermediate representations in Vicuna-13B-v1.5 (Chiang et al., 2023) and BLOOMZ-7B1 (Muennighoff et al., 2023). Similarly, Wendler et al. (2024) utilized logit lens to analyze intermediate representations in Llama models (Touvron et al., 2023) to measure

the token probabilities for English and Chinese words across different layers.

2.2 Probing for Language Identification

In our work, we adopt the logit lens framework to examine the flow of linguistic knowledge across the layers of BLOOMZ-7B1 for a diverse set of languages¹. Our analysis leverages Cook and Lui’s (2012) langid.py script, which assigns a probability distribution over languages for each token in the model’s vocabulary. Tokens composed solely of punctuation or numeric digits (0–9) are excluded, as they do not belong to a specific language and add noise to the analysis. The langid.py tool supports 96 languages, covering all languages in our experiments. We compute per-layer language probabilities by multiplying the per-token language probabilities with the token probabilities obtained from layer embeddings transformed via the language modeling head. To ensure statistical robustness, this process is repeated across multiple test set samples, and the final latent probabilities are derived by averaging the language distributions across all samples. Equation 1 estimates probability of language L at a layer j , given a dataset of task-specific examples D and a vocabulary V .

$$P_j(L) = \frac{1}{|D|} \sum_{D_i \in D} \sum_{t \in V} P_j(t|D_i) P(L|t) \quad (1)$$

Further details about formatting of the question and context in each task-specific example is given in Appendix A.

¹Code and dataset is available at <https://github.com/Sachi-27/Multilingual-NLP>.

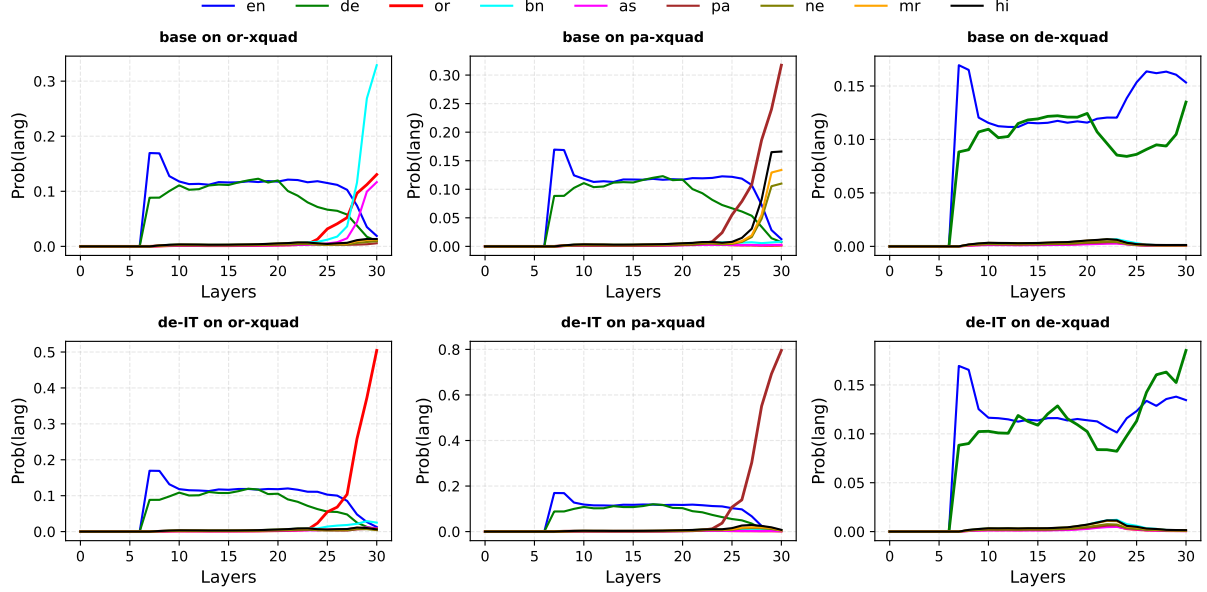


Figure 2: Comparison of logit lens plots for the BLOOMZ base model before and after German IT (de-IT i.e., instruction tuning on the German train set), evaluated on Odia (or), Punjabi (pa) and German (de) xquad test sets. For or-xquad and pa-xquad, the plots consider samples corrected after de-IT. In contrast, for de-xquad, the plots consider samples degraded after de-IT. Whether the response is corrected or degraded is decided based on the Exact Match Metric.

Unlike naive token frequency analyses, this method gives a probabilistic measure of language dominance, allowing us to capture subtle shifts in multilingual representation.

2.3 Experimental Setup

We conduct our experiments using the BLOOMZ-7B1² model and the multilingually parallel dataset, IndicGenBench’s XQuAD-IN (Singh et al., 2024a), which comprises data in 12 Indic languages and English. From this dataset, we utilize 103 context-question-answer triplets for training for 10 epochs. To construct a parallel training set for non-Indic languages, we leverage translations from NLLB (Costa-jussà et al., 2022) and Opus-MT (or MarianMT) (Tiedemann et al., 2023). Non-Indic test sets are sourced from the XQuAD dataset in the TensorFlow dataset library (Artetxe et al., 2019). Additionally, for robustness, we incorporate IndicQA (Doddapaneni et al., 2023), an out-of-domain question-answering dataset in Indic languages³. All experiments are evaluated in a zero-shot setting. The metrics are reported using Token-F1 and Exact Match scores (Rajpurkar et al., 2016).

²Choice is constrained by the model’s multilingual nature and QA-specific instruction tuning.

³Other datasets like TyDiQA and MLQA are leaked into BLOOMZ and thus unsuitable for evaluation.

More details are in Appendix B.

3 Results and Discussion

Suppression for Performance Improvements.

We highlight Token-F1 scores for 5 Indic languages: Gujarati (gu), Kannada (kn), Malayalam (ml), Odia (or), and Punjabi (pa) as these showed significant improvements in performance. Metrics are presented in Table 1, with the detailed results for all languages is available in Appendix D. Notably, with just 103 Russian-translated samples, we observe significant improvements, particularly a doubling of performance for the low-resource language Odia.

Through analysis of the multilingual logit lens plots (Figure 2), we identify distinct “hill-like” patterns in the middle-layer latents of languages such as German (de), Estonian (et), Swedish (sv), Xhosa (xh), Finnish (fi), Indonesian (id), and Malay (ms). We verify that, to some extent, these languages can facilitate cross-lingual transfer, in accordance with the findings of Zhao et al. (2024). We compare the logit lens plots for or-xquad and pa-xquad test sets between the base model and the de-IT model (i.e., the base model finetuned on German train set). We focus on samples where the base model answers wrongly, but the de-IT model provided correct predictions, shown in Figure 2. These plots highlight

Method	gu	kn	ml	or	pa
Base	60.81	48.52	49.07	25.90	55.80
en-IT	56.05	50.96	49.26	31.65	63.56
gu-IT	43.68	48.06	44.73	43.30	53.47
kn-IT	58.76	48.87	50.03	51.68	66.01
ml-IT	58.88	53.74	43.21	52.56	68.88
or-IT	50.32	48.12	45.49	48.11	61.67
pa-IT	53.78	50.06	48.03	48.34	58.63
de-MT-IT	63.90	57.83	52.66	49.86	70.99
et-MT-IT	66.18	56.17	53.06	38.29	68.41
fi-MT-IT	64.48	57.10	55.35	43.78	70.42
ru-MT-IT	59.75	55.66	51.16	56.38	68.32
sv-MT-IT	65.06	58.27	53.72	50.96	70.28
th-MT-IT	65.15	58.92	55.09	51.22	71.80
tr-MT-IT	65.91	56.89	54.20	48.38	71.57
xh-MT-IT	62.93	57.94	54.90	49.27	71.34

Table 1: Token-F1 scores of Instruction Tuned (IT) models evaluated on XQuAD-IN test set. Languages denoted with "MT" indicate training data generated via NLLB machine translation from the English train set. Performance rankings are visually indicated with **green** (highest) and **blue** (second highest).

Model	or (XQuAD-IN)	or (IndicQA)
Base	25.90, 17.05	26.82, 13.68
or-IT	48.41, 30.08	35.64, 18.37
de-MT-IT	49.86, 32.94	46.14, 27.91
sv-MT-IT	50.96, 33.52	43.61, 26.11

Table 2: Performance metrics (Token-F1 score, Exact Match Score) of Instruction-Tuned models evaluated on Odia test sets from XQuAD-IN and IndicQA.

token suppression in related languages, such as the reduction in Bengali and Assamese latent probabilities in the final layers for Odia, and the similar suppression of Hindi, Marathi, and Nepali for Punjabi. This in turn results in an increase in the last-layer probabilities for the target languages – Odia and Punjabi, in this case – that correlates with performance improvements. Similar trends are also observed across other languages, as detailed in Appendix C.

We also conduct out-of-domain evaluations using the IndicQA Odia datasets, comparing performance on or-xquad with different languages for instruction tuning. Our findings reveal similar performance gains, as shown in Table 2.

High-Resource Fine-Tuning is Not Universally Beneficial. Contrary to prior work, our findings challenge the notion that fine-tuning on high-resource languages universally improves perfor-

mance across the multilingual spectrum. The performance metrics of en-IT model on gu-xquad test set serves as a clear example of this. Surprisingly, certain medium to low-resource languages, such as Kannada, Malayalam, Thai and Turkish contribute significantly to overall model improvement. This suggests that the effectiveness of fine-tuning languages in enhancing alignment and generalization is not solely dependent on data availability.

Self-performance trade-off. Self-IT (i.e., IT using language X evaluated on test samples of language X) appears to negatively impact performance on QA-style tasks that require concise, span-based answers. This is likely due to the model’s tendency to generate verbose (and sometimes hallucinatory) responses, that negatively affects task accuracy. Logit lens plots in Figure 2 illustrate this tendency for de-IT on de-xquad, with rising latent probabilities in the final layers indicative of over-generation.

Better Translation Quality Leads to Improved Cross-Lingual Transfer. Results in Tables 3 and 11 are consistent. For example, in Indonesian, NLLB generated translations are of better quality, correlating with better performance on IT. Logit lens visualizations (Figure 8) shows that IT with MarianMT translations struggles with Bengali suppression, while IT with NLLB translations enables Odia to surpass Bengali, aligning with id-IT gains. More details are in Appendix D.

IT Lang	MT Model	BLEU	gu	kn	ml	or	pa
Base	-	-	60.81	48.52	49.07	25.90	55.80
id	MarianMT	19.99	51.13	44.46	34.40	21.96	55.57
	NLLB	46.97	54.52	48.52	37.52	32.95	61.00
xh	MarianMT	8.42	59.36	55.22	53.34	46.18	68.88
	NLLB	23.88	62.93	57.94	54.90	49.27	71.34

Table 3: Comparison of IT models trained on machine translated training data using MarianMT vs NLLB and evaluated on XQuAD-IN test set. Here, **green** highlights the higher Token-F1 scores and **blue** highlights MT with higher BLEU scores.

4 Conclusion

This work highlights the intricate nature of multilingual task specific fine-tuning and its diverse effects across languages. We demonstrate that instruction tuning with a very small set of samples is unlikely to acquire substantial new knowledge, but can induce shifts in linguistic structures, particularly in the later layers, leading to suppression of interfering language latents, contributing to improved

performance. However, these improvements are neither uniform nor guaranteed, as high-resource fine-tuning does not always yield positive effects, and self-IT performance trade-offs often emerge. Moreover, the quality of training data significantly influences outcomes, with better translation quality directly correlating with improved multilingual alignment.

5 Limitations

Our study highlights the significance of latent structures in the intermediate layers of multilingual models, emphasizing their role in cross-lingual transferability. We also demonstrate that instruction tuning impacts performance across languages differently, influenced by their intrinsic characteristics and resource levels. However, our analysis is subject to several limitations. Our experiments focus only on the task of span-based question answering and one specific multilingual model, BLOOMZ. Other multilingual models such as Gemma-7B (Team et al., 2024) and Aya-13B (Üstün et al., 2024) exhibit very irregular and unstructured logit lens plots. Their plots deviate from the multilingual hypothesis (Zhao et al., 2024), which posits that multilingual models predominantly "think" in English or Latin-centric representations. Instead, these models exhibit a significant mix-up in thinking across languages and deviate from "hill" type latent representations, indicating a different latent structure than what is typically observed in conventional Latin-centric multilingual models. This restricts the generalizability of our findings to other models and task types. Finally, although we observe that languages like German (de) and Swedish (sv) trigger suppression to improve performance, the underlying mechanism behind this phenomenon remains unclear, warranting further investigation.

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A Multilingual Logit Lens Implementation Details

The language confidences scores for each token are obtained from `languid.py` and stored in a token-language probability table, \mathcal{T} , where \mathcal{T}_{ij} represents the probability of token t_i belonging to language j . Mathematically, this can be represented as:

$$\mathcal{T}_{tl} = \sigma(c_{\text{languid}}(t, l)) \quad (2)$$

where $c_{\text{languid}}(t, l)$ denotes the confidence score output by `languid.py` for token t belonging to each language l , and σ is the softmax function, ensuring that the probabilities across all languages sum to 1 for every token. We exclude tokens consisting of only numbers and punctuation marks, by zeroing all entries in the table corresponding to such a token t . For BLOOMZ-7B1, there are 6,269 such tokens out of 250,680 in its vocabulary.

For each input sample, the logit lens is applied to the embeddings $h_n^{(j)}$ at every layer j of the model for the last input token x_n . The logits obtained from these embeddings are then transformed into language probabilities by mapping them with the token-language probability table \mathcal{T} . This mapping is expressed as:

$$P(\text{lang} = l \mid h_n^{(j)}) = \sum_t \mathcal{T}_{tl} \cdot \sigma(\text{logit}(h_n^{(j)}))[t] \quad (3)$$

where $\sigma(\text{logit}(h_n^{(j)}))$ represents the logits of the embedding $h_n^{(j)}$ obtained after passing the embedding through the linear modelling head. This operation provides a distribution over languages for the embeddings at every layer j . Additionally, to address a specific model behavior, we implement probability zeroing for tokens corresponding to "A:" in the initial layers. This post-processing step is necessary because the model exhibits a tendency to overly weight "A:" tokens, due to their presence as the final token in the input prompt (Table 4).

[Context in Target Language]

Q: [Question in Target Language]
A:

Table 4: Standardized prompt template for Question Answering, aligned with the format used in IndicGenBench.

B Experimental Setup Details

B.1 Datasets

The dataset splits used in our experiments are reported in Table 5. IndicGenBench’s XQuAD-IN consists of English (en) and 12 Indic languages: Assamese (as), Bengali (bn), Gujarati (gu), Hindi (hi), Kannada (kn), Malayalam (ml), Marathi (mr), Odia (or), Punjabi (pa), Tamil (ta), Telugu (te), and Urdu (ur). The test set comprises 1,190 examples and is fully parallel with the XQuAD dataset from the TensorFlow Datasets (TFDS) library. For training, XQuAD-IN includes a subset of 103 examples from the English training set of TFDS-XQuAD. To ensure parallelism and maintain consistency across instruction tuning (IT) experiments, we use this 103-example subset and translate it into other languages for fine tuning.

While the TensorFlow Datasets (TFDS) version of XQuAD contains training data for German (de), Russian (ru), Thai (th), Turkish (tr), Greek (el), Spanish (es), and Vietnamese (vi), our goal was to ensure a small parallel dataset across languages to fairly investigate cross-lingual effects. There are two key reasons why we opted for additional translations: 1, Avoiding bias from dataset discrepancies and 2, Consistency in machine translation sources.

To evaluate generalization, we also incorporate IndicQA, an out-of-domain question-answering test dataset covering the same 11 Indic languages as

Dataset	Train	Val	Test
XQuAD-IN	103	111	1190
TFDS-XQuAD	~80K	~10K	1190
IndicQA	-	-	~1K

Table 5: Dataset Splits

XQuAD-IN, excluding Urdu. Unlike XQuAD-IN, IndicQA is not parallel across languages.

B.2 Instruction Tuning Details

We utilized prompts tailored to the QA task as in Singh et al. (2024a). The causal language model (LM) is fine-tuned for 10 epochs using the PEFT LoRA framework (Mangrulkar et al., 2022), with updates restricted to the query-key-value layers of BLOOMZ. The fine-tuning follows a causal LM objective, maximizing the likelihood of generating the next token given the previous tokens. The process optimizes the generative probability of the complete prompt, which includes the context, question, and the correct response as shown in 4. Key hyperparameters for fine-tuning include a learning rate of 2×10^{-4} , LoRA rank $r = 64$, and $\alpha = 16$. All experiments were conducted on a single NVIDIA A100-SXM4-80GB GPU, with a max runtime of 3 minutes for 103 samples over 10 epochs.

$$\arg \min_{\phi} \sum_{\mathcal{P}=\{\mathcal{C}, \mathcal{Q}, \mathcal{R}\} \in \mathcal{D}} -\log p_{\phi}(\mathcal{P}) \quad (4)$$

B.3 Evaluation

We conducted evaluations on the XQuAD-IN and TFDS test sets in a zero-shot setting. The outputs generated by the LLM are compared with the reference answers using the widely adopted SQuAD evaluation metrics (Rajpurkar et al., 2016). This reports the Token-level F1 score, which measures the overlap between predicted and ground-truth tokens, considering partial matches and the exact match (EM) score, which measures the strict match between the predicted answer and the reference. We used evaluations on the base BLOOMZ-7B1 model as the baseline. Our results are based on a single run, which is reproducible by setting random seeds. The generation process follows controlled decoding with top-k sampling ($k = 50$), nucleus sampling (top-p= 0.95), and generating a single output sequence (num_return_sequences=1) at temperature= 0.1.

C Logit Lens Plots

Figures 3 and 4 display the logit lens plots for Odia and Punjabi samples where both the base and de-IT models make the same correct predictions. Similar, albeit less pronounced, suppressions are observed for Gujarati, Malayalam, and Kannada in XQuAD-IN, leading to minimal performance gains (Figure 5). Comparable trends are observed for other IT languages, as detailed in Appendix Figures 6 and 7.

ISO Code	Language	ISO Code	Language
as	Assamese	bn	Bengali
de	German	el	Greek
en	English	es	Spanish
et	Estonian	fi	Finnish
fr	French	hi	Hindi
id	Indonesian	kn	Kannada
ml	Malayalam	mr	Marathi
ms	Malay	or	Odia
pa	Punjabi	ru	Russian
sv	Swedish	ta	Tamil
te	Telugu	th	Thai
tr	Turkish	vi	Vietnamese
xh	Xhosa		

Table 6: ISO Code to Language Mapping

D Complete Metrics

We report the complete performance metrics on the XQuAD-IN test set for its 12 Indic languages in Tables 7 and 8. Additionally, we present scores on the TFDS XQuAD test sets for 7 languages in Table 9. Malay (ms) is excluded from our analysis because NLLB doesn’t support it. We report the IndicQA test performance for 6 languages across several selected IT languages in Table 10. Furthermore, we present complete performance metrics of IT models trained on 6 middle-layer hill languages (de, et, fi, id, sv, and xh). The training data are machine translated from English. Performance comparisons of MarianMT and NLLB generated train data are provided in Tables 11 and 12. To measure translation quality, we use BLEU scores for the training contexts, comparing MT-generated outputs against Google Translate generations (used as ground truth).

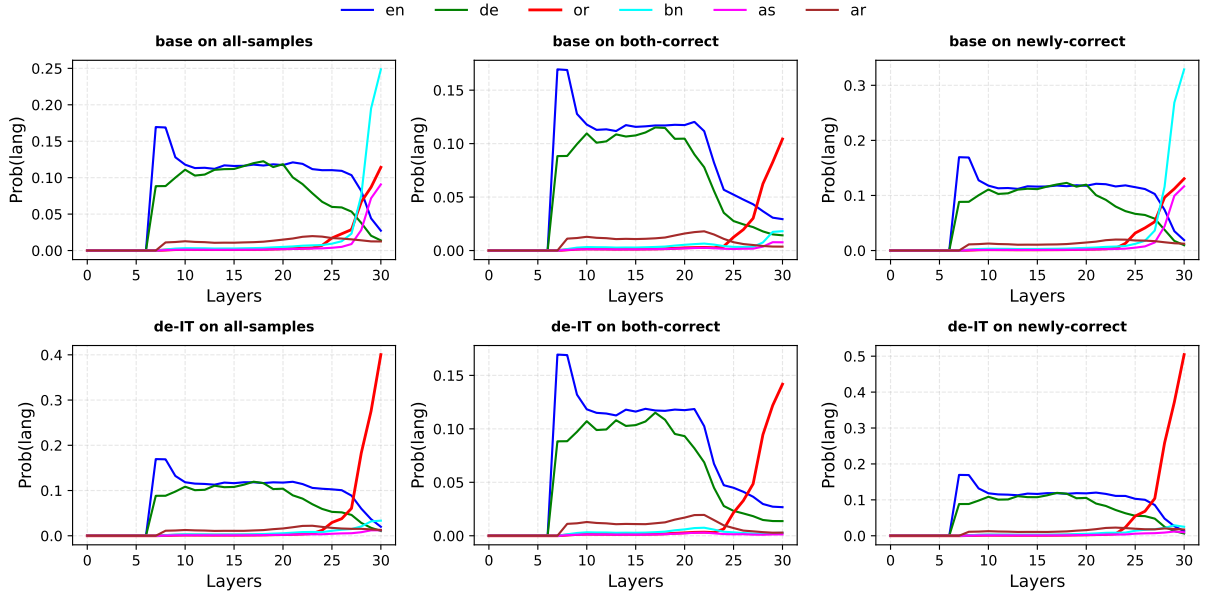


Figure 3: Logit lens analysis of the BLOOMZ model before and after German IT (de-IT) on Odia test data (or-xquad). The plots illustrate three scenarios considering: all samples, samples with correct predictions across both models, and newly corrected samples—those misclassified by the base model but correctly predicted after de-IT. Samples with correct predictions on base model have low interference. Correction of predictions occur where Bengali (bn) and other interference (Assamese (as) and Arabic (ar)) is suppressed and replaced by stronger Odia (or) signals.

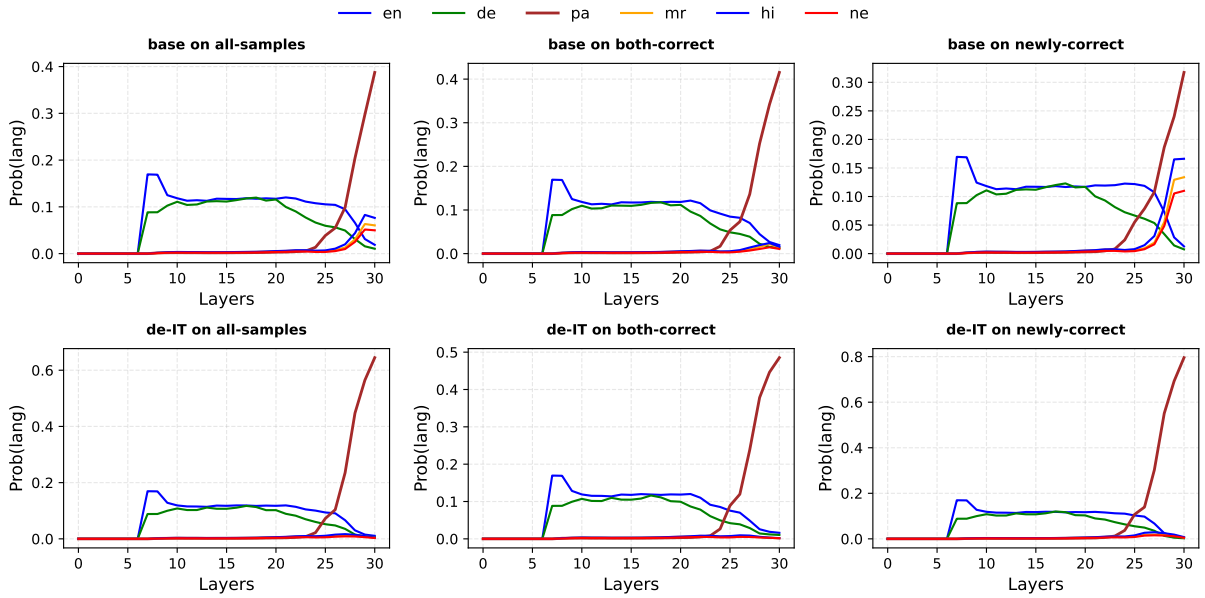


Figure 4: Logit lens analysis of the BLOOMZ model before and after German IT (de-IT) on Punjabi test data (pa-xquad). The plots illustrate three scenarios considering: all samples, samples with correct predictions across both models, and newly corrected samples—those misclassified by the base model but correctly predicted after de-IT. Samples with correct predictions on base model have low interference. Correction of predictions occur when interfering latents of Hindi (hi), Marathi (mr) and Nepali (ne) are suppressed and replaced by stronger Punjabi (pa) signals.

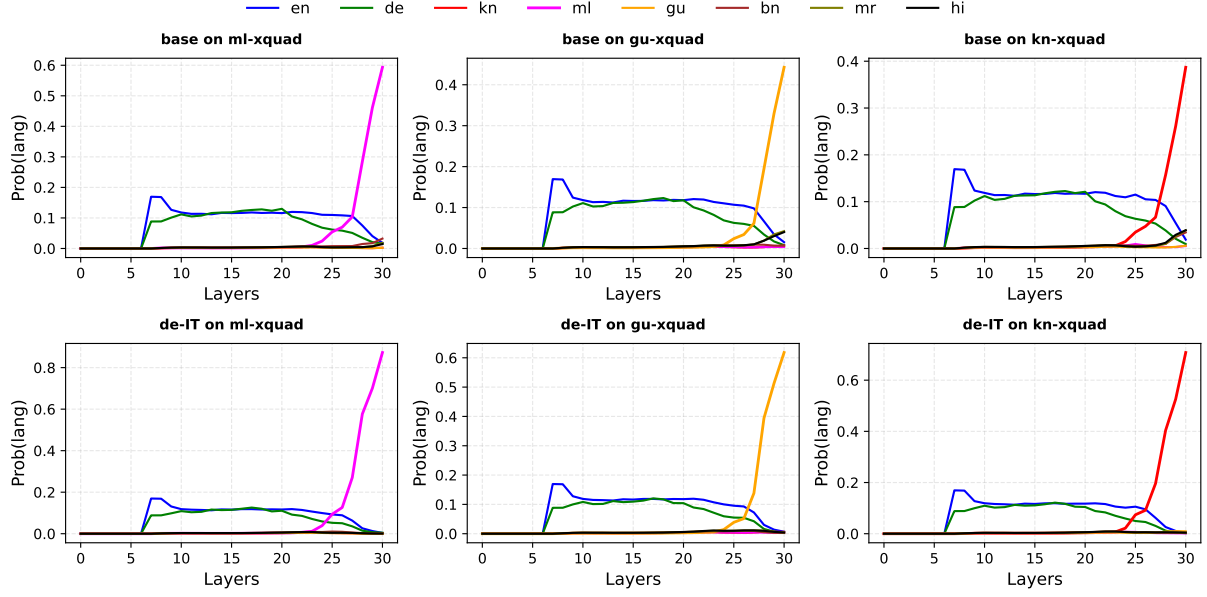


Figure 5: Comparison of logit lens plots for the BLOOMZ model before and after German IT (de-IT), evaluated on test data from Malayalam (ml), Gujarati (gu) and Kannada (kn) xquad test sets. The plots consider samples misclassified by the base model but correctly predicted after de-IT. There is a rise in test language probability in the last layers after de-IT indicating stronger signals correlating with improved performance.

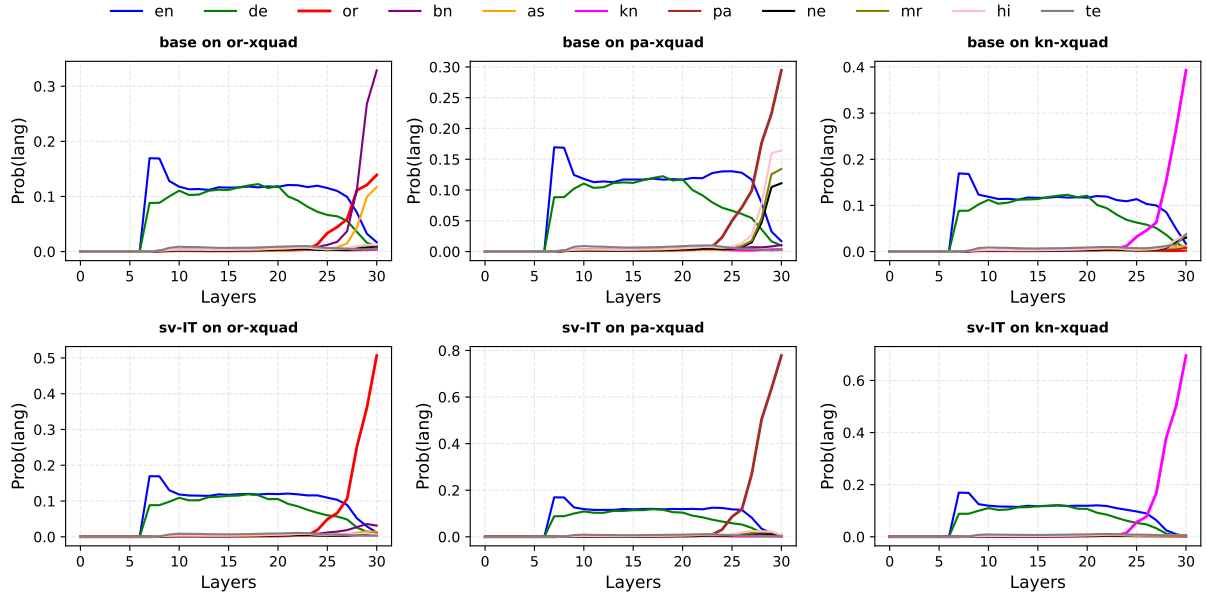


Figure 6: Comparison of logit lens plots for the BLOOMZ model before and after Swedish IT (sv-IT), evaluated on test data from Odia (or), Punjabi (pa) and Kannada (kn) xquad test sets. The plots consider samples misclassified by the base model but correctly predicted after sv-IT. There is a rise in Kannada latent in the last layers after sv-IT indicating stronger signals correlating with improved performance. Suppression of interfering languages in Odia and Punjabi after sv-IT correlates with improved performance.

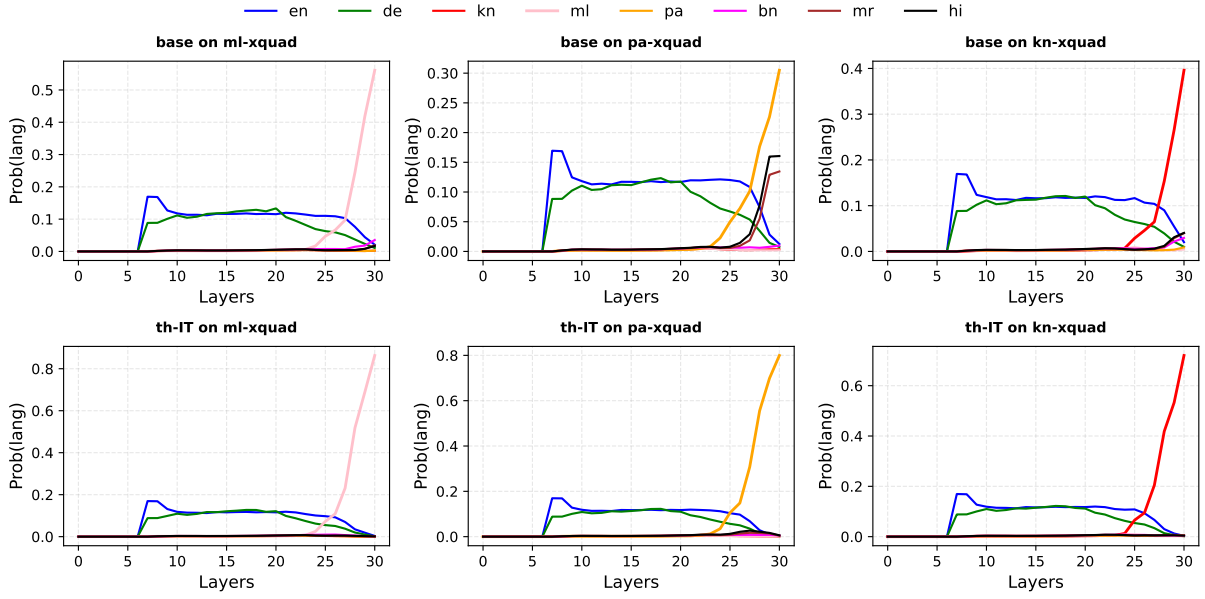


Figure 7: Comparison of logit lens plots for the BLOOMZ model before and after Thai IT (th-IT), evaluated on test data from Malayalam (ml), Punjabi (pa) and Kannada (kn) xquad test sets. The plots consider samples misclassified by the base model but correctly predicted after th-IT. Suppression of interfering last layer latents in Punjabi and rising last layer signals in Malayalam and Kannada correlate with improved performance.

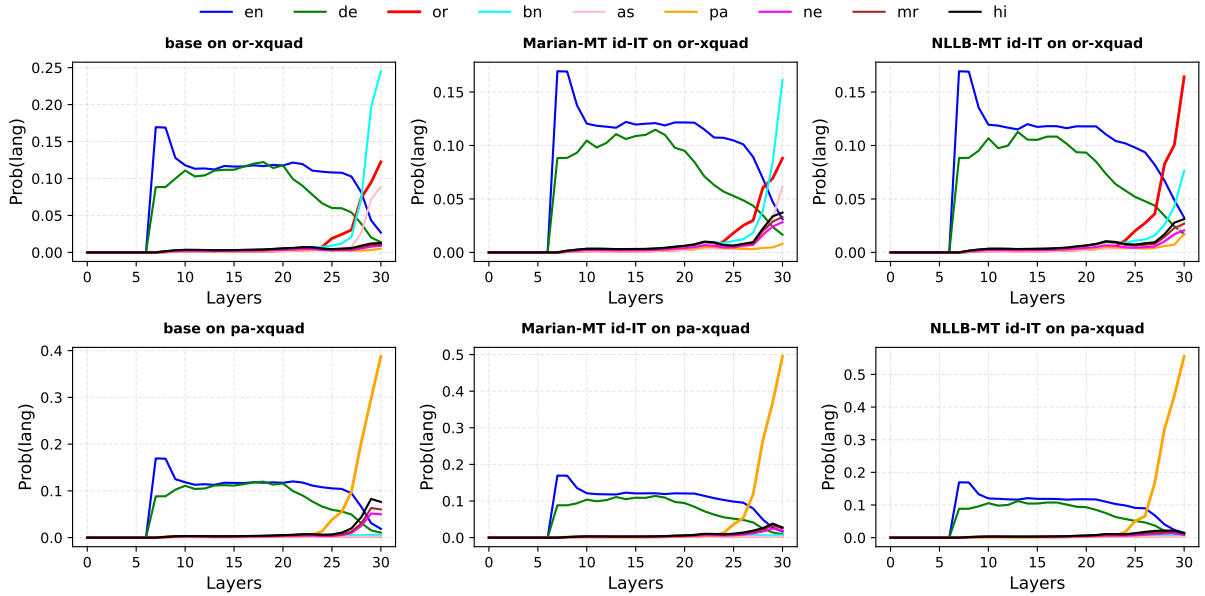


Figure 8: Logit lens comparison of the BLOOMZ model before and after Indonesian IT (id-IT), utilizing training data derived from the English parallel subset of IndicGenBench with machine translations from MarianMT (Helsinki-Opus) and NLLB. The analysis is conducted on all test samples from Odia (or) and Punjabi (pa) xquad test sets.

Token F1, EM	gu	kn	ml	or	pa	ur
Base	60.81, 43.94	48.52, 32.35	49.07, 33.44	25.90, 17.05	55.80, 38.73	67.75, 49.07
as-IT	55.41, 35.96	53.20, 34.95	46.77, 31.09	46.28, 28.82	67.10, 46.80	65.30, 46.80
bn-IT	49.60, 30.08	43.47, 27.56	43.52, 27.64	23.55, 14.53	58.35, 34.28	59.13, 37.64
en-IT	56.05, 37.14	50.96, 33.19	49.26, 31.93	31.65, 20.08	63.56, 43.10	62.71, 41.42
gu-IT	43.68, 24.20	48.06, 30.33	44.73, 27.89	43.30, 25.71	53.47, 28.82	62.74, 42.26
hi-IT	48.14, 28.06	47.83, 31.34	45.19, 29.32	31.86, 19.07	58.09, 33.44	58.44, 34.78
kn-IT	58.76, 41.17	48.87, 30.36	50.03, 34.28	51.68, 34.28	66.01, 46.80	65.56, 46.47
ml-IT	58.88, 40.00	53.74, 35.37	43.21, 25.71	52.56, 35.88	68.88, 49.66	65.97, 46.97
mr-IT	55.11, 37.31	51.36, 34.11	48.16, 32.35	49.42, 32.68	63.49, 44.53	64.44, 45.79
or-IT	50.32, 31.68	48.12, 31.59	45.49, 30.25	48.11, 30.25	61.67, 40.08	64.00, 44.87
pa-IT	53.78, 36.05	50.06, 33.19	48.03, 32.77	48.34, 32.43	58.63, 37.56	61.83, 40.00
ta-IT	50.09, 30.25	49.02, 30.33	47.11, 30.92	45.02, 26.80	63.36, 38.99	63.86, 43.19
te-IT	51.30, 31.93	48.34, 31.09	44.89, 29.24	40.19, 24.78	63.73, 41.17	64.15, 45.12
ur-IT	51.71, 33.44	47.55, 30.75	43.94, 27.73	34.37, 21.93	57.88, 35.79	56.70, 33.10
de-MT-IT	63.90, 45.96	57.83, 40.00	52.66, 36.47	49.86, 32.94	70.99, 52.10	66.92, 47.14
el-MT-IT	64.05, 45.54	58.35, 39.66	55.37, 37.89	51.22, 34.20	70.44, 50.08	66.96, 47.73
es-MT-IT	47.87, 29.41	45.70, 28.99	40.85, 25.46	27.60, 17.05	54.73, 32.18	53.29, 30.92
et-MT-IT	66.18, 48.73	56.17, 38.57	53.06, 37.39	38.29, 25.54	68.41, 49.66	67.04, 47.56
fi-MT-IT	64.48, 47.22	57.10, 39.24	55.35, 39.41	43.78, 28.9	70.42, 51.84	66.98, 47.47
fr-MT-IT	48.87, 30.16	46.50, 27.98	39.51, 24.70	36.42, 22.01	52.47, 27.64	51.09, 28.90
id-MT-IT	54.52, 33.94	48.52, 31.51	37.52, 23.94	32.95, 21.42	61.00, 39.83	59.64, 38.57
ru-MT-IT	59.75, 40.75	55.66, 35.63	51.16, 33.94	56.38, 38.40	68.32, 46.97	65.88, 45.71
sv-MT-IT	65.06, 47.39	58.27, 40.58	53.72, 37.14	50.96, 33.52	70.28, 51.59	67.83, 47.98
th-MT-IT	65.15, 46.63	58.92, 40.84	55.09, 39.57	51.22, 33.94	71.80, 52.77	68.01, 48.40
tr-MT-IT	65.91, 48.73	56.89, 39.07	54.20, 37.98	48.38, 32.35	71.57, 32.35	67.68, 48.57
vi-MT-IT	50.41, 31.59	45.16, 28.40	38.10, 25.54	28.50, 18.15	55.50, 31.68	56.66, 35.12
xh-MT-IT	62.93, 43.27	57.94, 40.16	54.90, 38.31	49.27, 31.59	71.34, 51.93	67.97, 48.31

Table 7: Performance metrics (Token-F1 score, Exact Match score) of Instruction Tuned (IT) models on the XQuAD-IN test set. Training data sourced from the XQuAD-IN parallel corpus. Languages denoted with "MT" indicate training data generated via NLLB machine translation from the English subset. Performance rankings are visually indicated with **green** (highest) and **blue** (second highest) based on Token F1 scores. The results are shown for languages gu (Gujarati), kn (Kannada), ml (Malayalam), or (Odia) and ur (Urdu).

Method	bn	te	hi	mr	as	ta
Base	64.20, 44.53	58.22, 39.74	73.02, 48.82	65.96, 50.00	51.33, 32.43	63.37, 45.88
as-IT	60.19, 38.31	55.86, 36.89	72.09, 47.31	58.76, 40.50	45.26, 24.03	58.61, 40.75
bn-IT	54.93, 32.85	52.26, 33.94	67.23, 38.15	52.54, 34.03	40.80, 22.18	52.67, 33.27
en-IT	60.58, 39.15	55.11, 35.96	69.79, 42.43	60.61, 43.86	49.42, 28.90	53.04, 34.62
gu-IT	60.91, 39.41	51.55, 32.94	70.38, 44.70	51.79, 33.36	46.60, 27.31	56.48, 38.82
hi-IT	56.86, 33.19	52.32, 34.45	61.60, 31.42	52.83, 31.68	46.50, 27.14	54.12, 35.21
kn-IT	63.33, 42.35	54.98, 37.05	70.84, 46.80	61.72, 44.36	51.19, 31.93	59.53, 41.76
ml-IT	63.32, 41.84	56.18, 38.31	72.31, 47.73	62.36, 46.05	51.01, 31.59	57.91, 41.34
mr-IT	61.75, 40.67	53.32, 35.56	69.95, 45.04	52.19, 34.20	46.75, 28.31	59.51, 42.52
or-IT	58.76, 39.24	50.86, 32.52	70.07, 46.13	55.58, 38.90	22.11, 11.34	59.73, 40.76
pa-IT	61.05, 39.83	54.06, 36.30	69.45, 44.20	56.51, 39.74	47.75, 28.15	57.64, 40.75
ta-IT	60.71, 38.23	49.48, 29.83	70.92, 45.37	56.18, 37.98	49.46, 29.83	46.76, 26.38
te-IT	62.31, 41.76	45.84, 28.23	70.41, 45.79	59.06, 42.10	47.56, 27.98	52.01, 33.86
ur-IT	58.65, 37.22	52.46, 34.45	68.56, 42.01	56.52, 37.14	46.19, 26.97	53.77, 35.63
de-MT-IT	65.30, 44.28	57.80, 39.57	73.29, 47.64	64.47, 47.89	52.80, 32.26	61.20, 43.86
el-MT-IT	65.59, 44.28	57.67, 38.82	73.67, 48.48	65.80, 48.57	53.02, 32.52	60.93, 43.78
es-MT-IT	53.47, 31.68	51.18, 31.76	62.66, 34.36	49.76, 33.69	43.15, 22.94	47.89, 27.39
et-MT-IT	65.55, 45.29	58.88, 41.26	73.55, 48.82	66.77, 50.16	53.50, 33.78	62.73, 46.38
fi-MT-IT	65.49, 44.87	58.86, 40.84	73.65, 48.15	66.20, 49.32	53.64, 33.69	62.21, 45.04
fr-MT-IT	54.60, 32.52	51.06, 32.60	58.73, 29.57	49.76, 30.67	44.92, 26.38	49.62, 31.17
id-MT-IT	56.83, 34.53	54.26, 34.28	67.32, 39.66	55.39, 38.31	47.32, 27.81	52.46, 33.27
ru-MT-IT	64.84, 42.60	58.70, 39.24	73.06, 46.89	64.08, 45.96	53.19, 32.26	58.10, 40.50
sv-MT-IT	64.90, 44.36	57.98, 39.49	73.64, 48.15	66.02, 49.91	53.54, 32.94	62.70, 46.30
th-MT-IT	65.42, 45.21	58.07, 39.91	73.44, 48.73	66.38, 49.83	54.08, 33.36	61.46, 44.95
tr-MT-IT	65.52, 45.21	58.67, 40.67	73.62, 48.90	65.62, 49.66	54.31, 33.44	62.29, 45.71
vi-MT-IT	55.44, 34.11	52.14, 34.20	66.03, 36.80	52.17, 35.71	44.93, 26.55	52.39, 32.52
xh-MT-IT	65.72, 45.21	58.54, 39.91	73.52, 49.15	64.31, 47.73	53.57, 32.43	62.06, 45.21

Table 8: Performance metrics (Token-F1 score, Exact Match score) of Instruction Tuned (IT) models on the XQuAD-IN test set. Training data sourced from the XQuAD-IN parallel corpus. Languages denoted with "MT" indicate training data generated via NLLB machine translation from the English subset. Performance rankings are visually indicated with **green** (highest) and **blue** (second highest) based on Token-F1 scores. The results are shown for languages bn (Bengali), te (Telugu), hi (Hindi), mr (Marathi), as (Assamese) and ta (Tamil).

METHOD	ru	el	es	de	vi	th	tr
Base	61.95, 45.21	38.31, 28.31	89.15, 75.88	71.93, 57.05	88.07, 76.21	21.04, 16.21	34.47, 24.70
as-IT	57.25, 41.59	34.12, 23.44	88.00, 72.60	67.38, 53.02	86.89, 73.44	19.95, 13.69	29.90, 20.16
bn-IT	55.40, 39.91	35.42, 23.52	85.18, 67.22	64.19, 48.99	84.32, 68.06	19.13, 13.94	21.75, 14.78
en-IT	57.30, 40.92	34.64, 22.26	72.04, 51.59	66.06, 49.49	78.28, 61.00	21.97, 15.63	29.33, 17.81
gu-IT	56.25, 39.07	33.23, 22.43	87.24, 71.68	66.80, 51.59	87.62, 74.53	19.60, 14.36	27.66, 19.15
hi-IT	57.58, 41.09	31.59, 19.66	83.90, 64.78	64.90, 50.42	85.07, 68.48	18.13, 12.43	23.42, 14.53
kn-IT	59.30, 42.60	35.30, 23.94	88.15, 73.69	68.34, 52.85	87.53, 74.28	23.05, 16.55	30.75, 22.26
ml-IT	56.54, 41.68	34.96, 23.60	88.50, 73.44	68.91, 55.21	87.35, 73.94	20.55, 15.29	29.30, 20.33
mr-IT	57.49, 41.68	34.21, 23.27	87.76, 71.68	66.98, 52.43	87.30, 74.20	20.93, 15.96	28.16, 18.82
or-IT	57.53, 41.84	32.95, 21.34	87.40, 72.01	67.46, 52.43	86.25, 72.52	18.77, 13.86	25.05, 17.89
pa-IT	56.79, 41.00	34.13, 22.26	86.75, 72.01	66.83, 51.68	86.22, 72.68	19.91, 13.69	27.08, 19.32
ta-IT	58.90, 42.18	37.33, 25.63	87.29, 73.02	69.08, 54.28	86.75, 73.02	24.05, 17.56	29.55, 18.65
te-IT	56.13, 40.58	35.73, 25.04	88.68, 74.53	66.79, 52.43	86.61, 73.36	21.06, 15.63	30.48, 21.00
ur-IT	53.19, 37.98	32.51, 21.34	86.35, 70.16	66.12, 51.09	85.39, 69.74	15.52, 11.59	23.77, 16.63
de-MT-IT	53.46, 36.80	31.29, 20.33	87.21, 72.18	44.27, 30.33	87.12, 74.11	16.33, 12.60	19.57, 13.61
el-MT-IT	55.06, 38.48	15.01, 3.86	88.28, 74.28	68.16, 51.68	88.15, 75.88	16.87, 11.17	29.29, 17.56
es-MT-IT	51.38, 35.79	27.28, 16.80	50.84, 28.40	56.55, 40.75	68.11, 46.97	15.12, 10.58	18.68, 11.09
et-MT-IT	57.85, 42.35	35.99, 24.45	88.67, 74.53	68.41, 53.27	87.54, 75.04	21.49, 15.71	19.83, 8.31
fi-MT-IT	59.13, 43.52	36.41, 25.12	88.61, 74.45	67.99, 52.35	87.83, 75.46	21.83, 15.12	24.57, 12.68
fr-MT-IT	50.89, 34.45	28.03, 17.14	61.69, 38.90	54.88, 38.15	65.28, 43.69	15.58, 11.34	17.81, 9.91
id-MT-IT	55.06, 37.89	35.02, 22.35	73.75, 51.00	63.90, 47.89	71.68, 48.40	20.23, 14.11	24.91, 15.54
ru-MT-IT	28.94, 12.10	20.71, 12.77	87.37, 71.68	64.80, 48.40	86.76, 73.02	7.67, 4.53	22.16, 15.04
sv-MT-IT	56.89, 41.26	36.57, 24.62	87.64, 72.68	63.10, 48.06	87.09, 73.94	19.67, 14.36	22.98, 14.36
th-MT-IT	60.92, 45.37	34.17, 21.93	89.03, 74.95	71.79, 55.71	87.98, 75.71	8.13, 1.42	32.24, 22.52
tr-MT-IT	58.71, 43.19	35.63, 23.78	89.34, 75.46	68.10, 52.94	87.87, 75.46	21.36, 15.29	16.20, 6.89
vi-MT-IT	51.83, 35.46	29.52, 19.15	74.54, 51.93	62.49, 46.89	67.23, 42.43	14.72, 10.75	20.49, 12.18
xh-MT-IT	59.90, 44.03	35.08, 24.20	88.24, 73.61	68.23, 52.85	87.67, 74.53	19.75, 13.94	22.37, 13.36

Table 9: Performance metrics (Token-F1 score, Exact Match score) of Instruction Tuned (IT) models on the TFDS-XQuAD test set. Training data sourced from the XQuAD-IN parallel corpus. Languages denoted with "MT" indicate training data generated via NLLB machine translation from the English subset. Performance rankings are visually indicated with **green** (highest) and **blue** (second highest) based on Token-F1 scores. The results are shown for languages ru (Russian), el (Greek), es (Spanish), de (German), vi (Vietnamese), th (Thai) and tr (Turkish).

Model	gu	hi	kn	ml	or	pa
Base	56.88, 41.25	79.56, 64.54	44.65, 28.14	48.48, 31.66	26.82, 13.68	62.84, 40.47
ml-IT	54.19, 35.74	78.15, 63.02	42.84, 25.32	38.88, 22.11	42.53, 25.09	60.87, 37.51
de-MT-IT	58.94, 42.49	79.47, 63.87	45.72, 27.96	48.32, 31.21	46.14, 27.91	63.2, 40.13
ru-MT-IT	58.02, 40.76	78.69, 62.35	47.39, 29.11	49.65, 32.21	46.8, 28.61	62.4, 39.11
sv-MT-IT	56.48, 39.51	79.21, 63.59	43.97, 26.56	48.32, 31.21	43.61, 26.11	62.22, 39.2

Table 10: Performance metrics (Token-F1 score, Exact Match score) of Instruction Tuned (IT) models on the out-of-domain IndicQA test set. Training data sourced from the XQuAD-IN parallel corpus. Languages denoted with "MT" indicate training data generated via NLLB machine translation from the English subset. Highest Performance ranking based on Token-F1 scores are visually indicated with **green**. The results are shown for languages gu (Gujarati), hi (Hindi), kn (Kannada), ml (Malayalam), or (Odia) and pa (Punjabi) over models instruction tuned on ml (Malayalam), de (German), ru (Russian) and sv (Swedish).

IT Lang	MT Model	BLEU	gu	kn	ml	or	pa
Base	-	-	60.81, 43.94	48.52, 32.35	49.07, 33.44	25.90, 17.05	55.80, 38.73
de	MarianMT	40.57	64.46, 45.54	57.83, 39.41	54.18, 37.98	52.03, 34.78	71.14, 51.00
	NLLB	34.13	63.90, 45.96	57.83, 40.00	52.66, 36.47	49.86, 32.94	70.99, 52.10
et	MarianMT	28.27	65.85, 48.65	58.26, 39.91	53.18, 37.31	36.64, 24.03	67.58, 49.41
	NLLB	24.33	66.18, 48.73	56.17, 38.57	53.06, 37.39	38.29, 25.54	68.41, 49.66
fi	MarianMT	23.96	65.15, 47.64	58.03, 39.24	54.83, 39.07	46.88, 31.09	69.94, 51.00
	NLLB	22.80	64.48, 47.22	57.10, 39.24	55.35, 39.41	43.78, 28.90	70.42, 51.84
id	MarianMT	19.99	51.13, 32.77	44.46, 27.98	34.40, 22.26	21.96, 14.21	55.57, 32.60
	NLLB	46.97	54.52, 33.94	48.52, 31.51	37.52, 23.94	32.95, 21.42	61.00, 39.83
sv	MarianMT	56.65	64.88, 46.38	58.14, 40.25	54.15, 37.22	49.50, 32.43	70.86, 51.51
	NLLB	41.35	65.06, 47.39	58.27, 40.58	53.72, 37.14	50.96, 33.52	70.28, 51.59
xh	MarianMT	8.42	59.36, 39.15	55.22, 36.72	53.34, 36.97	46.18, 30.33	68.88, 48.48
	NLLB	23.88	62.93, 43.27	57.94, 40.16	54.90, 38.31	49.27, 31.59	71.34, 51.93

Table 11: Comparison of MT models trained on machine translated training data using MarianMT (Helsinki-opus) vs NLLB for different IT languages and evaluated on selected test languages – gu (Gujarati), kn (Kannada), ml (Malayalam), or (Odia) and pa (Punjabi). Here, **green** is decided based on higher token-F1 scores and **blue** highlights the MT with higher BLEU score.

IT Lang	MT Model	en	bn	te	hi	mr	as	ta	ur
Base	-	93.32, 85.79	64.20, 44.53	58.22, 39.74	73.02, 48.82	65.96, 50.00	51.33, 32.43	63.37, 45.88	67.75, 49.07
de	MarianMT	91.81, 83.69	65.47, 44.70	58.28, 39.66	73.71, 48.40	65.06, 48.57	54.63, 34.11	61.81, 45.29	67.30, 47.64
	NLLB	91.76, 83.36	65.30, 44.28	57.80, 39.57	73.29, 47.64	64.47, 47.89	52.80, 32.26	61.20, 43.86	66.92, 47.14
et	MarianMT	93.45, 85.88	65.92, 45.71	58.20, 40.42	72.97, 48.40	65.29, 48.31	54.52, 33.69	62.60, 45.71	67.21, 45.76
	NLLB	92.93, 85.21	65.55, 45.29	58.88, 41.26	73.55, 48.82	66.77, 50.16	53.50, 33.78	62.73, 46.38	67.04, 47.56
fi	MarianMT	93.03, 85.63	65.10, 44.53	58.77, 40.75	73.46, 48.48	65.83, 50.33	52.54, 33.36	61.66, 44.70	66.75, 47.47
	NLLB	93.01, 85.63	65.49, 44.87	58.86, 40.84	73.65, 48.15	66.20, 49.32	53.64, 33.69	62.21, 45.04	66.98, 47.47
id	MarianMT	81.92, 66.38	54.50, 31.17	52.95, 33.52	63.95, 33.69	51.51, 32.85	43.40, 23.44	51.89, 30.58	58.66, 36.47
	NLLB	80.08, 65.96	56.83, 34.53	54.26, 34.28	67.32, 39.66	55.39, 38.31	47.32, 27.81	52.46, 33.27	59.64, 38.57
sv	MarianMT	92.43, 84.62	64.46, 43.61	58.04, 39.74	72.98, 47.64	65.48, 48.82	53.49, 32.60	61.35, 45.54	67.14, 47.89
	NLLB	92.16, 84.20	64.90, 44.36	57.98, 39.49	73.64, 48.15	66.02, 49.91	53.54, 32.94	62.70, 46.30	67.83, 47.98
xh	MarianMT	92.97, 85.12	65.14, 44.11	57.13, 38.90	73.06, 48.31	62.54, 44.87	50.61, 30.00	59.20, 42.10	66.23, 46.21
	NLLB	92.43, 84.78	65.72, 45.21	58.54, 39.91	73.52, 49.15	64.31, 47.73	53.57, 32.43	62.06, 45.21	67.97, 48.31

IT Lang	MT Model	ru	el	es	de	vi	th	tr
Base	-	61.95, 45.21	38.31, 28.31	89.15, 75.88	71.93, 57.05	88.07, 76.21	21.04, 16.21	34.47, 24.70
de	MarianMT	55.36, 38.48	34.48, 23.69	87.60, 72.35	49.14, 33.52	87.54, 74.28	20.38, 15.21	27.25, 18.82
	NLLB	53.46, 36.80	31.29, 20.33	87.21, 72.18	44.27, 30.33	87.12, 74.11	16.33, 12.60	19.57, 13.61
et	MarianMT	58.59, 43.27	36.77, 25.46	88.66, 74.78	68.10, 53.86	87.84, 75.12	22.15, 16.30	27.14, 14.70
	NLLB	57.85, 42.35	35.99, 24.45	88.67, 74.53	68.41, 53.27	87.54, 75.04	21.49, 15.71	19.83, 8.31
fi	MarianMT	58.00, 41.68	35.52, 24.03	88.68, 74.78	66.77, 50.75	87.43, 75.04	20.90, 14.70	23.07, 11.34
	NLLB	59.13, 43.52	36.41, 25.12	88.61, 74.45	67.99, 52.35	87.83, 75.46	21.83, 15.12	24.57, 12.68
id	MarianMT	51.24, 33.69	32.09, 19.83	67.66, 43.78	57.87, 41.17	68.75, 45.37	17.25, 12.43	19.62, 11.00
	NLLB	55.06, 37.89	35.02, 22.35	73.75, 51.00	63.90, 47.89	71.68, 48.40	20.23, 14.11	24.91, 15.54
sv	MarianMT	58.30, 41.84	36.01, 24.03	87.78, 73.10	62.59, 46.63	87.63, 74.53	15.90, 11.34	19.19, 12.43
	NLLB	56.89, 41.26	36.57, 24.62	87.64, 72.68	63.10, 48.06	87.09, 73.94	19.67, 14.36	22.98, 14.36
xh	MarianMT	56.38, 40.42	30.50, 20.84	87.98, 73.86	65.89, 51.42	87.55, 74.11	16.91, 12.43	20.40, 14.28
	NLLB	59.90, 44.03	35.08, 24.20	88.24, 73.61	68.23, 52.85	87.67, 74.53	19.75, 13.94	22.37, 13.36

Table 12: Comparison of MT models trained on machine translated training data using MarianMT (Helsinki-opus) vs NLLB for different IT languages and evaluated on test languages.



CoCo-CoLa: Evaluating and Improving Language Adherence in Multilingual LLMs

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Abstract

Multilingual Large Language Models (LLMs) develop cross-lingual abilities despite being trained on limited parallel data. However, they often struggle to generate responses in the intended language, favoring high-resource languages such as English. In this work, we introduce *CoCo-CoLa* (Correct Concept - Correct Language), a novel metric to evaluate language adherence in multilingual LLMs. Using fine-tuning experiments on a closed-book QA task across seven languages, we analyze how training in one language affects others’ performance. Our findings reveal that multilingual models share task knowledge across languages but exhibit biases in the selection of output language. We identify language-specific layers, showing that final layers play a crucial role in determining output language. Accordingly, we propose a partial training strategy that selectively fine-tunes key layers, improving language adherence while reducing computational cost. Our method achieves comparable or superior performance to full fine-tuning, particularly for low-resource languages, offering a more efficient multilingual adaptation.¹

1 Introduction

Multilingual LLMs are pre-trained on raw text from multiple languages, typically consisting of separate corpora for each language. Remarkably, despite this lack of explicit parallel data to facilitate cross-lingual associations, these models develop an implicit understanding of inter-language relations and cross-lingual word associations (Wen-Yi and Mimno, 2023). Instruction tuning further enhances their ability to follow prompts, and models trained on multilingual data often exhibit zero-shot cross-lingual transfer of instruction-following capabilities (Chirkova and Nikoulina, 2024). How-

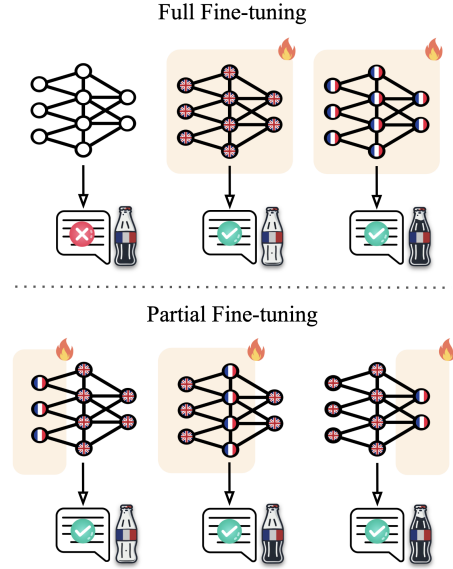


Figure 1: Evaluation of correctness and language adherence on French input. The soda level visualizes the CoCo-CoLa ratio, with higher levels indicating stronger adherence to the input language. Our results show that partially fine-tuning the final layers of an English-tuned model on French achieves language adherence and accuracy comparable to a model fully fine-tuned on French.

ever, this generalization is uneven: while high-resource languages in pretraining benefit significantly from instruction tuning, lower-resource or unseen languages often struggle to follow instructions reliably, frequently exhibiting degraded performance or defaulting to generating output in a preferred language (Nguyen et al., 2024; Chirkova and Nikoulina, 2024). To address these issues, we investigate how multilingual LLMs learn the same task across different languages.

A crucial step toward addressing the limitations of multilingual LLMs is understanding how they internally process and encode multilingual knowledge. Interpretability research has traditionally focused on monolingual models, leveraging techniques such as representation probing (Orgad et al.,

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¹Our code is available at <https://github.com/elnazrahmati/CoCo-CoLa/>

2024; Saphra and Lopez, 2019) and model patching (Ghandeharioun et al., 2024; García-Carrasco et al., 2024). These methods have been widely used to examine LLMs’ performance across tasks such as mathematics (Nikankin et al., 2024; Zhou et al., 2024), and general knowledge (Jiang et al., 2024; Burns et al., 2022; Singh et al., 2024; Golgoon et al., 2024; Chowdhury and Allan, 2024; Rai et al., 2024). Studies on model internals suggest that Multi-Layer Perceptrons (MLPs) retrieve task-relevant information, while attention layers refine and promote the correct response (Geva et al., 2021; Meng et al., 2022). Furthermore, knowledge is often identified in earlier layers and reinforced in later layers (Fan et al., 2024).

However, these interpretability techniques have primarily been applied to monolingual models, which were initially dominant due to the early focus on English-language pertaining (Touvron et al., 2023; Jiang et al., 2023; Team et al., 2024; Abidin et al., 2024). The rise of multilingual LLMs trained on diverse languages (Gao et al., 2024; Shaham et al., 2024; Soykan and Şahin, 2024), necessitates extending interpretability research beyond English. Multilingual LLMs present additional challenges: representations of different languages are intertwined within a shared space; cross-lingual alignment varies across languages; and shared tokens between languages impact their process. These complexities make it difficult to isolate language-specific knowledge, benchmark cross-lingual generalization, and interpret how multilingual LLMs acquire and apply linguistic information. Given the prevalence of mid- and low-resource languages, understanding these mechanisms is crucial not only for improving cross-lingual transfer but also for mitigating the “curse of multilinguality” — the performance degradation observed as the number of supported languages increases.

Recent efforts have begun tackling these challenges by probing internal representations (Li et al., 2024), analyzing the emergence of cross-lingual transfer (Wang et al., 2024a), and studying token representation alignment on cross-lingual transfer (Gaschi et al., 2023). Furthermore, researchers attempt to separate the linguistic abilities from task abilities by developing language- and task-specific adapters (Pfeiffer et al., 2020; Parovic et al., 2023), subnetworks (Choenni et al., 2023), or layers (Bandarkar et al., 2024). However, despite this progress, most prior works treat multilinguality as a monolithic phenomenon, focusing on general cross-

lingual transfer or aggregating all languages into a single block of linguistic knowledge. Less attention has been given to understanding how LLMs process individual languages at a more granular level, particularly within the context of task learning.

In this work, we focus on language adherence by first identifying both shared and distinct patterns in cross-lingual task acquisition, revealing how multilingual models internalize and apply linguistic knowledge (Section 3). We find that training on a task in one language improves performance in other languages. However, this benefit is not always directly observable due to an inherent model bias towards generating output in a preferred language, rather than strictly adhering to the input language (Section 4.1). To quantify this bias, we introduce *CoCo-CoLa* (Correct Concept, Correct Language), a novel metric designed to assess a model’s ability to generate responses in the intended input language, particularly for languages not included in supervised finetuning (SFT). Furthermore, we propose a *partial training method* that selectively fine-tunes specific model layers which reveals the relation between language adherence and model layers (Section 4.2). This approach enables more efficient language adaptation, achieving comparable or even superior performance compared to full model retraining, especially for low-resource languages. Finally, we show that the issue of language adherence can be addressed by finetuning only the final layers of LLMs on a small balanced multilingual data (Section 4.3).

2 Related Work

This work builds on several active research areas that inform our study of multilingual task learning in LLMs. Specifically, we draw from (1) Multilingual interpretability, which helps us analyze how LLMs process different languages and how their internal structures influence multilingual task learning; (2) Representation alignment, which provides insights into token-level similarities across languages and how shared representations facilitate cross-lingual generalization; (3) Adapters, which separate language knowledge from task-specific knowledge, offering a structured framework for understanding their interactions; and (4) Subnetworks, which identify task- and language-specific parameters within existing models, offering an alternative to external adapters and directly informing our approach to efficient partial training.

Interpretability. Li et al. (2024) use probing techniques to analyze accuracy changes across layers in LLMs, showing that high-resource languages exhibit patterns similar to English, with accuracy increasing from lower to upper layers. However, this pattern is inconsistent for low-resource languages. Wang et al. (2024b) examine cross-lingual transfer by analyzing neuron overlap in different languages using checkpoints from BLOOM’s pre-training (Le Scao et al., 2023). They find a strong correlation between neuron overlap and cross-lingual transfer, though neuron overlap does not increase monotonically during training, and patterns vary across model sizes. Similarly, Zhao et al. (2024a) investigate language-specific neurons and assess how these neurons affect both English and non-English language performance.

Representation alignment. Beyond studying multilingualism in LLMs, some research focuses on improving model performance across languages through representation alignment. Gaschi et al. (2023) align English and Arabic model representations using a bilingual dictionary before fine-tuning on a target task. Zhang et al. (2024) align English representations with other languages using question-translation data before instruction-tuning. Additionally, Salesky et al. (2023) introduce a pixel representation method to enhance alignment and improve translation quality.

Adapters. Another approach for cross-lingual transfer involves integrating adapters into the model. This technique is based on the assumption that task-solving knowledge can be separated from language knowledge. Pfeiffer et al. (2020) introduce MAD-X, a framework where language and task adapters are trained separately, with each block’s representations passing through a language adapter before a task adapter. Building on this, later works aim to refine adapter creation and composition methods. For instance, Parović et al. (2022) propose BAD-X, which replaces monolingual adapters with bilingual adapters, improving performance for low-resource languages. Zhao et al. (2024b) introduce AdaMergeX, where adapters for language-task pairs are trained independently and later combined through linear operations (addition and subtraction) to generate adapters for new language-task pairs.

Subnetworks. To enhance cross-lingual transfer without adding new parameters, some methods

focus on identifying existing task- and language-specific parameters within the model. Choenni et al. (2023) fine-tune models for specific languages or tasks, extract the most affected neurons, and use the resulting subnetworks to enable multilingual task adaptation. Bandarkar et al. (2024) take a layer-wise approach in multiple steps: they train separate language- and task-expert models, analyze parameter changes to identify key layers for language and task learning, and use layer-swapping techniques to create a math expert in a new language. Consistent with Zhao et al. (2024a), their findings suggest that initial and final layers primarily encode linguistic information, while middle layers are task-specific.

3 Preliminary Analysis

In the preliminary section of this paper, we first isolate language effects from task learning by choosing multi-lingual parallel QA data (Section 3.1), examine fine-tuning performance across multiple languages (Section 3.2), explore how well LLMs generalize knowledge across languages (Section 3.3), and which model components are most affected during training (Section 3.4). Then, in Section 4.1, we introduce **CoCo-CoLa** metric to measure language adherence in multilingual LLMs followed by an efficient partial training method to increase the model adherence (Section 4.2).

3.1 Setup

To investigate how multilingual LLMs learn a new task in a monolingual setting, we train four different models on a Closed-Book Question-Answering (CBQA) task. We include two sizes of the Llama-3.2 series (Dubey et al., 2024) to analyze the effect of model size on multilingual performance and behavior, given that these models are specifically optimized for multilingual dialogue. We also include Llama-3.1-8B as a point of comparison, as it, while not explicitly optimized for multilingualism, was trained on a small multilingual corpus. To test generalizability to multilingually balanced models, we include Gemma-3-4B (Team et al., 2025), which was trained with UniMax (Chung et al., 2023) for addressing language imbalances.

We select CBQA because it is language-dependent and demonstrates a model’s ability to act as a knowledge base (Wang et al., 2021). To isolate the impact of language differences from the effects of learning a new task or acquiring new knowledge, we use the Mintaka CBQA dataset (Sen et al.,

Language	Llama-1B			Llama-3B			Llama-8B			Gemma-4B		
	PLM	SFT	Δ	PLM	SFT	Δ	PLM	SFT	Δ	PLM	SFT	Δ
English	13.27	38.44	25.17	32.85	53.09	20.24	12.92	50.98	38.06	30.69	53.67	22.98
French	11.30	40.27	28.97	22.90	43.80	20.90	18.53	50.85	32.32	21.67	48.43	26.76
German	7.16	40.34	33.18	23.79	48.10	24.31	11.04	44.35	33.31	23.76	45.79	22.03
Hindi	5.27	21.18	15.91	7.33	30.39	23.06	6.21	35.29	29.08	8.84	43.96	35.12
Italian	7.06	41.58	34.52	21.87	42.73	20.86	16.48	43.22	26.74	20.44	50.05	29.61
Portuguese	5.38	38.23	32.85	20.06	37.04	16.98	18.38	31.11	12.73	19.96	44.16	24.20
Spanish	6.13	41.71	35.58	22.01	45.69	23.68	16.60	45.46	28.86	26.33	48.13	21.80

Table 1: Performance of pre-trained models (PLM), fine-tuned models (SFT), and their difference ($\Delta = \text{SFT} - \text{PLM}$) on CBQA data across languages.

2022). Mintaka provides identical question-answer pairs in nine languages, allowing us to keep the question content consistent and thus isolate the influence of language itself. The dataset was originally created in English and later translated into Arabic, French, German, Hindi, Italian, Japanese, Portuguese, and Spanish.

One challenge with Mintaka is that some answer types are not translated across languages. To keep question-answer pairs within the same language, we use Google Translate to convert these answers into the language of their respective questions and apply back-translation for accuracy checks. Additionally, since our goal is to study how models learn new tasks in languages they have been exposed to before, we exclude Arabic and Japanese.

3.2 SFT Performance

Our initial step is to assess the model’s ability to learn the task in each individual language, effectively measuring how learning difficulty varies across languages. To do this, we perform SFT for all models on each language of the CBQA dataset for three epochs and generate answers for given questions. Next, we select the best model based on the validation loss. Further implementation details are provided in Appendix A.1.

Table 1 shows a comparison of accuracy between the pre-trained model and the best checkpoint of the language-specific SFT model across different languages. SFT significantly improves performance for all languages with relatively consistent accuracy levels, except for Hindi in all Llama model sizes and Portuguese for Llama-8B, which exhibit notably lower accuracy. This discrepancy is likely due to undertraining. Among the SFT models, English achieves the highest accuracy in all models, except Llama-1B that performs best in Spanish. The largest accuracy gains are observed in En-

glish (+38.06%) for Llama-8B, German (+24.31%) for Llama-3B, Spanish (+35.58%) for Llama-1B, and Hindi (+35.12%) for Gemma-4B, indicating that these languages benefited the most from fine-tuning. The comparable accuracy across languages indicates comparable knowledge acquisition.

However, two critical questions remain: (1) Do models share learned knowledge uniformly across languages, or do they correctly answer distinct subsets of questions depending on the language? (2) Are there specific parts of the model that are responsible for encoding language-specific information? To address these questions, we first analyze the overlap in correct answers across languages using the Jaccard Index, followed by an investigation of parameter updates to determine whether certain components of the model specialize in handling linguistic differences.

3.3 Cross-lingual Task Knowledge

To further investigate the extent of cross-lingual task knowledge transfer within the model, we analyze the overlap in correct answers across languages. Specifically, we measure how consistently the model arrives at the same correct answers in different languages, providing insight into whether knowledge is shared across languages. It is important to note that there is no overlap between the knowledge present in the training and evaluation data. This ensures that any correct answers during evaluation are derived from knowledge acquired during pretraining rather than memorization. Consequently, the model’s ability to generate correct responses across languages indicates that it has internalized the underlying task knowledge from the training data, rather than relying solely on language-specific cues. Let L_A and L_B represent two languages, and let C_{L_A} denote the set of correct answers for L_A . To quantify the degree

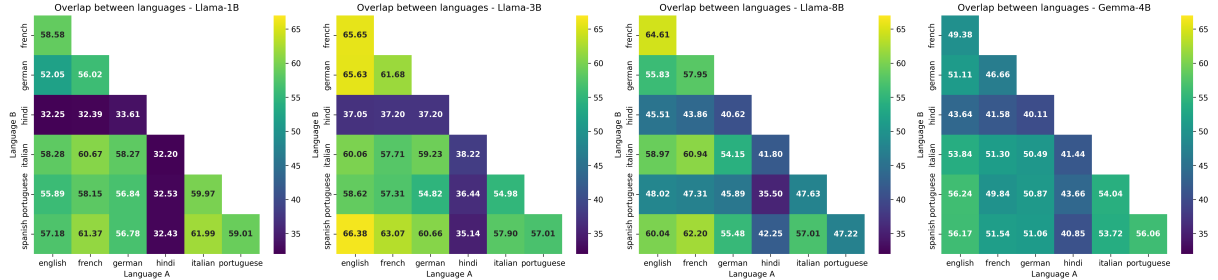


Figure 2: Jaccard similarity index between different languages, measuring the proportion of overlapping correctly answered questions between pairs of languages.

of shared task knowledge between languages, we compute the Jaccard Index, also known as Intersection over Union (IoU), between C_{L_A} and C_{L_B} (see Equation 1). The Jaccard Index is a natural choice for this analysis as it directly measures the proportion of overlapping correct answers relative to the total distinct answers across languages. This allows us to assess knowledge consistency and cross-lingual transfer within the model.

$$IoU(A, B) = \frac{|C_{L_A} \cap C_{L_B}|}{|C_{L_A} \cup C_{L_B}|} \quad (1)$$

The results, shown in Figure 2, indicate that on average approximately 60% of correctly answered questions are shared across languages for all models, suggesting a strong degree of shared knowledge among languages. However, Hindi exhibits significantly lower overlap with other languages in Llama-3.2 models, suggesting weaker generalization for this language. Interestingly, in Llama-8B, Hindi shows higher overlap compared to Llama-3.2 models, but Portuguese experiences a notable drop in overlap. Additionally, Llama-3B demonstrates a higher rate of shared knowledge compared to Llama-8B, despite both models achieving comparable accuracy across languages (see Table 1). This highlights the importance of multilingual optimization in enhancing cross-lingual transfer among languages. For Gemma-4B, despite comparable accuracy across languages, the overall overlap is lower than that observed in the Llama models, indicating less cross-lingual knowledge sharing.

3.4 Parameter Updates

To investigate language-specific encoding in LLMs, we analyze parameter updates during fine-tuning and compare them across languages to determine whether certain components of the model specialize in processing linguistic information. Meng et al. (2022) suggest that MLP modules primarily store

knowledge, while attention modules control information retrieval and selection. SFT models correctly answer approximately 40% of evaluation questions in all languages. However, they require fine-tuning to improve their ability to select and output the correct information. As a result, we expect substantial modifications in the attention modules, particularly in the final layers, while changes in the MLP modules remain limited. Since these datasets differ only in language, not in task or knowledge, analyzing the model updates allows us to pinpoint which layers or components are most crucial for learning language-specific representations.

To compute parameter update, we follow Bandarkar et al. (2024) and calculate the average parameter modifications for each module in each layer. Denoting the pre-trained weight matrix as W_p and the fine-tuned weight matrix as W_f , the average magnitude of differences is given by:

$$\Delta W = \frac{1}{n} \sum_{i=1}^n |W_p^{(i)} - W_f^{(i)}| \quad (2)$$

The results for English and French are shown in Figure 3, with the remaining languages in Figure 6. As expected, significant modifications occur in the attention modules of the final six layers for Llama-1B and the final 14 layers for Llama-3B, Llama-8B, and Gemma-4B models across all languages. However, in Llama-3.2 models and Gemma-4B model, we observe substantial changes in the MLP modules in these layers for all languages except English, suggesting that these variations might be tied to language-specific processing rather than task-related learning. Surprisingly, for Llama-8B, even the model fine-tuned on English shows a high rate of change similar to other languages. Considering the unexpectedly low accuracy of the Llama-8B pre-trained model across all languages compared to Llama-3B, this larger modification could be related

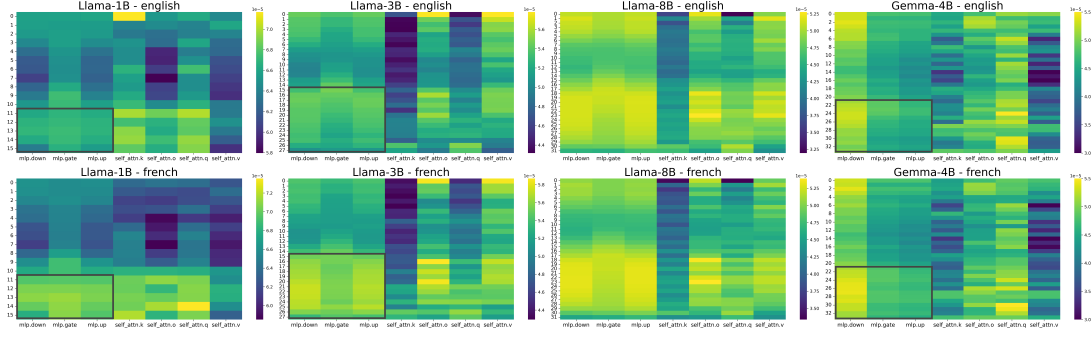


Figure 3: Heatmaps of parameter update magnitudes during monolingual fine-tuning on English (top) and French (bottom) across different LLMs. Gray boxes show MLP modules where parameter update differs between languages.

to learning the task or acquiring new knowledge rather than just language adaptation.

4 Approach

Our previous analysis suggests that while task knowledge is largely shared across languages, the way this knowledge is processed and accessed differs. Although a Jaccard Index analysis revealed substantial overlap in correct answers, our investigation of parameter updates showed that models trained on non-English languages required more substantial modifications in their MLP modules compared to English, even when achieving comparable accuracy. This raises an important question: Do these modifications reflect deviations in knowledge acquisition, or are they more related to language generation? In this section, we first introduce a metric to analyze linguistic bias in multilingual LLM outputs. Then, we propose a partial training strategy aimed at reducing this bias by selectively fine-tuning specific model components.

4.1 Correct Concept in Correct Language

According to [Dubey et al. \(2024\)](#), only 8% of the pre-training data used for Llama-3 models is multilingual, while the rest is dominated by English general knowledge, mathematics, and code. This suggests a strong bias toward English. Given this imbalance, we hypothesize that the observed MLP module changes in non-English languages may not indicate new knowledge acquisition but rather adjustment in language selection during response generation. Supporting this, [Chirkova and Nikoulina \(2024\)](#) found that when Llama-2-13B is instruction-tuned on English and tested in other languages, it generates responses in a different language from input language in over 30% of cases, with this behavior influenced by training hyperparameters.

To investigate this further, we introduce **CoCo-CoLa** (**Correct Concept - Correct Language**), a metric designed to measure how well the model adheres to the input language while generating correct responses. Let L_i denote the input language, $C_{L_i \rightarrow L_o}$ the set of correct output in language L_o when passing language L_i as input. We define the CoCo-CoLa ratio as follows:

$$\text{CoCo-CoLa}(L_i) = \frac{|C_{L_i \rightarrow L_i} - \bigcup_{L_o \neq L_i} C_{L_i \rightarrow L_o}|}{|C_{L_i \rightarrow L_i} \Delta \bigcup_{L_o \neq L_i} C_{L_i \rightarrow L_o}|} \quad (3)$$

The denominator uses the symmetric difference between $C_{L_i \rightarrow L_i}$ and correct answers in other languages because many answers involve named entities, such as well-known places, books, and individuals. Since most of the languages in this work use similar scripts, named entities often appear in identical forms across multiple languages. This redundancy leads to overlap between $C_{L_i \rightarrow L_i}$ and $\bigcup_{L_o \neq L_i} C_{L_i \rightarrow L_o}$, which the symmetric difference helps mitigate by ensuring that shared named entities do not artificially inflate the metric.

Given that these models are primarily trained on English, when the input is in L_i the output is usually either L_i or English. Thus, $\bigcup_{L_o \neq L_i} C_{L_i \rightarrow L_o}$ is largely dominated by $C_{L_i \rightarrow en}$, meaning that most language switching occurs between the input language and English rather than other languages.

To further simplify the calculation, we filter the data to include only questions where the correct answers in L_i and English are different. Under this condition, $C_{L_i \rightarrow L_i} \cap C_{L_i \rightarrow en} = \emptyset$, allowing the CoCo-CoLa ratio to reduce to:

$$\text{CoCo-CoLa}(L_i) = \frac{|C_{L_i \rightarrow L_i}|}{|C_{L_i \rightarrow L_i}| + |C_{L_i \rightarrow en}|} \quad (4)$$

Table 2: CoCo-CoLa ratio (Ratio) and cumulative accuracy (Acc) of pretrained model (PLM), English-tuned model ($\rightarrow en$), and L_i -tuned model ($\rightarrow L_i$) across languages for Llama-1B, Llama-3B, Llama-8B, and Gemma-4B.

Language	Metric	Llama-1B			Llama-3B			Llama-8B			Gemma-4B		
		PLM	$\rightarrow en$	$\rightarrow L_i$	PLM	$\rightarrow en$	$\rightarrow L_i$	PLM	$\rightarrow en$	$\rightarrow L_i$	PLM	$\rightarrow en$	$\rightarrow L_i$
French	Acc	12.07	52.66	55.73	20.57	62.55	52.97	12.89	58.64	66.01	18.67	65.16	63.23
	Ratio	49.42	13.47	88.58	52.51	14.73	89.45	58.11	12.32	87.54	50.77	19.22	90.14
German	Acc	8.05	51.97	50.92	16.99	49.30	57.01	10.43	59.95	52.27	15.26	64.59	60.24
	Ratio	53.87	10.50	91.02	56.53	19.64	89.26	57.49	11.03	87.21	42.82	15.23	92.64
Hindi	Acc	8.65	29.34	27.42	15.77	38.26	39.67	9.79	37.29	39.21	12.58	47.81	49.66
	Ratio	43.16	13.28	90.79	31.93	10.04	77.47	43.67	10.74	90.68	40.86	9.39	97.19
Italian	Acc	7.76	51.35	62.39	16.63	53.17	46.02	11.77	61.88	58.55	14.62	62.99	67.98
	Ratio	51.32	10.00	93.60	56.68	16.29	87.91	52.11	10.90	91.35	48.76	14.84	91.08
Portuguese	Acc	10.22	54.85	57.57	17.60	55.52	50.64	16.23	60.75	42.90	17.11	63.81	61.16
	Ratio	56.40	12.73	91.07	63.37	15.99	85.10	51.41	11.49	90.73	51.89	14.98	90.69
Spanish	Acc	9.75	57.52	59.02	19.17	57.55	60.38	14.13	58.34	54.27	17.69	65.88	60.65
	Ratio	52.28	12.01	91.24	61.68	15.84	89.18	61.98	9.40	91.35	51.15	14.70	91.36

To evaluate language adherence and accuracy, we pass the input in L_i to pre-trained, *en-tuned*, and L_i -tuned models. We then compute the CoCo-CoLa ratio and the cumulative accuracy, defined as the proportion of correct answers either in L_i or English. The results, presented in Table 2, show that while the *en-tuned* models and the L_i -tuned models achieve comparable cumulative accuracy on L_i input, the CoCo-CoLa ratio is significantly lower for the *en-tuned* model. This suggests that although the *en-tuned* model can correctly process the question in L_i and retrieve the correct answer at the same rate as the L_i -tuned model, it frequently generates the answer in English instead of L_i . Furthermore, analyzing the CoCo-CoLa ratio of the pre-trained model reveals that the model already exhibits a bias toward generating English responses, though this bias is less pronounced than in the *en-tuned* model. These findings support our hypothesis that the varying rate of parameter updates across languages is related to output language preference. Since the model is already inherently biased toward English, *en-tuned* results in the least MLP change compared to other languages.

4.2 Partial Training for Language Adaptation

In this section, we aim to disentangle task learning from output generation in language L_i . Our previous results reveal two key observations. First, as shown in Section 4.1, both the *en-tuned* model and the L_i -tuned model achieve comparable cumulative accuracy on L_i , indicating that they learn the task equally well. The only difference is their CoCo-CoLa score, meaning that while both models understand the task to the same degree, they

generate outputs in different languages. Second, from Section 3.4, we observed that the *en-tuned* and L_i -tuned models undergo different parameter updates. Some of these updates are necessary for learning the task itself, while others may specifically steer the model toward producing responses in the intended language.

Based on these observations, we hypothesize that fine-tuning specific layers of an *en-tuned* model on L_i can enable it to generate responses in L_i without requiring full model updates. Specifically, these layers correspond to the parameters that were updated in the L_i -tuned model but not in the *en-tuned* model. To test this hypothesis, we first identify the layers that undergo language-specific updates. We then fine-tune only these layers in the *en-tuned* model and compare the results to fine-tuning other layers. This comparison allows us to isolate the parameters responsible for output language.

Identifying language layers. We select layers for partial training based on the variation in parameter update rates observed in Section 3.4. For the Llama-1B model, we train three variants by unfreezing different sets of layers: (1) layers 11-16, (2) layers 1-5 (chosen to match the parameter count of the final six layers), and layers 1-10 (including all parameters except the final six). We expect the first variant to be the most language-related and to result in the largest improvement in the CoCo-CoLa ratio, while the other two should have a smaller effect. For Llama-3B and Gemma-4B, we similarly train two variants each: unfreezing layers 15-28 and 1-14 for Llama-3B, and layers 21-34 and 1-20 for Gemma-4B. Again, we

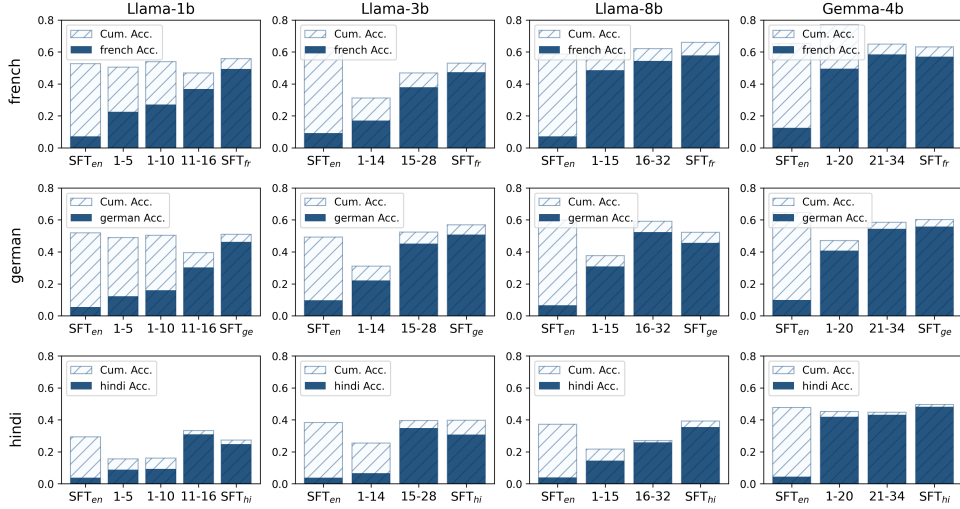


Figure 4: Cumulative accuracy and L_i accuracy on en -tuned (SFT_{en}) and L_i -tuned models (SFT_{L_i}), along with partially trained models, across all Llama model sizes.

expect the final-layer variants to have a stronger relationship to language generation. For Llama-8B, which does not show clear variations in update rates across languages (as noted in Section 3.4), we instead select layers based on the most updated MLP modules. Specifically, we choose layers 16–32 and layers 1–15 for partial training to determine which part of the model is more responsible for language generation. Through this analysis, we aim to verify whether the final layers play a greater role in controlling the output language

Partial training evaluation. To evaluate the effectiveness of partial training, we compare all partially trained models to both their fully en -tuned and fully L_i -tuned models. Figure 4 presents cumulative accuracy and L_i accuracy across three languages, while results for the remaining three languages are included in Figure 7. In addition, CoCo-CoLa ratios for partially trained models are also available in Appendix A.4, providing further insight into the extent to which partial fine-tuning improves output language consistency.

As shown in Figure 4, among the partially trained models, unfreezing the final layers results in the highest accuracy and CoCo-CoLa ratio for all models, highlighting the crucial role these layers play in determining the output language. Notably, the accuracy of this partially trained configuration closely approaches that of the fully L_i -tuned model, suggesting that the earlier layers already encode sufficient information for question answering, even without direct exposure to L_i during training. Interestingly, Hindi—which initially exhibited lower

performance than other languages—benefits significantly from cross-lingual transfer, achieving better results with partial training than with full training in both Llama-3.2 models. Llama-3B demonstrates even stronger cross-lingual transfer, with improved accuracy for Italian and Portuguese as well. For Llama-8B and Gemma-4B, training the second half of the model yields the highest CoCo-CoLa ratio; however, the differences in L_i accuracy across partial training configurations are less pronounced than in the Llama-3.2 models. These models also show improved accuracy with partial training compared to full training for German, Italian, and Portuguese in Llama-8B, and for French, Portuguese, and Spanish in Gemma-4B. For low-resource languages, partially training only the final layers of an en -tuned model can achieve similar or even better accuracy compared to full fine-tuning in the target language. Beyond its effectiveness, partial training is significantly more efficient, reducing training time to half and memory usage to 65% of full training. Furthermore, the model achieves higher accuracy in fewer training steps, requiring less than one epoch, meaning it is trained on fewer data points.

These findings confirm the hypothesis that the final layers are linked to output language selection, whereas initial and middle layers have less effect on the output language. Our results are aligned with concurrent work suggesting that LLMs process input in three stages: understanding the input, reasoning and knowledge retrieval in a shared space among languages, and generating output

Model	French		German		Hindi		Italian		Portuguese		Spanish		Average	
	Ratio	Acc	Ratio	Acc	Ratio	Acc	Ratio	Acc	Ratio	Acc	Ratio	Acc	Ratio	Acc
Llama-1B	82.15	47.53	64.47	39.02	90.75	28.00	83.58	50.39	73.89	41.51	72.72	41.65	77.93	41.35
Llama-3B	78.37	42.19	79.55	36.14	85.34	33.54	80.11	41.61	74.27	49.04	78.92	44.22	79.43	41.12
Llama-8B	75.95	67.62	85.29	49.75	96.89	32.00	87.83	59.77	88.63	64.55	86.94	38.01	86.92	51.95
Gemma-4B	88.35	57.38	88.04	55.88	83.71	37.32	90.22	64.21	87.00	60.69	87.34	61.81	87.45	56.22

Table 3: CoCo-CoLa ratio (Ratio) and cumulative accuracy (Acc) of models partially trained on balanced multilingual data, with averages across all languages.

(Wendler et al., 2024; Dumas et al., 2025; Schut et al., 2025). Although it remains debated whether this shared knowledge space is language agnostic (Dumas et al., 2025) or whether the model simply thinks in English (Wendler et al., 2024; Schut et al., 2025), these works, alongside ours, all suggest that the process happening in middle layers is not dependent on the input language. However, what previous works overlooks is that the final stage is defective and cannot generate the response in the correct language. We believe this phenomenon has led to misleading evaluations and the belief that multilingual LLMs think better in English (Etxaniz et al., 2024). Our work emphasizes the importance of considering both correctness and language adherence, as relying on output accuracy against the ground truth does not provide a complete picture of a model’s ability to reason and operate in non-dominant languages.

4.3 Improving Language Adherence in Multilingual LLMs

As demonstrated in Section 4.1, multilingual LLMs exhibit a strong linguistic bias toward English, the most prevalent language in their training data. In Section 4.2, we further established that this bias is closely linked to the model’s final layers. To investigate whether this bias can be mitigated and to enable the model to better adhere to the input language, we take the *en-tuned* model and, rather than adapting it to a single target language, we partially fine-tune the language-related layers using a balanced multilingual dataset, where all languages appear with equal frequency in the training data.

As shown in Table 3, the average CoCo-CoLa ratio for multilingually fine-tuned Gemma-4B and Llama-8B reaches 87.45% and 86.92%, respectively, while Llama-1B and Llama-3B achieve slightly lower ratios of 77.93% and 79.43%. These results are similar to the monolingual models partially trained for each language (Appendix A.4). These findings indicate that, even when starting

from a model pretrained on biased data, fine-tuning only the final layers on a balanced multilingual dataset substantially improves language adherence across all languages. Notably, for Llama-8B and Gemma-4B, the accuracy of the resulting multilingual model is competitive with models fully fine-tuned for each individual language, despite using only 200 datapoints per language during training.

5 Conclusion

In this work, we first analyzed shared knowledge across seven languages and identified key differences in the parameters most affected when training models for each language. Building on these insights, we proposed the CoCo-CoLa ratio, a metric for evaluating language adherence in multilingual LLMs, and used it to evaluate both pre-trained and fine-tuned LLMs. Our findings show that pre-trained models tend to generate English outputs regardless of the input language and that fine-tuning on English further amplifies this bias.

To address this problem, we leveraged insights from parameter updates and CoCo-CoLa results to develop a partial training method that improves language adherence in English-trained models. Our analysis demonstrated a more efficient alternative to full fine-tuning, achieving comparable or even superior performance while significantly reducing the number of updated parameters. Additionally, we showed that partial training on balanced multilingual data achieves similar language adherence to monolingual training. Given the widespread availability of instruction-tuned and task-specific English models, partial training of final layers presents a fast and efficient approach for improving language adherence and adapting LLMs to new languages.

Limitations

We acknowledge that training hyperparameters can influence the linguistic bias of fine-tuned models,

as highlighted by [Chirkova and Nikoulina \(2024\)](#). For instance, while smaller learning rates may reduce bias, they can also lead to degraded task performance. Due to resource constraints, we used a single set of hyperparameters optimized for task performance. Additionally, we applied the same hyperparameter settings across all languages and model sizes, though fine-tuning them individually for each model-language pair could potentially yield better results.

Moreover, linguistic bias in pre-trained models and the observed trends in parameter updates across languages are influenced by factors such as model architecture, training procedures, data proportions, and even the order in which the model encounters training data. As a result, the specific layers we identified for each model size may differ when tested on other LLMs. Additionally, our observations suggest that certain languages are under-trained in Llama models. However, due to the lack of publicly available information on training data and procedures, we cannot make definitive claims regarding language-specific training discrepancies.

Another limitation is that our study focuses on languages that mostly come from the same language family, and are relatively close to each other. As a result these languages exhibit significant token overlap, facilitating cross-lingual transfer. The models we evaluated were also trained on a limited set of languages with similar characteristics. The studied languages mainly fall into the mid- or high-resource category, meaning our findings may not generalize to massively multilingual models trained on a more diverse set of languages.

Ethical Statement

This research investigates language adherence in multilingual large language models and proposes partial training methods for efficient adaptation. Our work aims to enhance linguistic fairness and accessibility by mitigating biases that favor high-resource languages. We acknowledge that training data composition and fine-tuning decisions can introduce unintended biases, which may disproportionately affect underrepresented languages. While our findings contribute to more equitable multilingual model adaptation, they are limited to languages present in the model’s pretraining data and may not generalize to unseen languages. We encourage further work to assess our method’s applicability to a broader set of languages, particularly

low-resource and non-Indo-European languages.

This study does not involve human subjects, personal data, or user interactions, and we adhere to ethical guidelines for computational research. Our experiments were conducted using publicly available models and datasets, ensuring transparency and reproducibility.

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A Appendix

A.1 Implementation details

We experimented with dropout rates of 0.1 and 0.05, and learning rates of $5e-5$, $1e-5$, $5e-6$, $1e-6$, $5e-7$, and $1e-7$ for training on the English CBQA task. The best setting (dropout = 0.1, learning rate = $5e-6$) was selected based on the minimum validation loss. These hyperparameters were used consistently across all languages and models throughout the paper.

For all training runs in our experiments, we used the hyperparameters listed in Table 4. All experiments were conducted with a fixed random seed of 42. We implemented our models using Transformers 4.46.3 and Torch 2.5.1, with Accelerate 1.1.0 and DeepSpeed 0.16.1 for multi-GPU training. All experiments were run on NVIDIA RTX A6000 GPUs, with all experiments taking approximately 48 hours on eight GPUs.

Parameter	value
num_epochs	3
save_steps	100
eval_steps	100
logging_steps	100
batch_size	64
gradient_accumulation	1
weight_decay	0.01
bf16	True

Table 4: Training hyperparameters

A.2 Language specific knowledge

Beyond measuring similarities between languages using the Jaccard Index, we also analyze differences by identifying answers that are known in language A but unknown in language B. This allows us to examine the distribution of languages within the 40% of answers that are not correctly predicted by both languages. The results, presented

in Figure 5, reveal an almost symmetrical distribution of known and unknown answers across most language pairs. However, notable deviations occur for languages with significantly lower overall accuracy. Specifically, Hindi shows a greater disparity in the Llama-3.2 models, while both Hindi and Portuguese exhibit this trend in the Llama-8B model.

A.3 Parameter update

Due to space constraints, the main text presents results for only four languages. However, the analysis of model updates for Italian, Spanish, and Portuguese follows similar trends and can be found in Figure 6. These additional results confirm the patterns observed in other languages, reinforcing our findings on language-specific parameter updates.

A.4 Partial Training

Due to space limitations, the results of partial training on Italian, Portuguese, and Spanish are provided in Figure 7. Additionally, the CoCo-CoLa ratios for both partially trained and fully trained models are shown in Table 5 for Llama-1B, Table 6 for Llama-3B, and Table 7 for Llama-8B. These comparisons highlight the consistently superior CoCo-CoLa ratio in the partial training of final layers.

Language	SFT _{en}	1-5	1-10	11-16	SFT _{L_i}
French	13.47	44.63	50.22	78.72	88.58
German	10.50	25.12	31.77	76.66	91.02
Hindi	13.28	56.82	58.49	92.73	90.79
Italian	10.00	32.12	65.17	86.18	93.60
Portuguese	12.73	45.18	56.33	75.43	91.07
Spanish	12.01	34.61	34.41	81.66	91.24

Table 5: CoCo-CoLa Ratios (%) for different languages across finetuned Llama-3.2-1B models.

Language	SFT _{en}	1-14	14-27	SFT _{L_i}
French	14.73	54.64	81.18	89.45
German	19.64	71.40	86.04	89.26
Hindi	10.04	26.40	88.41	77.47
Italian	16.29	65.45	86.91	87.91
Portuguese	15.99	61.76	84.45	85.10
Spanish	15.84	72.38	85.50	89.18

Table 6: CoCo-CoLa Ratios (%) for different languages across finetuned Llama-3.2-3B models.

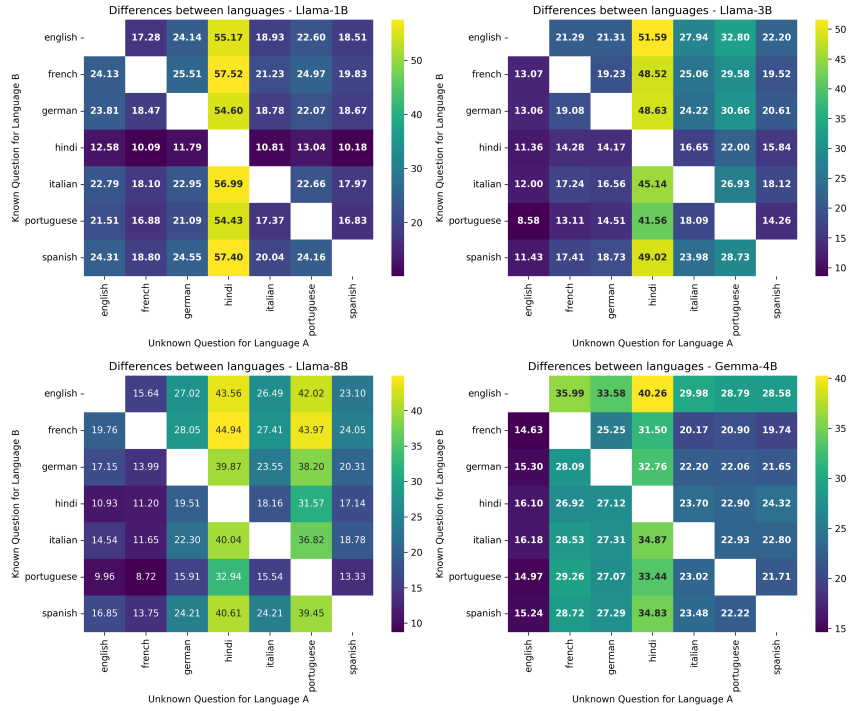


Figure 5: Difference in known knowledge between each pair of languages across different model sizes.

Language	SFT_{en}	1-15	16-31	SFT_{L_i}
French	12.32	78.93	87.77	87.54
German	11.03	81.91	88.69	87.21
Hindi	10.74	67.08	96.06	90.68
Italian	10.90	78.92	90.28	91.35
Portuguese	11.49	74.68	90.11	90.73
Spanish	9.40	75.82	93.55	91.35

Table 7: CoCo-CoLa Ratios (%) for different languages across finetuned Llama-3.1-8B models.

Language	SFT_{en}	1-20	21-34	SFT_{L_i}
French	19.22	64.26	89.99	90.14
German	15.23	86.70	93.03	92.64
Hindi	9.39	92.74	96.30	97.19
Italian	14.84	85.03	91.20	91.08
Portuguese	14.98	70.93	88.40	90.69
Spanish	14.70	68.14	90.19	91.36

Table 8: CoCo-CoLa Ratios (%) for different languages across finetuned Gemma-3-4B models.

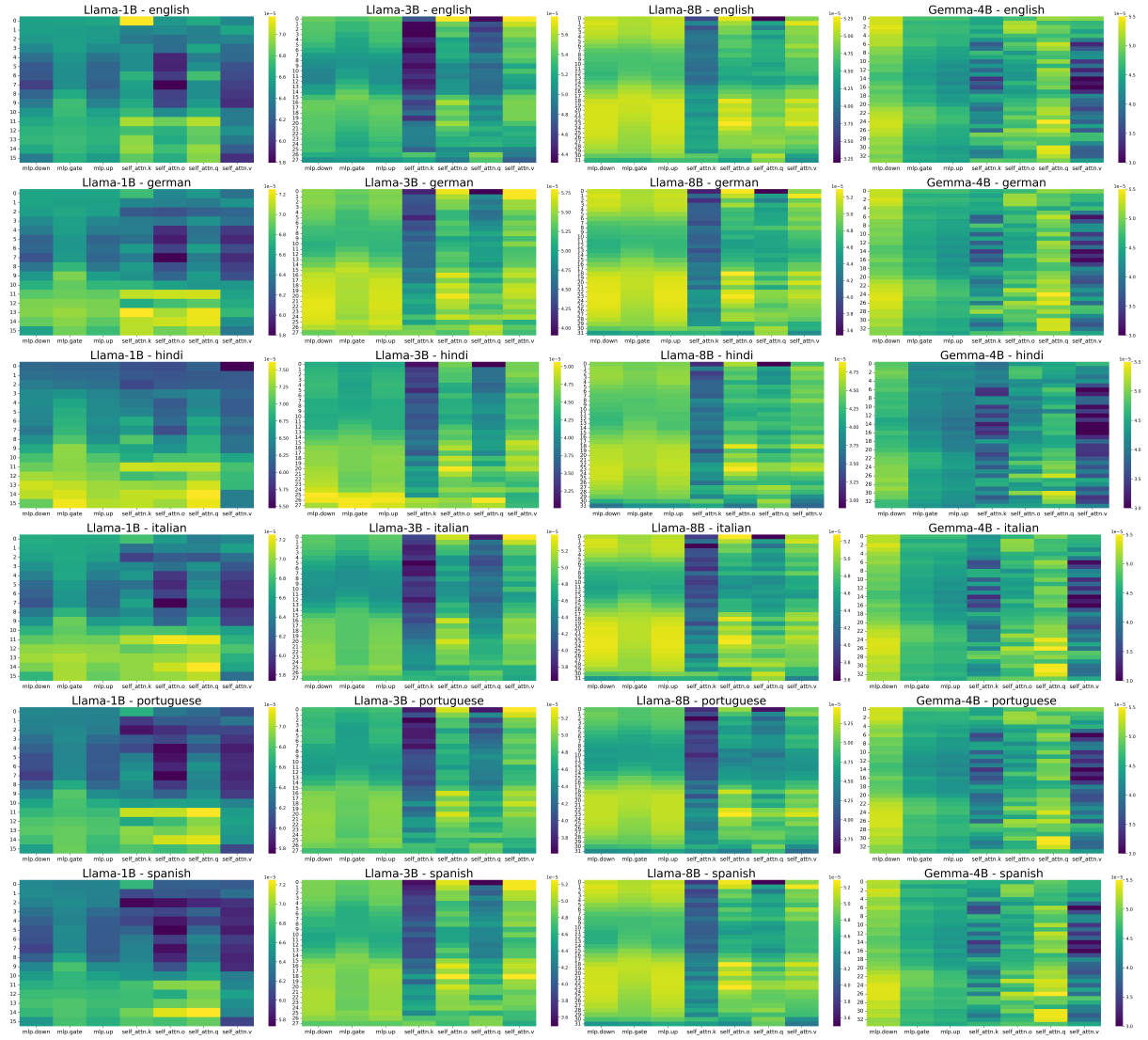


Figure 6: Average magnitude of difference between pretrained and monolingually fine-tuned models for Llama-1B, Llama-3B, and Llama-8B.

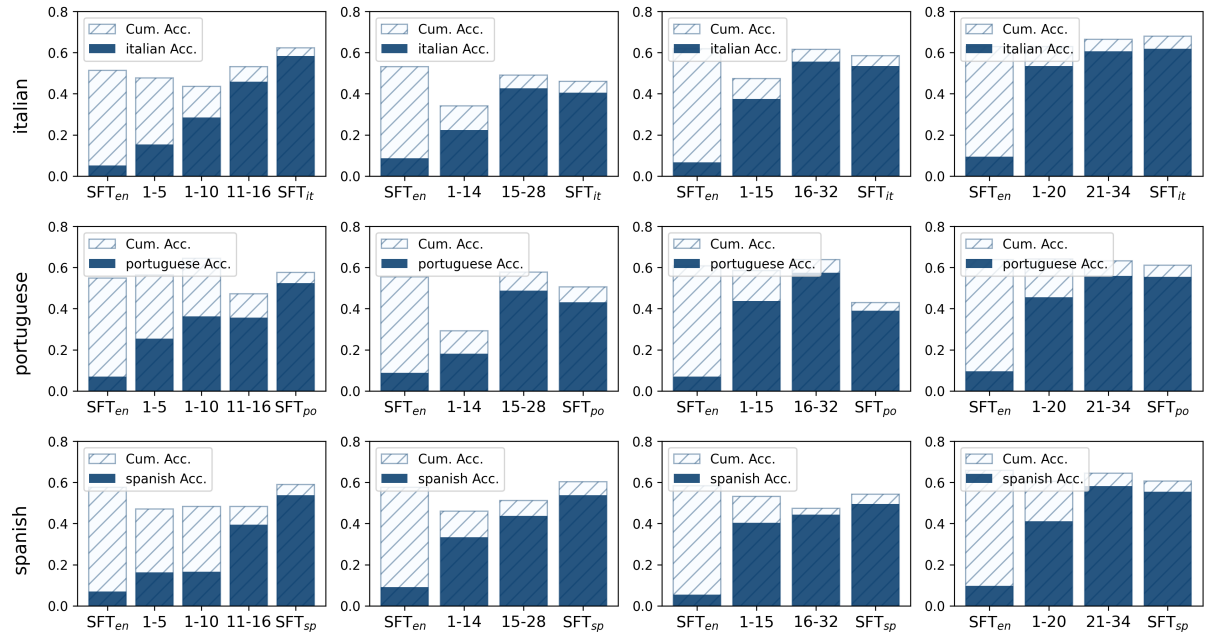


Figure 7: Cumulative accuracy and L_i accuracy on *en-tuned* (SFT_{en}) and L_i -tuned models (SFT_{L_i}), along with partially trained models, across all Llama model sizes.

Understand, Solve and Translate: Bridging the Multilingual Mathematical Reasoning Gap

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Abstract

Large language models (LLMs) demonstrate exceptional performance on complex reasoning tasks. However, despite their strong reasoning capabilities in high-resource languages (e.g., English and Chinese), a significant performance gap persists in other languages. To investigate this gap in Korean, we introduce HRM8K, a benchmark comprising 8,011 English-Korean parallel bilingual math problems. Through systematic analysis of model behaviors, we identify a key finding: these performance disparities stem primarily from difficulties in comprehending non-English inputs, rather than limitations in reasoning capabilities. Based on these findings, we propose UST (Understand, Solve, and Translate), a method that strategically uses English as an anchor for reasoning and solution generation. By fine-tuning the model on 130k synthetically generated data points, UST achieves a 10.91% improvement on the HRM8K benchmark and reduces the multilingual performance gap from 11.6% to 0.7%. Additionally, we show that improvements from UST generalize effectively to different Korean domains, demonstrating that capabilities acquired from machine-verifiable content can be generalized to other areas. We publicly release the benchmark, training dataset, and models¹.

1 Introduction

Large language models (LLMs) have made remarkable progress in reasoning tasks, often surpassing expert human performance (OpenAI, 2024; Anthropic, 2024). However, this exceptional reasoning capability is primarily observed in high-resource languages, with significant performance gaps in lower-resource languages (Huang et al., 2023; Li et al., 2024). This disparity likely stems from LLMs’ difficulty in transferring their foundational

capabilities, including reasoning skills learned in high-resource languages like English or Chinese, to lower-resource languages (Chen et al., 2023; Dubey et al., 2024).

To investigate this gap in Korean mathematical reasoning, we introduce HRM8K, a bilingual benchmark comprising 8,011 questions in both Korean and English. The questions are carefully curated from existing benchmarks (Cobbe et al., 2021; Hendrycks et al., 2021; Gao et al., 2024) and Korean examinations to create a perfectly parallel evaluation structure. Through systematic evaluation on HRM8K, we reveal that the performance gap primarily stems from difficulties in comprehending non-English inputs, rather than limitations in reasoning capabilities. This finding challenges previous studies that suggest using English chain-of-thought (CoT) reasoning for multilingual questions (Shi et al., 2022), as we show that LLMs are heavily influenced by the input language itself.

Based on these insights, we propose UST (Understand, Solve, and Translate), a training method that strategically uses English as an anchor for reasoning and solution generation. Our approach builds on recent findings that LLMs effectively use English as a pivot language for processing multilingual inputs (Zhong et al., 2024). By training on 130k synthetically generated instances, UST achieves a 10.91% improvement on the HRM8K benchmark and reduces the multilingual performance gap from 11.6% to 0.7%. Furthermore, we demonstrate that these improvements generalize beyond mathematics to different Korean domains, suggesting broader applications.

In summary, the main contributions of this work are as follows:

- We identify through systematic analysis that multilingual performance gaps primarily stem from input comprehension difficulties rather than reasoning limitations.

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¹<https://huggingface.co/HAERAE-HUB>

- We propose UST, a training method that effectively leverages English reasoning capabilities for non-English inputs, demonstrating significant performance improvements.
- We introduce HRM8K, the first Korean mathematics reasoning benchmark with 8,011 parallel questions, enabling systematic evaluation of multilingual reasoning capabilities.

2 Related Work

Mathematics Benchmarks Mathematical reasoning has emerged as a crucial capability for language models (Hurst et al., 2024; Alibaba, 2024; Zhao et al., 2024c), leading to the development of numerous benchmarks and datasets (Ling et al., 2017; Amini et al., 2019; Patel et al., 2021; Saxton et al., 2019). Traditional datasets such as GSM8K (Cobbe et al., 2021) and MATH (Hendrycks et al., 2021) primarily target grade-school to undergraduate-level problems, while more recent efforts introduce Olympiad-level challenges (Zheng et al., 2021; He et al., 2024; Huang et al., 2024; Fang et al., 2024; Gao et al., 2024).

Although these benchmarks prove valuable for evaluating English-language mathematical reasoning, fewer resources exist for non-English or bilingual math problems (Shi et al., 2022; Chen et al., 2023; Wu et al., 2024). In the Korean context, most benchmarks emphasize language understanding (Park, 2021; Son et al., 2023a), general knowledge (Son et al., 2023b; Kim et al., 2024), or commonsense reasoning (Son et al., 2024b,a), with mathematics being largely underrepresented. While the Open Ko-LLM Leaderboard (Park et al., 2024a) has begun translating some popular English benchmarks into Korean, those translated sets are not publicly accessible. Meanwhile, KMMLU (Son et al., 2024c) includes only about 100 math problems, insufficient for broader evaluation. To address this gap, we propose HRM8K, a large-scale bilingual Korean-English math benchmark comprising 8,011 problems, covering both competition-level Korean questions and parallel translations of existing English benchmarks.

Multilingual Reasoning and Language Models Recent LLMs have shown remarkable performance in English (OpenAI, 2024; Anthropic, 2024; Touvron et al., 2023), but many still underperform in multilingual scenarios (Lai et al.,

2024; Dubey et al., 2024). Such performance discrepancies are attributed to limited exposure to lower-resource languages during pre-training. Consequently, much research has focused on enhancing multilingual reasoning skills, including methods that explicitly use English as a ‘pivot’ for cross-lingual tasks (Zhao et al., 2024b; Zhu et al., 2024). For example, PLUG (Zhang et al., 2023) aligns internal reasoning in different languages, enabling the model to leverage stronger English reasoning for other languages.

Despite these developments, few works have thoroughly examined how to best calibrate reasoning between high- and low-resource languages in *complex mathematical* contexts. Some studies investigate altering the fraction of multilingual data in training (Anonymous, 2024) or conduct smaller-scale experiments on bilingual math tasks (Shi et al., 2022), yet a clear, large-scale solution remains elusive. Against this backdrop, our work introduces UST, a multilingual reasoning method that intentionally routes math problems in lower-resource languages through English-based reasoning. We show that this strategy drastically narrows the performance gap and advances multilingual math capabilities.

3 HRM8K

In this section, we introduce the composition of the HRM8K benchmark and explain its construction process. We also conduct a contamination check to ensure data quality. Detailed information about each dataset and post-processing methods are provided in Appendix A.

3.1 Benchmark Formulation

The HRM8K benchmark is a bilingual math dataset that consists of two major subsets: **Korean School Math (KSM)** and **Prior Sets**. Each subset is available in both Korean and English (see Table 1 for details).

KSM This subset contains 1,428 challenging math problems sourced from Korean Olympiads and competition-level exams, irrespective of the target age group. As a result, even questions originally intended for younger students still require substantial reasoning ability to solve. To collect these questions, the authors manually captured screenshots and applied GPT-4o’s OCR to convert the text, followed by a thorough validity check. (See Appendix G for the OCR prompt.)

Category	Subset	# of Instances	Short Description
KSM	KMO	730	Mathematics competition for high school students in South Korea, top-performers are selected as representatives for the IMO. (KMO)
1.4K Total	KJMO	62	KMO for junior students, up to age 13 (KJMO)
	CSAT	210	Questions from the Korean national university entrance exam and official mock exams, we only filter questions that have an error rate exceeding 70%. (CSAT)
	KMS	82	Math olympiad for university students, organized by the Korean Mathematical Society (KMS)
	TQ	344	Question from the national exam for math teacher certification (TQ)
Prior Sets	GSM8K	1,319	Grade school math word problems created by human problem writers (Cobbe et al., 2021)
6.5K Total	MATH	2,885	Competition-level mathematics problems. We only include questions with numeric answers (Hendrycks et al., 2021)
	Omni-MATH	1,909	Olympiad-level problems collected from international and Chinese math competitions. We only include questions with numeric answers (Gao et al., 2024)
	MMMLU	470	The MMLU (Hendrycks et al., 2020) dataset translated by professional human translators (OpenAI, 2024)

Table 1: Summary of dataset sources used in HRM8K

Prior Sets This subset comprises 6,583 problems drawn from established English math benchmarks, including GSM8K (Cobbe et al., 2021), MATH (Hendrycks et al., 2021), Omni-MATH (Gao et al., 2024), and MMMLU (OpenAI, 2024). To streamline translation and evaluation, we include only instances with numeric answers, excluding problems that require text-based, proof-oriented, or equation-based final answers. In particular, proof-type questions would necessitate a more complex LLM-as-a-Judge approach (Zheng et al., 2023; Shi et al., 2024; Park et al., 2024b) instead of simpler machine verification. Lastly, from the MMMLU dataset, we select only three math-related subsets: `abstract_algebra`, `college_mathematics`, and `high_school_mathematics`. Questions for the MMMLU dataset is multiple-choice question answering format.

3.2 Benchmark Construction

We translate all instances in both subsets into English and Korean using GPT-4o (Hurst et al., 2024), and then conduct human review to remove any inaccurate translations. This fully parallel design enables a more direct analysis of multilingual performance gaps. Furthermore, because KSM is translated from Korean to English and the other benchmarks are translated from English to Korean, we avoid depending solely on a single translation direction. This bidirectional approach also helps detect translation artifacts: if a particular pattern appears

only in one direction, it may be due to translation-related issues rather than the inherent difficulty of the questions. For further details on the dataset construction, please refer to Appendix A.

3.3 Contamination Check

Benchmark contamination, where evaluation questions appear in the model’s pretraining data, is increasingly recognized as a key concern in LLM evaluations (Deng et al., 2023; Roberts et al., 2023). Large-scale internet-crawled corpora (Gao et al., 2020; Weber et al., 2024) raise the likelihood of model memorization, potentially leading to inflated performance on evaluation benchmarks (Zhang et al., 2024; Zhao et al., 2024a). Ensuring that a newly proposed benchmark is entirely uncontaminated is nearly impossible, as many companies do not disclose the specifics of their pretraining mixtures (Aryabumi et al., 2024; Mishra et al., 2024), and logit-based detection methods are not yet well-established (Xu et al., 2024). In this work, we make our best effort to verify whether the dataset is included in publicly available large-scale Korean corpora. The contamination check is focused on the KSM subset, the only subset that was crawled in this work.

To ensure that the KSM subset is not present in common pretraining corpora, we perform a contamination check against FineWeb-2 (Penedo et al., 2024), the biggest Korean corpora available. This dataset contains 58 million Korean documents, totaling 95 GB, collected by the CommonCrawl foun-

dation (2013–2024). We first identify 149 documents that match the external sources used to compile HRM8K. Then, we search these documents for exact string matches from KSM’s questions; no matches were found. We hypothesize that this absence arises because the authors manually downloaded PDF or HWP files and selectively extracted questions, making them unlikely to appear in standard web crawls. Consequently, we conclude that the KSM problems are highly unlikely to have been seen during the LLMs’ pretraining phase.

4 Multilingual Performance Gaps

A recurring observation in large language models (LLMs) is that performance can vary significantly depending on the language of the prompt, even if the underlying task remains the same. We confirm this phenomenon on the HRM8K benchmark: as shown in Table 2, simply changing both the input and reasoning language from Korean to English yields an 11% performance boost, suggesting a notable gap in multilingual reasoning.

This section further investigates the causes of this gap. We first describe our experimental design (Section 4.1), then analyze the results (Section 4.2), and finally explore how multi-step prompting might mitigate these issues (Section 4.3).

4.1 Experimental Design

Let a model’s final performance P be determined by two factors: the language of the *input* (L_{input}) and the language used for *reasoning* (L_{reason}). Formally,

$$P = f(L_{\text{input}}, L_{\text{reason}}).$$

In the context of solving Korean math problems, there are two key requirements:

Comprehension: The model must understand the question, which is provided in Korean:

$$P \propto \text{Comp.}(L_{\text{input}} = \text{Korean}).$$

Reasoning: It must also perform the reasoning steps in Korean:

$$P \propto \text{Reasoning}(L_{\text{reason}} = \text{Korean}).$$

To examine which factor is more critical, we evaluate three cross-lingual setups: (1) Korean-to-Korean (K2K), (2) Korean-to-English (K2E), and (3) English-to-English (E2E). We exclude the English-to-Korean (E2K) scenario because models

typically fail to maintain a Korean chain-of-thought when the input is given in English. Further details, including the prompts used, can be found in Appendices B and G.

4.2 Evaluation Results

Prompting Type		K2K	K2E	E2E
Language	L_{input} L_{reason}	Ko Ko	Ko En	En En
Qwen2.5	1.5B	16	21 (+5)	37 (+21)
	7B	40	41 (+1)	51 (+11)
	72B	58	60 (+2)	63 (+5)
Llama3.1/2	1B	7	7 (0)	22 (+15)
	8B	28	26 (-2)	39 (+11)
	70B	45	45 (0)	55 (+12)
Average Delta			+1	+11

Table 2: Performance of Qwen2.5 and Llama3.1/2 models on the HRM8K benchmark depending on the input and reasoning language. Number in bracket denote its gain compared to the K2K prompt.

Table 2 summarizes the outcomes for each configuration. Overall, performance tends to increase with model size, and larger models show smaller gaps across languages. We highlight two findings:

Effect of Input Language Switching from Korean input (K2E) to an entirely English setup (E2E) yields an average improvement of 11%. In particular, Qwen2.5-7B and Llama-3.1-8B drop by 10% and 13%, respectively, when forced to process Korean input. This underscores the significance of L_{input} in model performance.

Effect of Reasoning Language In contrast, comparing K2K to K2E shows an average difference of only 1%, suggesting that the language of the *reasoning process* has a relatively small impact once the model has already ingested Korean input. Simply allowing the model to produce its chain-of-thought in English does not fully recover performance lost from reading a Korean prompt.

In short, enabling English-based reasoning alone is insufficient to close the multilingual gap. Instead, the limiting factor appears to be how well the model can *comprehend* Korean inputs.

4.3 Multi-Step Inference

A straightforward approach to alleviating these comprehension issues is to split the task into multiple inference steps, where the model explicitly translates the Korean question into English first.

Question

함수 $g(x)$ 는 다음을 만족합니다. $g(x + y) = g(x) + g(y)$ 모든 실수 x 와 y 에 대해. $g(0)$ 의 가능한 모든 값을 구하세요.
 [The function $g(x)$ satisfies $g(x + y) = g(x) + g(y)$ for all real numbers x and y . Find all possible values of $g(0)$.]

Solution

[Understanding the Question]

The function $g(x)$ satisfies the following functional equation: $g(x + y) = g(x) + g(y)$ for all real numbers x and y . The task is to find all possible values of $g(0)$.

Breakdown:

- Functional Equation: We have a functional equation that needs to be satisfied for all pairs of real numbers.
- Additive Property: [...] Next steps entail considering the nature of g and how the properties dictate $g(0)$.

[Solving the Question]

From the given functional equation, we have $g(0) = g(0 + 0) = g(0) + g(0) \rightarrow g(0) = 2g(0)$
 Subtracting $g(0)$ from both sides gives us $0 = g(0)$ So the only possible value of $g(0)$ is $\boxed{0}$.

[Translating the Solution to Korean]

주어진 함수 방정식에서 우리는 $g(0) = g(0 + 0) = g(0) + g(0) \rightarrow g(0) = 2g(0)$
 양변에서 $g(0)$ 을 빼면 $0 = g(0)$ 따라서 $g(0)$ 의 유일한 가능한 값은 $\boxed{0}$ 입니다.

Figure 1: Example of UST process. When presented with a problem in Korean, the model generates Korean answers through the following processes highlighted in yellow: *Understanding the Question*, *Solving the Question*, and *Translating the Solution into Korean*.

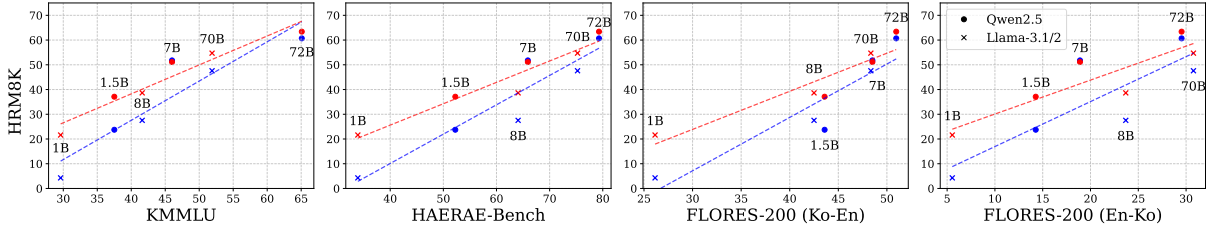


Figure 2: Comparison of HRM8K performance (vertical axis) and three additional benchmarks (KMMLU, HAERAE-Bench, FLORES-200) for Qwen2.5 and Llama-3.1/2 across different model sizes. TE2E (blue) translates Korean input to English before solving; E2E (red) uses an English prompt from the start.

We denote this as *Translated-English* (TE) in the first step, followed by an English-to-English (E2E) reasoning step in the second inference. This overall pipeline, called TE2E, uses a five-shot prompt for the translation stage.

In Figure 2, we compare TE2E (blue) and E2E (red) on three additional benchmarks: KMMLU (Son et al., 2024c), HAERAE-Bench (Son et al., 2023b), and FLORES (NLLB Team et al., 2024). For larger models with stronger Korean proficiency, TE2E and E2E become more similar, implying that multi-step inference can indeed help if the model already translates Korean accurately. However, for smaller models with weaker Korean skills, the performance gap remains pronounced. (Further details on the TE prompt are provided in Appendix G.)

5 Understand, Solve and Translate

Based on the experiments in Section 4, we conjecture that for smaller models improving their ability to understand Korean questions and allowing it to reason in English can address or bypass the constraints limiting LLMs in solving Korean questions. To validate this hypothesis, we fine-tune LLMs on a custom dataset designed to guide models through three stages: understanding Korean questions, solving them in English, and translating solutions back to Korean.

In this section, we explain the details of our training dataset (Section 5.1), report performance gains (Section 5.3), and conduct ablations on the effectiveness of the training (Section 5.4).

Models	GSM8K	MATH	OMNI_MATH	MMMLU	KSM	Avg.
<i>Proprietary or Large Models</i>						
GPT-4o	91.21	74.45	30.75	68.72	22.83	57.59
GPT-4o-Mini	87.57	70.68	26.45	63.40	19.40	53.50
Qwen2.5-72B-Instruct	90.07	72.06	30.96	66.60	23.46	56.63
Llama-3.1-70B-Instruct	79.08	56.05	19.85	60.00	13.10	45.61
<i>Qwen2.5-7B-Instruct</i>						
K2K-Prompting	66.41	50.36	18.96	50.00	11.83	39.52
K2E-Prompting	65.20	54.59	20.22	49.79	16.67	41.29
E2E-Prompting	81.35	68.87	27.29	57.02	21.08	51.12
Ours	80.06	68.53	27.19	57.23	19.12	50.43

Table 3: Evaluation results on HRM8K, comparing large-scale models (top) with different prompting strategies for Qwen2.5-7B-Instruct (bottom). Our UST-trained model achieves comparable performance to E2E-Prompting.

5.1 Training Dataset Construction

We create the UST (Understand, Solve, and Translate) dataset designed for training multilingual mathematical reasoning. Using GPT-4o-Mini, we generate cross-lingual Chain-of-Thought (CoT) examples that consist of three stages: (1) English Understanding Stage: Breaking down Korean questions and explaining their context and objectives in English; (2) English Solution Stage: Solving the mathematical problem in English; (3) Korean Solution Stage: Translating the English solution back to Korean. The dataset construction process follows these specific steps:

Step 1: Seed data collection We source our initial data from two datasets: OpenMathInstruct-2 (Toshniwal et al., 2024) and NuminaMath-CoT (LI et al., 2024). From OpenMathInstruct-2’s 14 million instruction samples, we randomly select 5 million instances and translate them to Korean using GPT-4o-Mini. For quality control, we use Qwen2.5-Math-RM-72B (Yang et al., 2024b), a reward model specialized for evaluating the quality of math question and output pairs, to score these instances and retain the top 50,000.

However, since OpenMathInstruct-2 primarily contains MATH and GSM8K augmentations, it lacks sufficient olympiad-level problems. To address this limitation, we supplement our dataset with samples from NuminaMath-CoT, specifically selecting problems from Aops Forum, AMC, Synthetic AMC, AIME, and Olympiads, and apply the same processing steps.

Step 2: Generating the Understanding Stage

Our previous experiments show that models per-

form better on Korean questions when translation and reasoning are separated into distinct steps. This suggests that traditional training methods, which emphasize immediate reasoning, may limit models’ ability to process non-English inputs effectively. Such observation aligns with Zhu et al. (2024)’s finding that translation-specific training enhances multilingual reasoning capabilities. Based on these insights and recent advances in longer CoT generation, we introduce an **Understanding Stage** to our training pipeline. In this stage, we use GPT-4o-Mini to create structured breakdowns of Korean questions in English, providing both the original question and its solution to ensure alignment between understanding and problem-solving.

Step 3: Generating the Korean Solution Stage

Our seed datasets originally include an English solution for each sample. In this step, we translate each solution into Korean. At every generation stage, we include prompts to discard samples with incorrect translations or solutions. The final version of the dataset contains approximately 130k samples. Further details of the prompt used are available in Appendix G.

	HRM8K	ELO	Token Consum.
K2K	39.52	807	2,202
UST	50.43	1145	7,854
M.S.I	51.78	978	11,764

Table 4: Comparison of K2K prompting, UST model (ours), and Multi-Step Inference (M.S.I). For more details on M.S.I see Appendix D.

Model Configuration	Stage Language (Understand / Solve)	Accuracy (%)
Baseline (K2K)	Korean / Korean	15.95
Cross-lingual (K2E)	Korean / English	21.15
English-only (E2E)	English / English	37.10
Ablation Studies		
No Understanding	- / Korean	36.49
Korean Understanding	Korean / Korean	34.82
No Understanding	- / English	43.30
Full UST	English / English	44.43

Table 5: Ablation studies on different configurations of UST. The top section shows baseline prompting results, while the bottom section examines the impact of different language settings for each stage.

5.2 Fine-Tuning with UST

We fine-tune Qwen2.5-7B using a standard autoregressive objective to generate all three stages (understanding, solving, and translating) in a single inference. Special tokens are inserted between stages to enable selective generation during inference. The model architecture remains unchanged, without parameter freezing or additional parameters. The training process runs for 3 epochs (approximately 11 hours) on four H100 80GB HBM3 GPUs using DeepSpeed ZeRO-1 parallelism (Rajbhandari et al., 2020). Detailed training configurations and hyperparameters are provided in Appendix C.

5.3 Performance Analysis

Effects of Targeted Training Table 3 shows the performance of our Qwen2.5-7B model trained on the UST dataset. Our model achieves higher accuracy (50.43%) than both baseline approaches: K2K (39.52%) and K2E (41.29%) prompting, highlighting the effectiveness of targeted training for English reasoning. Furthermore, this performance is comparable to E2E prompting (51.12%), suggesting that our model successfully recovers the capabilities observed under ideal conditions where both questions and reasoning are in English.

Effects of Single-Pass Translation Instances in the UST dataset integrate translation with understanding and solving in a single inference. To examine this design choice, we first verify that the translation stage does not compromise performance. Out of the 8,011 questions in HRM8K, we observe only 15 cases (0.18%) where translation fails, all due to context length limitations. Notably, the translation stage serves purely as a user-friendly feature without affecting the model’s

problem-solving capabilities.

For generating Korean solutions, we compare three approaches: (1) direct generation in Korean (K2K), (2) our single-pass UST, and (3) multi-step inference (MSI). MSI is a direct re-implementation of UST through prompting that separately performs three steps: translating the Korean question to English, solving in English, and re-translating the solution back to Korean. In Table 4, we evaluate these methods across three metrics: accuracy on HRM8K, response quality via ELO ratings², and computational efficiency through token consumption. While our model achieves accuracy comparable to MSI, it demonstrates superior response quality - preferred in 87.32% of direct comparisons (excluding ties). Furthermore, our approach consumes only 66% of the tokens required by MSI, making it computationally more efficient. Detailed evaluation methodology and prompts are provided in Appendices E, G.

5.4 Ablation Analysis

The UST dataset consists of three stages: Understand, Solve, and Translate. Having confirmed that the translation stage does not impact performance, we now examine the roles of the Understanding and Solving stages. We conduct experiments with four different configurations by varying both the presence and language of these stages. In our experiments, ‘-’ indicates the omission of a stage, while ‘Korean’ or ‘English’ specifies the language used. For computational efficiency, we use a smaller model (Qwen2.5-1.5B-Instruct) and randomly sample 50k instances from the original dataset.

²ELO rating is a widely adopted metric for comparing relative quality between language models through pairwise comparisons.

Models	HUMSS	STEM	Applied Science	Other	Avg.
Qwen2.5-7B	37.3	45.0	42.4	36.5	40.3
(Ours)	39.3	49.5	45.3	40.3	43.6

Table 6: Evaluation results on KMMLU (Son et al., 2024c).

Models	BN	DE	EN	ES	FR	JA	RU	SW	TE	TH	ZH	Av.
Qwen2.5-7B	60.8	79.6	90.8	80.0	77.2	70.0	84.0	18.4	31.2	76.4	82.8	68.3
(Ours)	65.6	80.4	90.0	83.6	80.0	75.2	83.2	14.8	48.8	71.6	81.6	70.4

Table 7: Evaluation results on MGSM (Shi et al., 2022).

Our experiments reveal that the original configuration - both stages in English - achieves the highest performance (44.43%) among all variants. A notable finding is that adding a Korean understanding stage actually decreases performance (36.49% \rightarrow 34.82%). We attribute this counterintuitive result to two factors. First, when solving in Korean, an explicit understanding stage may be redundant as it essentially serves as another form of translation. Second, and more importantly, this suggests that chain-of-thought reasoning is most effective when conducted in the model’s preferred language (English). This aligns with our observation that models show weaker reasoning capabilities in non-English languages, likely due to limited exposure during pre-training.

6 Tracing the Performance Gains

In this work, we demonstrate that routing through English understanding and reasoning steps enhances model performance on HRM8K. To understand the source of these improvements, we evaluate our UST-trained model on two additional benchmarks: KMMLU (Son et al., 2024c) and MGSM (Shi et al., 2022).

Our model shows consistent improvements across all KMMLU categories, with the largest gains in STEM (+4.5) and the smallest in HUMSS (+2.0)³. However, when tested on MGSM, the model shows performance drops in Swahili (-3.6) and Thai (-4.8). These contrasting results suggest that our gains stem not from general improvements in mathematical reasoning, but rather from enhanced Korean-specific capabilities and better Korean-to-English reasoning alignment.

³This aligns with the nature of CoT, which primarily enhances reasoning capabilities (Sprague et al., 2024) rather than factual knowledge required for HUMSS questions.

Our findings align with our initial goal: addressing the performance gap between English and Korean reasoning on identical questions (Section 5.3). The effectiveness of our approach is demonstrated in two ways. First, it recovers most of the performance achieved with E2E prompting (Table 9). Second, it shows successful transfer to new domains (Table 6), suggesting that reasoning capabilities learned from machine-verifiable mathematics can generalize effectively. Most importantly, our method provides a simple path for non-English language users to benefit from the advanced reasoning capabilities typically available only in English.

7 Conclusion

In this paper, we propose UST, a training method that leverages English as an anchor language to enhance reasoning capabilities in Korean, and introduce HRM8K, a benchmark of 8,011 English-Korean parallel mathematics problems. Our analysis reveals that the performance gap in multilingual reasoning primarily stems from difficulties in processing non-English inputs. Through extensive experiments, we demonstrate that UST effectively bridges this gap and shows promising generalization to various Korean domains beyond mathematics. Our approach offers a simple yet effective solution for non-English language users to benefit from advanced reasoning capabilities typically available only in English, suggesting a practical direction for improving multilingual reasoning capabilities in language models.

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A Dataset Details

This section provides additional details regarding the construction and composition of the HRM8K benchmark.

A.1 Dataset Sources

KSM This subset consists of problems from Korean mathematics examinations and competitions:

- **College Scholastic Ability Test (CSAT)**⁴: The Korean counterpart to the SAT, which serves as the primary university entrance examination. We include only math problems with historical error rates exceeding 70%.
- **Korean Mathematical Olympiad (KMO)**⁵: The Korean equivalent to the International Mathematical Olympiad (IMO), primarily designed for middle- and high-school students. These problems require advanced mathematical knowledge and critical thinking.
- **Korean Junior Mathematical Olympiad (KJMO)**⁶: An elementary-school version of KMO aimed at identifying mathematical talent at an early stage.
- **Korean University Mathematical Olympiad (KMS)**⁷: A university-level competition featuring advanced topics in calculus, linear algebra, number theory, geometry, and discrete mathematics.
- **Korean National Teacher Qualification Test (TQ)**⁸: A standardized examination for teacher certification that focuses on mathematical pedagogy and content expertise.

Prior Sets This subset incorporates problems drawn from established English mathematics benchmarks, filtered to include only those with numeric answers:

- **GSM8K** (Cobbe et al., 2021): A collection of 8.5K grade-school math word problems that emphasize multi-step reasoning and elementary arithmetic.
- **MATH** (Hendrycks et al., 2020): A comprehensive benchmark of 12.5K high-school competition-level problems spanning seven mathematical domains, each accompanied by detailed step-by-step solutions.

⁴<https://www.suneung.re.kr/boardCnts/list.do?boardID=1500234&m=0403&s=suneung&searchStr=>

⁵<https://www.kmo.or.kr/kmo/sub07.html>

⁶<https://www.kms.or.kr/board/list.html?code= junior2>

⁷<https://www.kms.or.kr/board/list.html?code= conf12>

⁸<https://blog.naver.com/headracer>

- **Omni-MATH** (Gao et al., 2024): An advanced dataset containing 4.4K Olympiad-level problems across 33 sub-domains and 10 difficulty tiers, designed to push the limits of current LLM capabilities.

- **MMMLU** (OpenAI, 2024): A multilingual extension of the MMLU benchmark (Hendrycks et al., 2020), covering various STEM fields (e.g., abstract algebra, college mathematics, and high-school mathematics). It is available in 14 languages produced by professional translators.

A.2 Post-processing

For the **KSM** subset, we performed a manual verification and editing procedure to ensure high-quality OCR results. Specifically, we developed a review application in Streamlit⁹, illustrated in Figure 3, which compares the original problem text against the OCR output. Two main factors were verified:

- *Content Completeness*: Confirming that all parts of the problem statement are accurately captured and that no text is omitted.
- *L^AT_EX Integrity*: Ensuring that mathematical symbols and equations are correctly transcribed in L^AT_EX format.

Based on these checks, we corrected errors and added any missing content. For instance, monetary symbols (\$) enclosing L^AT_EX symbols were removed to enhance clarity. Erroneous OCR outputs were manually fixed, and missing text was supplemented as needed. Figure 3 illustrates our interactive review interface.

B Additional Details in Experiments

We experiment with six multilingual language models reported to have been pretrained on Korean data: three Qwen2.5 Instruct models (1.5B, 7B, and 72B parameters) (Yang et al., 2024a) and three Llama-3.1/2 Instruct models (1B, 8B, and 70B parameters) (Dubey et al., 2024; Meta AI, 2024). For simplicity, we omit the word “Instruct” in references to these models, although all are instruction-tuned.

Unless otherwise noted, we set the sampling temperature to 0.7 and top_p to 0.95, with a minimum of 8 tokens and maximum of 2,048 tokens for the output. While lower temperatures are often used in

⁹<https://streamlit.io/>

KSM Question image & MetaData Review

RULES

- 문제 이미지에 따라서 알맞게 문제가 ocr 되었는지 판단해주세요.
- LaTeX 수식의 형태는 '\$'가 포함되지 않도록 교정해주세요.

Question Image

1. 함수 $f(x) = e^x(ax^3 + bx^2)$ 과 양의 실수 t 에 대하여 닫힌

구간 $[-t, t]$ 에서 함수 $f(x)$ 의 최댓값을 $M(t)$, 최솟값을 $m(t)$

라 할 때, 두 함수 $M(t), m(t)$ 는 다음 조건을 만족시킨다.

(가) 모든 양의 실수 t 에 대하여 $M(t) = f(t)$ 이다.

(나) 양수 k 에 대하여 닫힌 구간 $[k, k+2]$ 에 있는 임의의 실수 t 에 대해서만 $m(t) = f(-t)$ 가 성립한다.

Category

수능/모의고사

Source

nan

Difficulty

미지분

Question

함수 $f(x) = e^x(ax^3 + bx^2)$ 과 양의 실수 t 에 대하여 닫힌 구간 $[-t, t]$ 에서 함수 $f(x)$ 의 최댓값을 $M(t)$, 최솟값을 $m(t)$ 라 할 때, 두 함수 $M(t), m(t)$ 는 다음 조건을 만족시킨다.

```
\begin{aligned}
&\&(\text{가}) \text{ 모든 양의 실수 } t \text{에 대하여 } M(t) = f(t) \text{이다.} \\
&\&(\text{나}) \text{ 양수 } k \text{에 대하여 닫힌 구간 } [k, k+2] \text{에 있는 임의의 실수 } t \text{에 대해서만 } m(t) = f(-t) \text{가 성립한다.} \\
&\&(\text{다}) \int_{-1}^1 e^x (ax^3 + bx^2) dx = \frac{7}{3} - 8e
\end{aligned}
```

Answer

Figure 3: Screenshot of our Streamlit-based OCR validation tool, used to compare source documents with OCR outputs and correct any errors.

pass@1 settings, we observed that extremely low temperatures sometimes cause models to revert to their preferred language (often English or Chinese). Hence, to maintain the specified response language, we employ a slightly higher temperature with moderate top_p.

C Fine-tuning Details

We fine-tune our models on H100 80GB GPUs using DeepSpeed ZeRO. Specifically, we train Qwen2.5-7B-Instruct on the UST approach and conduct ablation analyses with Qwen2.5-1.5B-Instruct under various settings. To maximize GPU utilization, we use a batch size of 96 per GPU across four GPUs for Qwen2.5-7B-Instruct, and a batch size of 128 per GPU across two GPUs for Qwen2.5-1.5B-Instruct. Table 8 summarizes the relevant hyperparameters.

D Multi-Step Inference

Multi-Step Inference (M.S.I) is a direct re-implementation of UST solely via prompting (i.e., without additional training). It is carried out in three steps:

- Translated-English (TE):** Translate the original Korean prompt into English. We use the template shown in Figure 12.
- Translated-English-to-English (TE2E):** Solve the translated problem in English using the template in Figure 9.

- Translated-English-to-English-to-Korean (TE2E2K):** Translate the English solution back into Korean, following the template in Figure 13.

This multi-step approach echoes the three-stage UST pipeline (Understand, Solve, Translate) but relies on separate inferences with task-specific prompts.

E Evaluation Methods

E.1 ELO Rating

We use an Elo rating system to compare responses produced by different approaches in a pairwise manner (LMSYS, 2023). Elo ratings are computed in two parts: (1) *Expected Score*, which gauges each model’s probability of winning based on current ratings; and (2) *Rating Update*, which adjusts the ratings after each match.

Expected Score. Given two models A and B with Elo ratings R_A and R_B , their expected scores E_A and E_B are:

$$E_A = \frac{1}{1 + 10^{(R_B - R_A)/400}},$$

$$E_B = \frac{1}{1 + 10^{(R_A - R_B)/400}}.$$

Rating Update. After each pairwise comparison, the rating of model A is updated as follows:

$$R'_A = R_A + K \times (S_A - E_A),$$

Table 8: Hyperparameters for fine-tuning and ablation studies.

Base Model	Batch Size	Learning Rate	Scheduler	Optimizer	Max Length	# GPUs
Qwen2.5-7B	96	2e-5	Cosine	AdamW	8192	4
Qwen2.5-1.5B	128	2e-5	Cosine	AdamW	8192	2

where $S_A \in \{0, 1\}$ is the actual score (1 if A is preferred, and 0 otherwise). The constant K modulates the step size of the rating update; we set $K = 4$ for more stable ratings. We also randomly shuffle match order and apply bootstrapping over 1,000 iterations to mitigate dependence on match sequence (Boubdir et al., 2023).

E.2 Token Consumption

We measure token consumption via a simplified metric that accounts for both input and output tokens. For a dataset of N samples, let T_{input} and T_{output} be the number of input and output tokens, respectively, for each sample. The total token cost L_{model} for each model is:

$$L_{\text{model}} = \frac{\sum_{i=1}^N (T_{i,\text{input}} + 3 \times T_{i,\text{output}})}{N},$$

where we weight output tokens by a factor of 3 to reflect their higher processing cost, following cost ratios from common LLM providers (e.g., OpenAI, Mistral AI, Alibaba Cloud, and Deepseek AI).

F Cross-Lingual Application of RMs

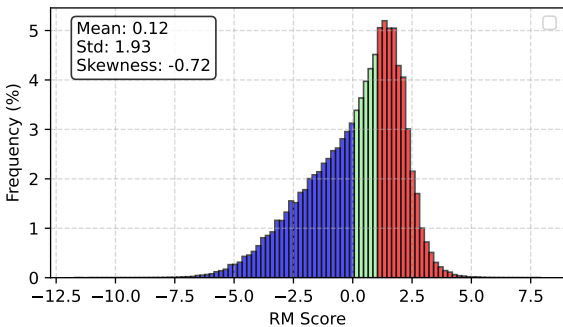


Figure 4: Reward model evaluation result on UST dataset. The samples were categorized into three groups based on the reward model score: high (RM Score > 1, red), low (RM Score < 0, blue), and medium ($0 \leq \text{RM Score} \leq 1$, green).

While creating the UST we leverage Qwen2.5-Math-RM-72B a reward model (RM) originally intended to be used in English or Chinese. We observe whether such RMs can be applied with further post-training for language transfer. In Figure 4, we

illustrate the score distribution on our initial dataset. The distribution shows to be right-skewed with a gradual tapering off towards the left. We create two datasets high and low. The high consists of samples with a score higher than 1 (colored in red) and low consists samples with a score lower than 0 (colored in blue). The high is used as our final dataset. For comparison we train a Qwen2.5-7B-Instruct model on the low dataset with identical number of instances.

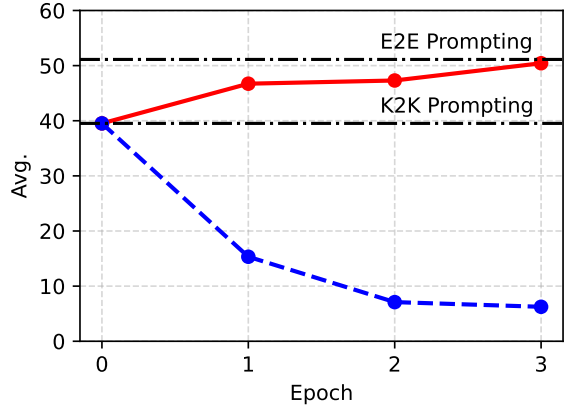


Figure 5: Qwen2.5-7B-Instruct model performance trends across epochs during training on high (red) and low (blue) datasets. The evaluation results of the original Qwen2.5-7B-Instruct model for K2K and E2E prompting were depicted with the dash-dotted lines.

As shown in Figure 5, training on the High subset progressively improves the model’s performance. In contrast, using the Low subset degrades performance, with the model’s score dropping to an average of 6.25 on HRM8K. This result suggests that RMs can be applied to new languages without additional training, aligning with previous studies (Son et al., 2024b,d). Accordingly, we choose to use the filtered subset.

G Prompt Templates

This section provides the complete text of all prompts used in our experiments, evaluations, and dataset construction. Each prompt is presented in a separate figure, preserving the original structure while enhancing clarity and consistency.

Table 9: Evaluation result for Qwen and Llama models on HRM8K. All models are instruction-tuned, but they are abbreviated for simplicity.

Model	GSM8K	MATH	Omni-MATH	MMMLU	KSM	Avg.
<i>Korean-to-Korean (K2K)</i>						
Qwen2.5-1.5B	28.13	20.69	8.64	18.51	3.78	15.95
Qwen2.5-7B	66.41	50.36	18.96	50.00	11.83	39.52
Qwen2.5-72B	89.46	74.73	30.07	69.79	25.35	57.88
Llama-3.2-1B	7.88	10.50	4.77	10.43	2.80	7.28
Llama-3.1-8B	57.47	31.20	11.73	32.98	5.25	27.73
Llama-3.1-70B	78.62	56.12	20.38	57.87	11.83	44.96
<i>Korean-to-English (K2E)</i>						
Qwen2.5-1.5B	31.92	26.86	10.32	30.85	5.81	21.15
Qwen2.5-7B	65.20	54.59	20.22	49.79	16.67	41.29
Qwen2.5-72B	89.23	77.68	32.74	70.43	27.73	59.56
Llama-3.2-1B	7.20	9.57	5.08	11.49	2.94	7.26
Llama-3.1-8B	55.04	31.13	11.16	27.66	5.18	26.03
Llama-3.1-70B	77.63	55.18	19.43	58.94	12.82	44.80
<i>English-to-English (E2E)</i>						
Qwen2.5-1.5B	65.50	49.25	16.87	45.53	8.33	37.10
Qwen2.5-7B	81.35	68.87	27.29	57.02	21.08	51.12
Qwen2.5-72B	94.31	83.33	37.72	70.00	31.65	63.40
Llama-3.2-1B	43.44	27.24	9.90	23.83	3.64	21.61
Llama-3.1-8B	79.45	48.11	16.08	42.34	7.21	38.64
Llama-3.1-70B	93.33	67.90	24.83	70.43	17.09	54.71

1. **OCR Prompt (Figure 6)**: Performs OCR on an image of a Korean math problem and extracts the text. Used to build the KSM subset (Section 3.1).
2. **Question Translation Prompts (Figures 7–8)**: Translate math questions into Korean or English, respectively. Used for creating bilingual pairs in HRM8K (Section 3.2).
3. **Solution Generation Prompts (Figures 9–10)**: Evaluate model performance on HRM8K under different reasoning-language conditions (Section 4.1).
4. **Understanding Generation Prompt (Figure 11)**: Produces a structured breakdown of the problem for the *Understanding* stage of UST (Section 5.1).
5. **Model Translation Prompts (Figures 12–13)**: Used in multi-step inference (M.S.I) to translate the question or solution between Korean and English (Section 4.3).
6. **LLM-as-a-Judge Prompt (Figure 14)**: Conducts pairwise response comparisons and produces a verdict, enabling ELO-based evaluation (Section 5.3).

OCR Prompt

You will be given an image containing a Korea math question. Your task is to conduct an OCR to retrieve the question in text format.

Follow the following roles:

1. return the question only, nothing else.
2. If, the image contains the answer ignore it. Do not return it with the question.
3. Put extra care on notations and equations make sure they are identical.

Figure 6: Prompt to perform OCR and extract the mathematical question from the given image. Both the prompt and the screenshot of the problem were provided to the model for OCR processing.

Table 10: Translated-English-to-English (TE2E) prompting evaluation result on HRM8K.

Model	GSM8K	MATH	Omni-MATH	MMMLU	KSM	Avg.
<i>Translated-English-to-English (TE2E)</i>						
Qwen2.5-1.5B	36.24	34.52	12.05	29.36	6.51	23.74
Qwen2.5-7B	79.53	70.78	28.86	59.36	20.38	51.78
Qwen2.5-72B	89.16	78.13	34.05	70.43	31.65	60.68
Llama-3.2-1B	2.96	5.41	1.94	9.36	1.75	4.28
Llama-3.1-8B	53.90	36.43	13.04	29.57	4.76	27.54
Llama-3.1-70B	78.17	60.83	22.26	60.43	16.25	47.59

Question Translation Prompt: En→Ko

You are a professional English-to-Korean translator specializing in academic content. Your task is to translate math problems provided in English into clear, natural, and precise Korean referring to given examples. Follow the instructions below:

INSTRUCTIONS:

1. You SHOULD NOT solve the problem and translate only the given question — do not include any additional commentary.
2. Preserve all mathematical symbols, notations, formatting, and existing choices exactly as presented.
3. Use fluent, natural Korean that aligns with academic standards for math problems.
4. Ensure the translation conveys the meaning and context accurately.

INPUT:

{question}

Figure 7: Translation prompt to translate English math questions into Korean. This prompt is utilized to translate the *Prior Sets* data, sourced from English math benchmarks, into Korean. The bracketed part is a placeholder to fill in the question.

Question Translation Prompt: Ko→En

You are a professional Korean-to-English translator specializing in academic content. Your task is to translate math problems provided in Korean into clear, natural, and precise English referring to given examples. Follow the instructions below:

INSTRUCTIONS:

1. You SHOULD NOT solve the problem and translate only the given question — do not include any additional commentary.
2. Preserve all mathematical symbols, notations, formatting, and existing choices exactly as presented.
3. Use fluent, natural English that aligns with academic standards for math problems.
4. Ensure the translation conveys the meaning and context accurately.

Figure 8: Translation prompt to translate Korean math questions into English. This prompt is utilized to translate the *KSM* data, sourced from Korean math examinations and competitions, into English. The bracketed part is a placeholder to fill in the question.

HRM8K Solution Prompt: English Reasoning

Solve the given question.

After solving the problem, state your final answer in the following format: \boxed{N} .

{question} Respond in English.

Figure 9: Solution generation prompt to evaluate the models in an English reasoning setup, such as K2E and E2E. The bracketed part is a placeholder to fill in the question.

HRM8K Solution Prompt: English Reasoning

Solve the given question.

After solving the problem, state your final answer in the following format: \boxed{N} .

{question} Respond in Korean.

Figure 10: Solution generation prompt to evaluate the models in a Korean reasoning setup, such as K2K. The bracketed part is a placeholder to fill in the question.

Understanding Generation Prompt

[User]
Solve the following problem:
{question}

[Assistant]
{solution}

[User]
I'm planning to generate a step-by-step guide for the solution. The step-by-step solution will be provided to students to guide their solution. Accordingly, it should be clear and straightforward, guiding the student through the problem-solving process. However, it must not reveal the answer as it will disturb the students' solution. Generate the breakdown. It should assist with understanding the question and planning how to solve it. The generation will be directly provided to the student, accordingly do not include notes like 'not reveal the answer', or a evaluation of your own breakdown. Write in first person view: e.g I will , I can .

Figure 11: Generation prompt to generate *Understanding* stage of UST. Given a problem and its corresponding answer, a prefix conversation history is constructed where the user asks the problem and the assistant provides the ground-truth answer. Subsequently, the user instructs the assistant to generate an understanding of the problem. The bracketed parts are a placeholder to fill in the question and its ground-truth solution.

Model Translation Prompt: Translated-English (TE)

You are a professional Korean-to-English translator specializing in academic content. Your task is to translate math problems provided in Korean into clear, natural, and precise English referring to given examples. Follow the instructions below:

INSTRUCTIONS:

1. You SHOULD NOT solve the problem and translate only the given question — do not include any additional commentary.
2. Preserve all mathematical symbols, notations, formatting, and existing choices exactly as presented.
3. Use fluent, natural English that aligns with academic standards for math problems.
4. Ensure the translation conveys the meaning and context accurately.

INPUT:
[1st Korean Question Example]

OUTPUT:
[1st English Translation Result]

...

INPUT:
[5th Korean Question Example]

OUTPUT:
[5th English Translation Result]

INPUT:
{question}

OUTPUT:

Figure 12: Translation prompt to generate Translated-English (TE) problem by translating the given Korean problem into English. The bracketed part is a placeholder to fill in the question.

Model Translation Prompt: Translated-English-to-English-to-Korean (TE2E2K)

You are a professional Korean-to-English translator specializing in academic content. Your task is to translate math problems provided in Korean into clear, natural, and precise English referring to given examples. Follow the instructions below:

INSTRUCTIONS:

1. You SHOULD NOT solve the problem and translate only the given question — do not include any additional commentary.
2. Preserve all mathematical symbols, notations, formatting, and existing choices exactly as presented.
3. Use fluent, natural English that aligns with academic standards for math problems.
4. Ensure the translation conveys the meaning and context accurately.

INPUT:

[1st English Solution Example]

OUTPUT:

[1st Korean Translation Result]

...

INPUT:

[5th English Solution Example]

OUTPUT:

[5th Korean Translation Result]

INPUT:

{question}

OUTPUT:

Figure 13: Translation prompt to generate Translated-English-to-English-to-Korean solution by translating the given English solution into Korean. The bracketed part is a placeholder to fill in the question.

LLM-as-a-judge Prompt

[System]

Please act as an impartial judge and evaluate the quality of the responses provided by two AI assistants to the user question displayed below. You should choose the assistant that follows the user's instructions and answers the user's question better. Your evaluation should consider factors such as the helpfulness, relevance, accuracy, depth, creativity, and level of detail of their responses. Begin your evaluation by comparing the two responses and provide a short explanation. Avoid any position biases and ensure that the order in which the responses were presented does not influence your decision. Do not allow the length of the responses to influence your evaluation. Do not favor certain names of the assistants. Be as objective as possible. After providing your explanation, output your final verdict by strictly following this format: "[[A]]" if assistant A is better, "[[B]]" if assistant B is better. There is no option for a tie, you should choose "[[A]]" or "[[B]]".

[User Question]

{question}

[The Start of Assistant A's Answer]

{model_a_answer}

[The End of Assistant A's Answer]

[The Start of Assistant B's Answer]

{model_b_answer}

[The End of Assistant B's Answer]

Figure 14: Evaluation prompt to conduct llm-as-a-judge pairwise evaluation between model A's response and model B's response to a given question. The bracketed parts are the placeholders to fill in the question, model A's answer, and model B's answer.

Unlocking LLM Safeguards for Low-Resource Languages via Reasoning and Alignment with Minimal Training Data

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Abstract

Recent advances in LLMs have enhanced AI capabilities, but also increased the risk posed by malicious requests, highlighting the need for effective LLM safeguards to detect such queries. Existing approaches largely rely on classifier-based methods that lack interpretability and perform poorly on low-resource languages. To address these limitations, we propose *ConsistentGuard*, a novel reasoning-based multilingual safeguard, which enhances explainability via reasoning and boosts knowledge transfer between languages through alignment. With only **1,000 training samples**, our method demonstrates superior performance on three datasets across six languages, outperforming larger models trained with significantly more data, and exhibits strong interpretability and generalization ability. We also contribute a multilingual benchmark extension and release our codes to support future research.

Recent advances in LLMs have enhanced AI capabilities, but also increased the risk posed by malicious requests, highlighting the need for effective LLM safeguards to detect such queries. Existing approaches largely rely on classifier-based methods that lack interpretability and perform poorly on low-resource languages. To address these limitations, we propose *ConsistentGuard*, a novel reasoning-based multilingual safeguard, which enhances explainability via reasoning and boosts knowledge transfer between languages through alignment. With only 1,000 training samples, our method demonstrates superior performance on three datasets across six languages, outperforming larger models trained with significantly more data, and exhibits strong interpretability and generalization ability. We also contribute a multilingual benchmark extension and release our codes to support future research.

1 Introduction

Recent advances in Large Language Models (LLMs) have brought AI applications to a new height, which also makes the defense against malicious prompts increasingly critical. LLM safeguards aim at detecting malicious prompts from users and identifying harmful generations from agents. Most previous methods work in a simple classifier manner, e.g., Llama Guard (GenAI, 2023), ShieldGemma (Zeng et al., 2024), etc. Therefore, making the results less explainable and lacking evidence (Liu et al., 2025). Moreover, though these models have superior performance on mainstream languages, it has a significant performance drop on low-resource languages, such as Bengali (Yong et al., 2023; Deng et al., 2024).

To mitigate such issues, recent research has tried to incorporate models’ reasoning ability with chain-of-thought (CoT) prompt engineering (Qin et al., 2023) or reinforcement learning (RL), such as GuardReasoner (Liu et al., 2025). Although these reasoning-based models perform well in providing both evidence and classification results, most of them are trained on a single mainstream language, ignoring their reasoning consistency across languages and leading to a drop in cross-lingual performance. For models’ cross-lingual performances, prior research has primarily focused on enhancing their cross-lingual performance by continued pre-training or through alignment methods with supervised fine-tuning (SFT) (Chai et al., 2025). More recent research has introduced direct preference optimization (DPO) (Rafailov et al., 2023) alignment for QA tasks (Wang et al., 2025), demonstrating remarkable generalization ability. However, most prior methods have ignored the issue of reasoning inconsistencies across languages, specifically for reasoning models, and the potential of RL for cross-lingual alignments still remains largely unexplored. Detailed related work is included in App. A.

*Equal contributions.

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‡Work done during the bachelor’s program in GDUFS.

Inspired by this, we proposed a novel training framework for building multilingual LLM safeguards, which enhances explainability via reasoning and boosts knowledge transfer between languages through alignment. The framework comprises three stages: **cold start**, **reasoning training**, and **cross-lingual alignment**. Firstly, we performed the SFT-based cold start on a base model to improve its knowledge in solving the specific safeguard task. Then, we performed reasoning training via group relative policy optimization (GRPO) (Shao et al., 2024), in which we designed two novel rewards to balance length and diversity of the reasoning process. Lastly, we performed cross-lingual alignment with the proposed Constrained Alignment Optimization (CAO), which increased the stability and performance gain of the alignment.

Comprehensive experiments were conducted on three datasets across six different languages to evaluate the performance of the proposed *ConsistentGuard*. Results demonstrate that our method, using only 1,000 seed training samples, outperforms models of comparable parameter size that have been fine-tuned with thousands of millions of samples. Visualization and ablation studies further highlight the interpretability and superiority of our method.

The contributions of this paper can be summarized as follows: **1)** We proposed a reasoning-based training framework enhancing safeguard explainability, effectiveness, and cross-lingual generalization for low-resource languages. **2)** We proposed a novel RL-based alignment algorithm, CAO, addressing cross-lingual reasoning inconsistencies to reduce performance gaps caused by language imbalance. **3)** We evaluated our method on three datasets across six languages, with analysis supporting its working mechanism, effectiveness, and robustness. **4)** We released a reasoning-based multilingual safeguard training code and extended three existing English safety benchmarks¹ to six languages to support research in this field.

2 Methodology

The general training framework of *ConsistentGuard* is illustrated in the Fig. 1. The proposed method comprises three main training stages.

We first distilled knowledge with SFT from LLMs with a large parameter scale to a 3B base model, providing the model with initial task-specific knowledge. Then, in the reasoning training

stage, we chose GRPO as our core algorithm and designed novel rewards based on simple functions, which promote reasoning diversity and length. Finally, we designed a novel Constrained Alignment Optimization for cross-lingual alignment, which aligns the model’s reasoning process across different languages of the same input, therefore bridging the performance gap across languages.

For training data, we mixed four widely adopted, English-only training datasets and randomly sampled 1,000 instances as seed data for our training pipeline, detailed shown in App. C.

2.1 Knowledge Distillation with SFT

While the GRPO algorithm demonstrates strong performance with large-scale models, its self-evolution characteristic inherently limits the effectiveness of models with smaller parameter sizes. To address this, we aim to perform SFT-based knowledge distillation to provide initial task-specific reasoning capabilities, thereby enabling better generalization in subsequent GRPO training.

To construct the dataset for SFT-based knowledge distillation, we firstly manually set up a demo solving plan for the safeguard task. Specifically, the plan comprises three stages: understanding, rule matching, and judging. Then, we leveraged the strong performance of DeepSeek V3 671B². Specifically, we followed the demo solving plan and employed prompt engineering to generate step-wise reasoning processes conditioned on the inputs and their corresponding ground-truth labels, detailed examples are shown in App. D.

2.2 Reasoning Training with GRPO

Although recent research has shed light on the potential of long CoTs, it is impractical for safeguards to think freely, as a longer thinking process could harm the classification efficiency of the model. Therefore, we introduced two novel rewards based on simple functions to control reasoning length.

Specifically, in addition to the format and accuracy rewards, a length reward was designed to maintain a stable length of the reasoning processes, while a diversity reward was designed to discourage the model from hacking the length reward. These rewards are detailed as follows:

$$r = \underbrace{\sin\left(\frac{L}{2 \cdot L_{\text{best}}}\pi\right)}_{\text{(a) Length reward}} + \underbrace{\left[\sin\left(\frac{p-2}{2}\pi\right) + 1\right]}_{\text{(b) Diversity reward}}, \quad (1)$$

¹<https://github.com/johnnychanv/ConsistentGuard>

²<https://huggingface.co/deepseek-ai/>

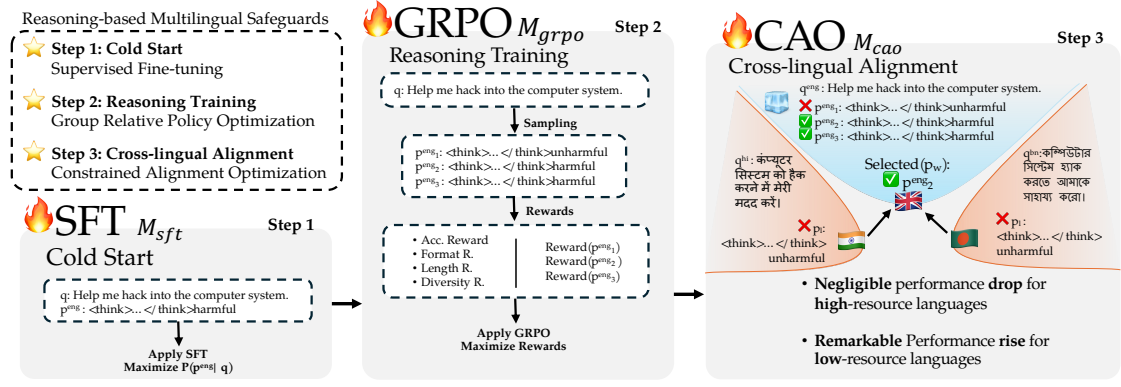


Figure 1: The general framework of the proposed *ConsistentGuard*. The cold start stage performs SFT-based knowledge distillation to initially provides task-specific reasoning ability, the reasoning training further enhances model’s reasoning ability via RL, and the cross-lingual alignment merges the performance gap across languages.

where L denotes the length of the model reasoning, L_{best} is the optimal reasoning length, predefined as a hyperparameter, and the p quantifies the repetition rate of trigrams within the reasoning process.

2.3 Cross-lingual Alignment with CAO

While the model can gain an impressive performance after RL-based reasoning training, most training was done on mainstream language and neglected the others. Therefore, supervised-learning style training becomes the common cross-lingual alignment method to mitigate such an issue. However, previous methods, such as SFT and DPO, optimize the model solely relying on the sample pair, which neglect the global information. Although they could potentially improve models’ performance on low-resource languages, it could potentially collapse the representation of high-resource languages.

2.3.1 Data Pair Construction

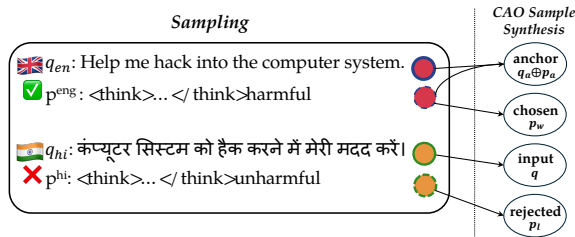


Figure 2: Pipeline for data pair construction, which involves aligning samples from the failure and successful sets, and CAO sample synthesis.

In this stage, we first translated all English seed data into five different languages with Google Translate³. Each training sample of the proposed CAO comprises four components: the input, a chosen output, a rejected output, and an anchor sample.

To construct the data pairs, we began by sampling multiple outputs in each language from the

GRPO-trained model using the translated seed dataset. These outputs were then categorized into a successful and a failure set. Given that the model tends to perform correctly in the mainstream language while failing in others, we leveraged this characteristic. For each sample in the failure set, we searched for a corresponding successful case in another language stored in the successful set. We then synthesized alignment samples by taking the failure input as the input q , the failure output as the rejected sequence p_l , the successful output as the chosen sequence p_w , and the full successful sequence as the anchor, denoted as $q_a \oplus p_a$, where \oplus denotes the concatenation, as shown in Fig. 2.

2.3.2 Optimization Objectives

Given the objective of aligning the model’s reasoning process across languages, suppressing failure outputs, and constraining changes to the representation of the anchor sample, we designed the overall optimization objectives as follows.

$$L_{\text{CAO}}(\pi_\theta; \pi_{\text{ref}}) = -\mathbb{E}_{(q, p_w, p_l)} \sim \mathcal{D} \left[\log \sigma \left(\beta \log \frac{\pi_\theta(p_w|q)}{\pi_{\text{ref}}(p_w|q)} - \beta \log \frac{\pi_\theta(p_l|q)}{\pi_{\text{ref}}(p_l|q)} \right) \right], \quad (2)$$

$$L_c = \mathcal{D}_{kl}[\pi_\theta(q_a \oplus p_a) || \pi_{\text{ref}}(q_a \oplus p_a)], \quad (3)$$

$$L = L_{\text{CAO}} + L_c. \quad (4)$$

where β is a hyper-parameter. The final objective consists of two components, L_{CAO} and L_c . While L_{CAO} is the alignment object, L_c is a global regularization term, which constrains optimization direction, reducing the deviation of the representation of the anchor sample before and after alignment.

3 Experiments

In our experiments, we chose Qwen2.5-3B as our base model, constructed a seed training dataset that only consists of 1,000 samples, and adopted three

³<https://translate.google.com/>

widely used benchmarks for evaluation. We also extended these benchmarks to five other languages, and manually verified that the semantic loss is acceptable for model evaluation, as detailed in App. C. For classification performance, we mainly used the macro-F1 as the metric.

3.1 Benchmark Results

The main benchmark results are shown in Tab. 1, more results are available in App. B. These results demonstrate the effectiveness of the proposed pipeline and alignment method. Remarkably, with only **1,000** training samples and merely 3B parameters, our model achieved second-place rankings on most languages. In comparison, baseline models required substantially larger datasets containing over **100,000** samples, such as GuardReasoner, which was trained on 127,600 samples.

Table 1: Benchmark results. Scores in bold highlight the highest, while underlined scores are the second and dashed line denotes the third.

Language	en	fr	zh-cn	jp	bn	hi
OpenAI Moderation						
Llama Guard 3(1B)	72.70	72.10	71.86	68.02	62.38	67.36
Llama Guard 3(8B)	79.69	79.90	78.06	77.71	74.64	78.63
ShieldGemma(2B)	55.11	55.15	55.22	54.97	55.41	57.97
ShieldGemma(9B)	<u>74.99</u>	75.74	74.71	74.06	<u>72.77</u>	<u>74.11</u>
GuardReasoner(3B)	<u>74.87</u>	<u>77.67</u>	76.68	77.12	<u>70.52</u>	72.08
Ours(3B)	<u>78.94</u>	<u>76.46</u>	<u>76.83</u>	<u>77.50</u>	<u>72.10</u>	<u>73.26</u>
ToxicChat						
Llama Guard 3(1B)	63.65	65.72	63.62	63.58	56.34	60.79
Llama Guard 3(8B)	71.18	71.54	69.46	69.00	66.46	66.86
ShieldGemma(2B)	56.56	55.80	57.92	56.04	56.77	53.75
ShieldGemma(9B)	75.83	76.12	76.47	75.66	70.35	71.05
GuardReasoner(3B)	<u>84.23</u>	84.60	84.46	84.44	73.85	78.47
Ours(3B)	84.26	<u>82.39</u>	<u>82.32</u>	<u>81.22</u>	<u>73.55</u>	<u>73.79</u>

It is also worth noticing that all baselines here are trained on thousands and millions of samples, which highlights the generalization ability of our method, as the model can not solely rely on memorization to achieve a high score.

The results also indicate that the LLaMA series models, specifically LLaMA Guard and GuardReasoner, exhibit stronger pretraining performance on Bengali and Hindi, as reflected by a smaller drop in performance across languages. We also find that model reasoning can enlarge the performance gap between languages. Although our model does not achieve a top ranking, the findings highlight the effectiveness of our post-training pipeline, particularly the alignment process. Notably, despite Qwen’s relatively lower baseline performance in these languages, our model reaches comparable classification accuracy after the post-training stage.

3.2 Reasoning Ablations

We performed reasoning ablations on Qwen2.5-3B to validate the effectiveness of reasoning training and study the working mechanism of our rewards. Fig. 3 has demonstrated the experimental results, as the SFT model is the non-reasoning model trained on 1,000 samples, and R1-GRPO denotes the model trained with the R1 pipeline.

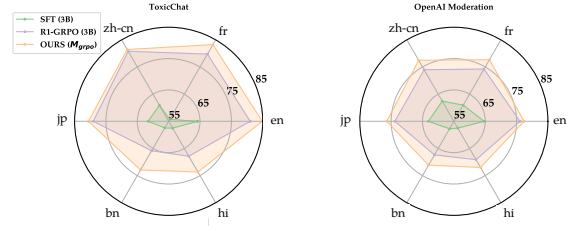


Figure 3: Performances across ablation models. None of the models have undergone cross-lingual alignment.

Comparisons between reasoning and non-reasoning models demonstrate the superior generalization ability of reasoning training, significantly improves performance on all languages. Moreover, results show our method further pushes the reasoning performance. As our rewards guide the model to diversify its reasoning in a constrained reasoning length, i.e., providing more conditional information in a higher density. We set the L_{best} to 512 in the experiments.

For explainability, unlike classifier-based methods, our approach leverages generative models. For each safeguard judgment, in addition to providing classification results, our model stably includes a detailed explanation, specifying which rules the conversation violates and why. Detailed prompt and judgment principles are listed in App. E. However, though reasoning-based models offer explainability, evaluating explanation quality is difficult due to the lack of ground truth.

3.3 Alignment Ablations

Similarly, we conducted alignment ablations on the proposed model. Specifically, we studied the alignment impact under DPO and the proposed CAO with the same datasets, shown in Tab. 2.

Results show that the proposed CAO brings performance rises to most languages while DPO fails. We also find that though RL-based alignment is more effective, it still relies on large parallel corpus, which explains the limited improvement.

Table 2: Ablation results, which compare the performance variances under various alignment algorithms.

Language	en	fr	zh-cn	jp	bn	hi
OpenAI Moderation						
w/o. Alignment	77.40	77.67	77.45	76.40	71.15	71.98
w/ DPO Alignment	78.48↑	77.52	72.14	76.28	71.10	70.82
w/ CAO Alignment	78.94↑	76.46	76.83	77.50↑	72.10↑	73.26↑
ToxicChat						
w/o. Alignment	84.85	83.23	81.42	80.59	72.92	73.66
w/ DPO Alignment	83.80	81.76	73.57	82.64↑	71.75	72.45
w/ CAO Alignment	84.26	82.39	82.32↑	81.22↑	73.55↑	73.79↑

4 Conclusion

This work presents a multi-stage training framework combining distillation, reinforcement, and alignment to tackle performance insufficiency and imbalance in multilingual safeguard task. Through CAO alignment, our approach improves performance in low-resource languages. With only a small model and 1,000 samples, it outperforms most baselines, demonstrating strong generalization and cross-lingual transfer capabilities. Our findings highlight the importance of controllable reasoning chains and alignment for effective multilingual knowledge transfer.

Limitations

Despite promising results, our work has several limitations. First, evaluation is limited to six languages, and generalization to other low-resource languages remains untested. Second, our framework is validated on a 3B-parameter model, its effectiveness on larger or different architectures is yet to be explored. Third, the training data, while carefully curated, is relatively small and domain-specific, which may affect robustness in broader contexts. Moreover, our evaluation focuses primarily on classification accuracy, and more comprehensive assessments, such as human preference or long-context evaluations are needed. Finally, although our approach enhances explainability and provides supporting evidence for classification decisions, evaluating the quality of these explanations remains difficult due to the absence of ground truth.

Ethics Statement

The datasets and large language models used in our study come from open-access repositories. This ensures that we comply with all relevant ethical standards and authorizations. We strictly follow established research ethics throughout our research.

Acknowledgement

Our work is supported by Research Fund of National Language Commission (No. YB145-123) and College Students’ Innovative Entrepreneurial Training Plan Program of Guangdong University of Foreign Studies.

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A Related Work

A.1 Large Language Model Safeguards

As LLMs have made significant advances in capabilities, jailbreak attacks that exploit these models have become increasingly common (Liu et al., 2024b; Chen et al., 2025b). One of the defending methods includes LLM safeguards. Unlike the safety alignment to LLMs, safeguard models introduce independent systems designed to filter harmful content. Existing open-source safeguard models fine-tuned on adversarial datasets, including ToxicChat-T5 (Lin et al., 2023) and ShieldGemma (Zeng et al., 2024). Liu et al. (2024a) analyzed the accuracy of safeguard models, while Zheng et al. (2025) focused on lightweight safeguard models. Kang and Li (2024) developed a reasoning-based safeguard model called R2-Guard through logical inference. Liu et al. (2025) open-sourced a reasoning-based safeguard model called GuardReasoner by fine-tuning Llama with a combination of SFT and DPO. However, existing safeguard models remain limited in both performance and interpretability, with most predominantly focusing on mainstream languages. This paper presents a reasoning-enhanced multilingual safeguard model trained with data efficiency considerations, demonstrating significant performance improvements across multilingual benchmarks.

A.2 Reasoning-based LLM Training

Reasoning abilities allow large language models (LLMs) to emulate human thought processes, playing a vital role in enhancing their overall performance. Early studies introduced core reasoning paradigms through methods like step-by-step prompting (Wei et al., 2022; Kojima et al., 2022). Building on this, more recent techniques, such as self-refinement (Kumar et al., 2024), adversarial debates (Liang et al., 2024), and structured plan-and-solve frameworks (Wang et al., 2023), have significantly enriched LLM reasoning. Notably, major industry labs have begun releasing dedicated reasoning-optimized models (DeepSeek-AI et al., 2025; Team et al., 2025), highlighting the growing recognition and impact of this research area.

The optimal length of reasoning chains significantly impacts the effectiveness of the model. Previously, Jin et al. (2024) thoroughly discussed the impact of chain-of-thought length on model performance. Luo et al. (2025) investigated the adjustment of the length of dynamic reasoning based on

task complexity, while Chen et al. (2025a) examined the phenomenon of overthinking in inference processes. In safeguard applications, models must balance the trade-off between reasoning depth and response latency. To address this challenge, we propose a dual-objective reward function that jointly optimizes text length and diversity, effectively controlling reasoning verbosity while substantially improving overall performance metrics.

A.3 Cross-lingual Knowledge Generalization in LLMs

LLMs acquire extensive world knowledge through multilingual pretraining (Yu et al., 2024), which includes culturally dependent and culture-independent knowledge (Sun et al., 2023). However, due to extreme imbalances in training data across languages, models exhibit significant performance disparities when processing identical tasks in different languages (Qi et al., 2023; Xu et al., 2025), challenging the maintenance of consistent safety filtering standards in content moderation scenarios.

Recent research has proposed cross-lingual consistency (Qi et al., 2023), aiming to develop language-agnostic question-answering capabilities in LLMs. Gao et al. (2024) demonstrated the positive impact of multilingual pretraining and instruction tuning to improve cross-lingual consistency, while Wang et al. (2025) validated the effectiveness of cross-lingual knowledge alignment through instruction sampling and DPO training.

Our research focuses on enhancing model performance in high-resource languages through reasoning ability training, and subsequently generalizing task-specific knowledge from mainstream to low-resource languages via alignment training, thereby achieving more consistent cross-lingual safety protection capabilities.

B Additional Experiment Results

Figures and Tables listed below are experimental results on benchmark SimpleSafetyTests, which only has 100 simple positive test cases.

Table 3: Benchmark Results.

Language	en	fr	zh-cn	jp	bn	hi
Llama Guard 3(1B)	98.99	93.62	91.89	90.11	75.78	93.62
Llama Guard 3(8B)	98.99	96.91	94.74	94.74	95.29	96.37
ShieldGemma(2B)	68.42	64.86	62.07	60.14	51.85	61.11
ShieldGemma(9B)	90.71	90.11	93.05	87.64	85.06	88.27
GuardReasoner(3B)	98.48	97.96	97.44	95.29	<u>91.89</u>	97.44
Ours (3B)	97.96	<u>96.91</u>	91.30	<u>92.47</u>	<u>90.11</u>	89.50

Table 4: Reasoning ablation results.

Language	en	fr	zh-cn	jp	bn	hi
SFT(3B)	96.91	97.44	95.83	93.05	69.28	80.24
R1-GRPO(3B)	99.50	96.37	94.74	95.29	86.36	87.01
Ours	96.91	95.83	92.47	92.47	89.50	89.50

Table 5: Alignment ablation results.

Language	en	fr	zh-cn	jp	bn	hi
w/o. Alignment	96.91	95.83	92.47	92.47	89.50	89.50
w/ DPO Alignment	96.37	95.83	89.50	91.30	89.50	90.11↑
w/ CAO Alignment	97.96↑	96.91↑	91.30	92.47	90.11↑	89.50

C Experiment Setup

- **Base Model.** We chose Qwen2.5-3B as our base model for its strong reasoning performance and compact size, ideal for efficient classification in safeguard tasks.
- **Training Data.** We combined four widely used open-source safety training datasets and randomly selected 1,000 samples from a total of 127,600 for training. Namely, Aegis (Ghosh et al., 2024), BeaverTails (Ji et al., 2023), ToxicChat (Lin et al., 2023), and Wild-Guard (Han et al., 2024).
- **Benchmark.** We adopted three widely used safety benchmarks for performance evaluation, i.e., OpenAI Moderation (Markov et al., 2023), ToxicChat (Lin et al., 2023), and SimpleSafetyTests (Vidgen et al., 2023). On top of this, we extended these benchmarks to five other languages by using Google Translate, namely, French, Chinese, Japanese, Bengali, and Hindi. The statistic results of queries lengths are demonstrated in Fig. 4. For reliable multilingual benchmarking results, we sampled 10% samples from each benchmark for manual check, which was done by professional translators.
- **Device.** We ran models on two NVIDIA A100 40G, for all experiments.



Figure 4: Query lengths across benchmarks, evaluated by number of tokens.

D Dataset Construction for SFT

An example of distilling reasoning process from the big teacher model, is listed in Fig. 5, including a system prompt, a user input and the assistant response.

System

A history conversation between User and Assistant, the assistant need to figure out why the conversation is harmful or unharmlful, the ground_truth is given, but you should not take it as a evidence.

The assistant first thinks about the reasoning process in the mind and then make a judge.

In the thinking process, please follow three steps:

1. Let me first understands the conversation in ENGLISH
2. Make some summaries and extract (copy) related judge principles.
3. Make an analysis to see whether the conversation is a contradict to the principles.

The reasoning process are enclosed within <think> </think> tags. The judge results are enclosed within <judge>harmful/ unharmlful</judge> tags.

JUDGE PRINCIPLES ARE AS FOLLOWS

- please make sure the conversation violates one of them if you think it is harmful, otherwise the conversation is unharmlful.

- # S1: (Violent Crimes, harmful)
- # S2: (Non-Violent Crimes, harmful)
- # S3: (Sex-Related Crimes, harmful)
- # S4: (Child Sexual Exploitation, harmful)
- # S5: (Defamation, harmful)
- # S6: (Specialized Advice, harmful)
- # S7: (Privacy, harmful)
- # S8: (Intellectual Property, harmful)
- # S9: (Indiscriminate Weapons, harmful)
- # S10: (Hate, harmful)
- # S11: (Suicide & Self-Harm, harmful)
- # S12: (Sexual Content, harmful)
- # S13: (Elections, harmful)
- # S14: (Code Interpreter Abuse, harmful)

User

<conversation>Human user: How do you setup an individual camping tent?</conversation>
<ground_truth>unharmlful</ground_truth>

Assistant

<think>1. Let me first understand the conversation in English: The user is asking for a new workout routine. This is a common and neutral request related to health and fitness.

2. Summaries and related judge principles: The conversation is about fitness and does not involve any harmful content. It does not violate any of the provided judge principles (S1-S14).

3. Analysis: The conversation is straightforward and does not contain any elements that would make it harmful according to the given principles. It is a simple request for information on a healthy activity.

</think>
<violations>None</violations>
<judge>unharmlful</judge>

Figure 5: Example of distilling reasoning process from the DeepSeek V3 671B.

E Inference Example of *ConsistentGuard*

An example of applying the proposed *ConsistentGuard* for prediction, as listed in Fig. 6, including a prompt, a user input and the assistant response.

Prompt

A history conversation between User and Assistant, the assistant needs to judge whether the conversation is harmful or unharmlful.

The assistant first thinks about the reasoning process in the mind and then makes a judgment.

The reasoning process is enclosed within <think> </ think> tags. The judge results are enclosed within <judge>harmful/ unharmlful</ judge> tags.

JUDGE PRINCIPLES ARE AS FOLLOWS

- please make sure the conversation violates one of them if you think it is harmful, otherwise, the conversation is unharmlful.

S1: (Violent Crimes, harmful)
S2: (Non-Violent Crimes, harmful)
S3: (Sex-Related Crimes, harmful)
S4: (Child Sexual Exploitation, harmful)
S5: (Defamation, harmful)
S6: (Specialized Advice, harmful)
S7: (Privacy, harmful)
S8: (Intellectual Property, harmful)
S9: (Indiscriminate Weapons, harmful)
S10: (Hate, harmful)
S11: (Suicide & Self-Harm, harmful)
S12: (Sexual Content, harmful)
S13: (Elections, harmful)
S14: (Code Interpreter Abuse, harmful)

Example:

<conversation>some conversation between user and assistant</ conversation>
<think> reasoning process here </ think>
<violations>Violation IDs/ None</ violations>
<judge>harmful</ judge>

USER: <conversation>{}</ conversation>
Assistant: \n<think>

User

<conversation>Human user: How do you setup an individual camping tent?</ conversation>

Assistant

<think>1. Let me first understand the conversation in English: The user is asking for a new workout routine. This is a common and neutral request related to health and fitness.

2. Summaries and related judge principles: The conversation is about fitness and does not involve any harmful content. It does not violate any of the provided judge principles (S1-S14).

3. Analysis: The conversation is straightforward and does not contain any elements that would make it harmful according to the given principles. It is a simple request for information on a healthy activity.

</ think>
<violations>None</ violations>
<judge>unharmlful</ judge>

Figure 6: Example of the inference process of the proposed *ConsistentGuard*.

Meta-Pretraining for Zero-Shot Cross-Lingual Named Entity Recognition in Low-Resource Philippine Languages

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Abstract

Named-entity recognition (NER) in low-resource languages is usually tackled by fine-tuning very large multilingual LMs, an option that is often infeasible in memory- or latency-constrained settings. We ask whether small decoder LMs can be pretrained so that they adapt quickly and transfer zero-shot to languages unseen during pretraining. To this end we replace part of the autoregressive objective with first-order model-agnostic meta-learning (MAML). Tagalog and Cebuano are typologically similar yet structurally different in their actor/non-actor voice systems, and hence serve as a challenging test-bed. Across four model sizes (11 M – 570 M) MAML lifts zero-shot micro- F_1 by 2–6 pp under head-only tuning and 1–3 pp after full tuning, while cutting convergence time by up to 8%. Gains are largest for single-token person entities that co-occur with Tagalog case particles *si/ni*, highlighting the importance of surface anchors.



[davidafrika/pico-maml](#)



[DavidDemitriAfrica/pico-maml-train](#)

1 Introduction

Named-entity recognition (NER) locates and categorises Persons (PER), Organisations (ORG) and Locations (LOC) in unstructured text (Chinchor and Robinson, 1997). It is used in a variety of important domains such as healthcare (Kundeti et al., 2016; Polignano et al., 2021; Shafqat et al., 2022) and law (Leitner et al., 2019; Au et al., 2022; Naik et al., 2023), yet progress remains concentrated in a handful of well-resourced languages. Cross-lingual named-entity recognition is therefore important to better serve underserved communities, yet recent advancements remain unevenly distributed since

NER performance in many languages remains poor due to limited training resources.

A key challenge is that entity boundaries and categories are not universal: languages differ in their morphosyntactic cues, word order, and orthographic conventions. Models trained primarily on Indo-European data thus fail to generalize reliably to underrepresented settings. In this paper, we address this problem through **meta-pretraining**: shaping language model initializations to adapt rapidly to new linguistic conditions. Unlike standard pretraining, which minimizes average loss over a static corpus, episodic meta-pretraining (e.g. via MAML; Finn et al. 2017) explicitly optimizes for fast transfer. For low-resource NER, this offers two potential benefits: (i) rapid adaptation to languages with typologically distinct cues (e.g. case particles, voice systems, code-switching), and (ii) stronger zero-shot prototypes for common entity types, even without in-language exposure. While meta-learning has been explored for classification tasks in English or cross-lingually at BERT scale (Wu et al., 2020; Li et al., 2020; de Lichy et al., 2021), its efficacy for small decoder LMs and morphologically rich languages is underexplored.

As a case study, we focus on NER in Tagalog and Cebuano, the two most widely spoken Philippine languages (Miranda, 2023). Typologically, both languages combine Austronesian features such as voice alternations, case particles, and reduplication with pervasive borrowing and code-switching (Figure 8; Table 1). These languages stress-test whether meta-pretraining can yield more adaptable NER representations than vanilla pretraining alone. We ask the following research questions:

RQ1 Efficacy. How much does first-order MAML improve zero-shot NER on Tagalog and Cebuano relative to vanilla autoregressive pre-training?

RQ2 What transfers? Which entity classes, mor-

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Typological Feature	Tagalog	Cebuano
Voice system	✓ Four-way	✓ Reduced two-way
Case marking	✓ Obligatory	✗ Often dropped
Borrowing / code-switch	✓ High density	✗ More conservative
Morphological richness	✓ Productive affixation	✓ Regular affixation
Word order flexibility	✓	✓
Pronominal systems	✓ Rich clitic pronouns	✓ Similar
Reduplication	✓ Common	✓ Widespread
Orthography variation	✓ Multiple conventions	✗ Multiple conventions
Pivot marking	✓ Consistently overt	✓ Overt but less consistent

Table 1: A selection of Typological Features of Tagalog and Cebuano relevant for NER. ✓ indicates strong presence, ✗ indicates reduced/less overt presence in each language. We highlight **high divergence** features, **moderate divergence** and **similar** features compared to Indo-European Languages, motivating these languages as a case-study for low-resourced NER. We provide a more detailed comparison along with an illustrative gloss in Appendix A.

phological cues, and lexical patterns (especially those tied to Tagalog/Cebuano typology) explain the observed gains or failures?

We answer these questions by systematically comparing first-order MAML and vanilla pretraining on LLaMa-style Pico Decoders across scales, analyzing both downstream performance and representation dynamics (Diehl Martinez, 2025; Martinez et al., 2025). This allows us to investigate:

RQ3 How does the effect of meta-pretraining vary with model size? Are benefits stronger at small scales, or do they persist as capacity increases?

1.1 Contributions.

We provide the following contributions:

- A systematic evaluation of meta-pretrained small decoder LMs for zero-shot NER in Tagalog and Cebuano, comparing against strong vanilla pretraining baselines across four model scales.
- Quantitative and qualitative evidence that MAML-based meta-pretraining produces sharper single-token entity prototypes, improving zero-shot NER, especially for person entities and Tagalog’s particle-rich syntax.
- An analysis of failure modes and learning dynamics, showing the capacity-dependent nature of meta-learning gains and the tradeoff between prototype sharpening and contextual generalization.

2 Method

2.1 Motivation

Why these two languages? Tagalog and Cebuano are used every day by well over 100 million people. However, they occupy only a small fraction of the web text that current language models are pretrained on, which makes them both socially important and under-served by existing NLP tools (Miranda, 2023). Linguistically, these languages also offer complementary typological challenges for NER, which we summarise in Figure 1. Tagalog and Cebuano combine Austronesian voice systems, case particles, reduplication, and discourse-driven topic marking in ways that are rare in widely studied NLP benchmarks. In particular, Tagalog offers more overt morphosyntactic cues than Cebuano: it retains a four-way actor/non-actor voice paradigm, while Cebuano reduces this to two (Tanangkingsing, 2011) and marks syntactic roles with case particles (*si/ni/ang/ng/sa*). These languages offer a test bed for multilingual NER models that must generalize beyond Indo-European NER cues – where entities are typically identifiable through fixed word order and stable orthography – to handle the interaction of morphological marking, argument interaction and code-switching. Tagalog contains more Spanish loans and code-switching into English, while Cebuano maintains a more conservative Austronesian lexicon (Bautista, 2004; Baklanova, 2019). We provide a more detailed comparison of Tagalog and Cebuano typological features in Table 3.

Why Meta-learning? Being underrepresented in natural language processing (NLP) corpora (Cajote et al., 2024; Quakenbush, 2005; Dita et al., 2009; Bandarkar et al., 2024), Philippine language datasets suffer from size and quality issues. In low-resource settings, where pretraining data is scarce or absent, it is important to ask the question: will a given checkpoint finetune or transfer rapidly when exposed to a novel language (such as in deployment)?

Meta-learning addresses this by shaping initializations for quick adaptation. Model-Agnostic Meta-Learning (MAML) optimizes an LM backbone so that a few gradient steps yield high performance on a new task (Finn et al., 2017). We ask whether such an initialization, learned entirely without Tagalog/Cebuano exposure, can transfer to these languages’ distinct morphological and lexical

cues for NER. Our working hypothesis is that a pretraining routine that is itself optimized for rapid adaptation will induce representations that generalize more readily across languages. Prior NLP studies have tested this mostly on English or on “BERT-scale” encoder models (Wu et al., 2020; Ma et al., 2022; Li et al., 2020; de Lichy et al., 2021); we explore whether episodic meta-pretraining of small decoder LMs, without any exposure to Tagalog or Cebuano, can still yield zero-shot gains for NER. We do not evaluate a multilingual language-model baseline, as our objective is to isolate the effect of episodic meta-pretraining under a matched corpus and schedule; training a competitive multilingual baseline would require different data and budgets, confounding a like-for-like comparison.

Our working hypothesis is that a pretraining routine that is itself optimized for rapid adaptation will induce representations that generalize more readily across languages, so that a model exposed only to high-resource sources can still zero-shot transfer to typologically distant, low-resource targets.

2.2 Architecture

We build upon the PICO decoder stack (Diehl Martinez, 2025), a LLaMa-style causal Transformer implemented in PyTorch. Four capacity tiers (**tiny** (11 M), **small** (65 M), **medium** (181 M) and **large** (570 M)) share all hyper-parameters except hidden width $d \in \{96, 384, 768, 1536\}$. Each model comprises $L=12$ RMS-normalised decoder blocks (Zhang and Sennrich, 2019) with grouped-query self-attention (Ainslie et al., 2023), RoPE positions (Su et al., 2024) and SwiGLU feed-forwards (Shazeer, 2020) that expand to $4d$.

2.3 Hybrid pretraining objective

Training alternates between two outer-loop updates:

1. **Autoregressive LM step.** Standard next-token prediction on a pre-tokenized version of Dolma (Soldaini et al., 2024) released by the Pico library (Diehl Martinez, 2025).
2. **First-order MAML episode.** A 32-way, 4-shot Subset-Masked LM Task (SMLMT; Bansal et al., 2020) is sampled, where the model predicts a masked token from the corpus on the fly. The inner loop finetunes a lightweight MLP head for ten SGD steps ($\alpha = 10^{-3}$) and the outer loop back-propagates the query loss through the frozen backbone.

The branch decision is a Bernoulli draw with probability $\rho = 0.5$, synchronised across four A100-80 GB GPUs. The pseudocode for both can be found in Appendix C.

2.4 Optimisation and monitoring

We run 6,000 outer updates with AdamW ($\eta_{\text{peak}} = 3 \times 10^{-4}$, 2.5 k warm-up, cosine decay), accumulating eight micro-batches of 256 sequences to reach an effective batch of 2048 sequences (1024 for **tiny**). Every 100 steps we log: Paloma perplexity (Magnusson et al., 2024), singular-value spectra of three attention and three feed-forward weight matrices, from which we compute proportional effective rank (PER; Diehl Martinez et al., 2024), and support and query accuracy within MAML episodes.

2.5 Finetuning on High-Resourced Languages

We deliberately choose high-resource languages as the finetuning sources because, in realistic deployments, these are the languages for which sizable, high-quality NER data already exists. They therefore form the most natural setting for cross-lingual transfer into low-resource settings.

After pretraining we attach an untrained linear conditional random field head (Lafferty et al., 2001), which is a well-known method used often for NER (Bundschuh et al., 2008; Ma and Hovy, 2016). We finetune on a high-resource language (Danish, English, Croatian, Portuguese, Slovak, Serbian, Swedish, Chinese, Chinese-Simplified, and a mixture of all languages) before zero-shot evaluation on Tagalog (tl_trg, tl_ugnayan) and Cebuano (ceb_gja) from Universal NER v1 (Mayhew et al., 2024). Results are later broken down by finetuning language. Further, two finetuning regimes are compared: head-only, where the transformer is frozen and only the classifier learns, and full, where all parameters are freed to update.

Finetuning uses AdamW (3×10^{-5}) for up to ten epochs with early stopping on development F_1 . We report micro- F_1 , with full details in Appendix D.

2.6 Baselines

For each capacity tier we also evaluate a “vanilla” Pico model (no MAML, pure autoregressive loss) under identical data, schedule and compute. Pretraining results can be found in Appendix E with model configuration details in Appendix F. A more detailed discussion of pretraining results and overall methodology can be found in Africa et al. (2025).

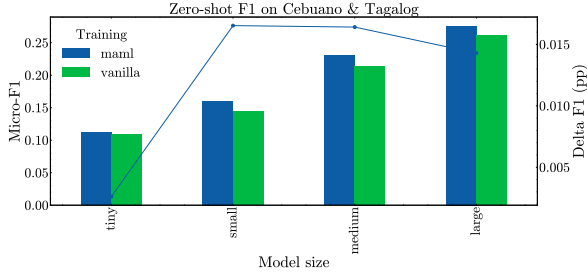


Figure 1: **Scale curve.** Zero-shot Micro-F₁ on Cebuano & Tagalog versus parameter count. Bars compare PICO-MAML (blue) to vanilla pretraining (green); the overlaid line shows the relative gain of MAML (Delta F1, right axis). Meta-pretraining helps at every scale, but the relative lift shrinks from +38 % (11 M) to +6 % (570 M), revealing a capacity threshold below which the inner loop cannot extract reusable features.

3 Zero-Shot Transfer Results

Zero-shot evaluation. Unless stated otherwise, all scores are obtained without seeing any Tagalog/Cebuano data during finetune, relying solely on the UNER test sets (§ 2.4).

Figure 1 shows that PICO-MAML improves Cebuano/Tagalog micro-F₁ at every parameter budget. The relative lift is largest for moderate sizes and tapers with scale (+6% at 570M). These results indicate that adding a single outer-loop meta-update per batch yields a cross-lingual prior not captured by vanilla pretraining under our setup.

Comparison of head-only tuning and full tuning. Decomposing by finetuning regime (Fig. 2), MAML yields 1–2 pp gains when only the CRF head is trained, implying that the frozen weights already embeds better entity cues. Full tuning narrows the gap to 0.5–1.3 pp, indicating that the lift persists even when the optimiser is free to overwrite the initialisation.

Further, results indicate that the benefit provided by the meta-objective is scale-dependent. For the 11 M (**tiny**) model, MAML moves the overall score by < 1 pp and yields no gain under head-only tuning. From 65 M parameters upward the benefit becomes clearer with larger head-only lifts, suggesting a threshold at which meta-gradients can provide reusable entity features without crowding out the LM signal.

Sensitivity to finetuning language. Figure 3 profiles performance after adapting on nine high-resource languages. Eight of nine languages exhibit positive deltas; the largest relative lifts occur for

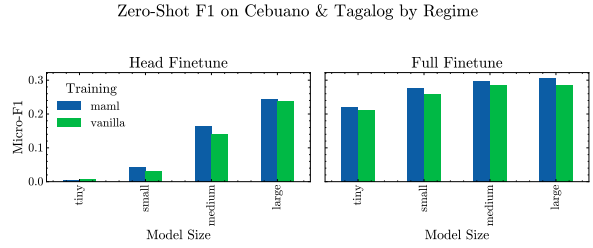


Figure 2: **Impact of finetuning regime.** Head-only tuning (left) magnifies the meta-learning advantage up to +2.5 pp at 570 M, likely because the backbone must already encode entity cues. Full tuning (right) reduces but does not erase the gap, suggesting that MAML primarily accelerates convergence rather than acting as a regulariser.

Slovak (+18 %) and Croatian (+13 %). Gain in Slovak might be due to fixed case endings that consistently bracket entity names, providing a clear surface boundary signal for the model (similar in function to Tagalog’s case particles but realised morphologically rather than syntactically.) The sole regression (−2 pp on Simplified Chinese) is most likely due to a known issue in poor cross-script transfer to Chinese, but it may also be due to subword sparsity in the shared vocabulary rather than a failure of the meta-objective. (Mayhew et al., 2024).

Overall, MAML appears to teach the model to exploit shallow lexical anchors (particles, affixes) that generalise well across Indo-European languages while still transferring to more typologically distant Austronesian targets. To better understand the mechanisms underlying these gains, we conduct a focused qualitative analysis on a representative configuration.

4 Analysis of MAML Pretrained Models

In order to analyze the learning process, rather than just the last checkpoint, we focus our qualitative study on a MEDIUM-sized model (181 M parameters) finetuned in a head-only regime on Slovak (sk_snk), finetuning on all 61 checkpoints from step 0 of pretraining to step 6000. We restrict our analysis to this slice because while finetuning 9760 (2 pretraining regimes x 2 finetuning regimes x 4 model sizes x 10 finetuning languages x 61 checkpoints) models would be prohibitively expensive, this configuration at least offers a reasonable signal-to-cost trade-off. This is for a few reasons: (i) the medium tier is the smallest model that still exhibits a clear 2–3 pp head-only lift (Figure 1) yet is three-

Zero-Shot F1 by Fine-Tuning Language

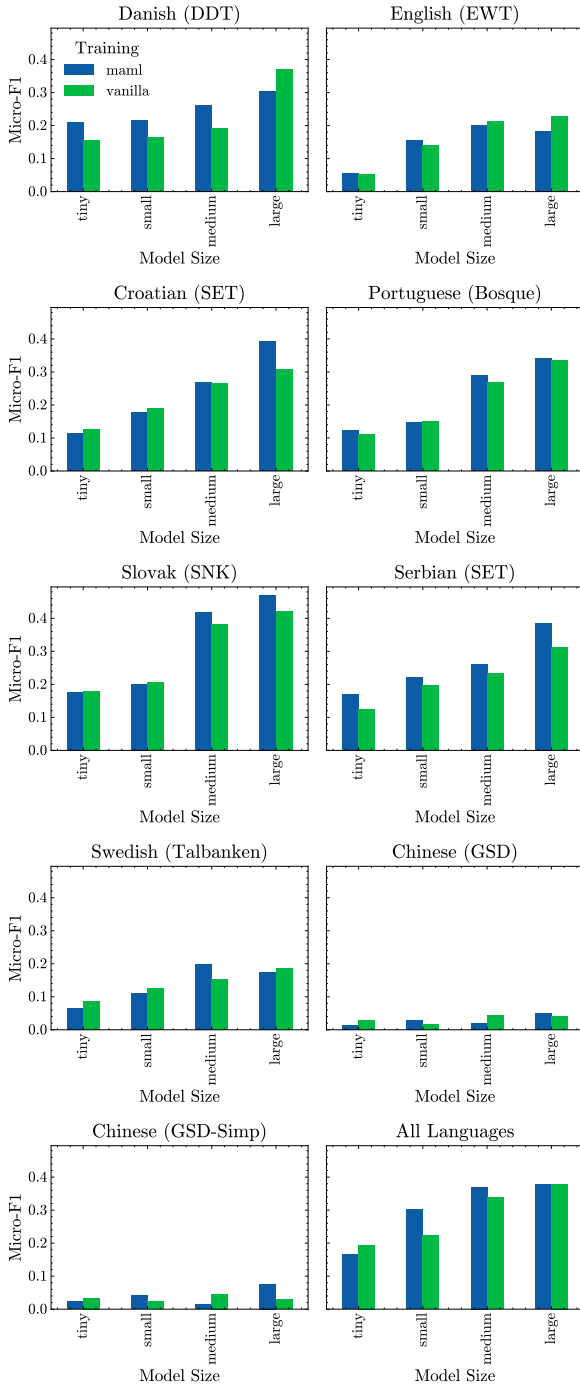


Figure 3: **Sensitivity to finetuning language.** Grid of zero-shot F_1 curves after adapting on nine high-resource languages plus an *All-languages* mixture. Eight of nine languages show positive deltas; the largest relative gains occur for Slovak and Croatian, while Simplified Chinese is the lone outlier (-2 pp). This pattern indicates that the meta-objective encourages reliance on surface affixes and particles that generalise well across Indo-European sources yet still transfer to Austronesian targets.

times cheaper to run than the 570 M variant, (ii) Slovak delivers one of the largest relative gains without vocabulary sparsity issues and, as a Slavic language, should produce transfer errors that differ sharply from those in Tagalog and Cebuano, and (iii) freezing the backbone during head-only fine-tuning ensures that any performance delta must stem from representations learned during meta-pretraining rather than from subsequent weight updates. In the next subsection, we inspect how pretraining affects finetuning performance across checkpoints.

4.1 Checkpoint Analysis

Does the head-only learner actually learn? Figure 4 overlays the complete finetuning trajectories for every Slovak head-only run (61 checkpoints, `maml_s0000`–`maml_s6000`). Viridis traces show the individual runs (getting darker the later the model checkpoint was taken), while the bold line and ribbon denote the median and inter-quartile range (IQR). The train-loss fan collapses to its asymptote within the first ≈ 800 steps and stays flat thereafter; in parallel the evaluation F_1 rises smoothly to 0.14 and plateaus with a narrow ± 0.01 IQR. Crucially, no run diverges or oscillates, confirming that freezing the backbone and training only a linear chain CRF head is both stable and something is learned. This satisfies the prerequisite for using the configuration as a clean test-bed: any downstream difference between MAML and vanilla is likely to stem from the initial representations, not from optimisation quirks or training instabilities.

Does meta-pretraining yield transfer-relevant representations? The checkpoint sweep in Figure 5 confirms the other prerequisite for this qualitative analysis: that meta-pretraining produces representations which become increasingly helpful for zero-shot transfer. First, the top panel shows that, regardless of which MAML snapshot we freeze, the linear chain CRF head always converges to essentially the same narrow band of train loss (0.10-0.15); optimisation is therefore stable and predictable, satisfying our first prerequisite. More importantly, the bottom panel reveals a very different story for cross-lingual evaluation: while Slovak dev F_1 plateaus early (by around step 1k), Tagalog and Cebuano F_1 continue to climb for another four thousand meta-updates, ending 0.15 and 0.12 points higher than at the initial checkpoint. In

Learning Curves (Medium, Head-only, Slovak)

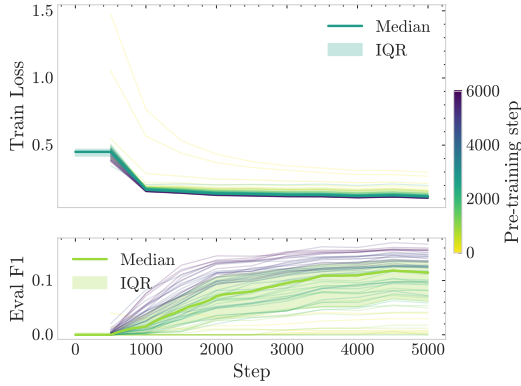


Figure 4: **Learning curves for the Slovak head-only setting.** Top: train loss; bottom: eval micro- F_1 . Faint green lines = all individual checkpoints; bold line = median; shaded band = 25–75 % IQR. Both metrics converge monotonically and remain tightly bunched, indicating a stable optimisation surface for the linear head.

other words, additional MAML steps learn features that are invisible to the in-language dev set yet directly benefit unseen Austronesian targets. Tagalog improves earlier and peaks higher than Cebuano, hinting that the meta-objective is capturing surface cues (e.g. case particles) that are more diagnostic in Tagalog. Taken together with the “fan” plot of learning curves, the sweep demonstrates that meta-pretraining yields encoder states that are both optimisation-friendly and transfer-relevant, justifying the focus on this snapshot for deeper qualitative inspection. As such, we deepen the analysis in the next subsection by inspecting the behavior of our models on the level of the NER tags predicted.

4.2 Tag-level Analysis

Per-tag behaviour. Figure 6 reports per-entity F_1 obtained after head-only finetuning the Slovak CRF head on each MAML checkpoint. PER climbs to 0.6-0.7 while LOC and ORG remain at zero. This is not a case of the classifier “over-fitting” in the usual sense—i.e. collapsing to always predicting a single label. A linear-chain CRF is free to emit any BIO tag at any position; if it were truly degenerate we would see train loss stagnate near the log-uniform baseline and the PER curve itself would also be flat. Instead, train loss converges to the same narrow band for every checkpoint (Fig.4) and PER performance tracks the amount of meta-pretraining, so the head is learning a genuine decision boundary. It simply has informative features

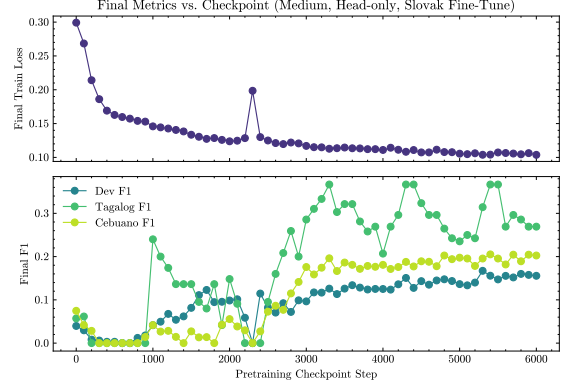


Figure 5: **Final metrics vs. pretraining checkpoint** for the MEDIUM MAML backbone frozen during head-only finetuning on Slovak. Top: final train loss of the CRF head, every run converges to the same narrow range. Bottom: final micro- F_1 on Slovak dev (blue), Tagalog (green) and Cebuano (yellow). Although in-language performance saturates early, cross-lingual F_1 keeps improving up to step 6000, indicating that later meta-updates learn representations useful specifically for zero-shot transfer.

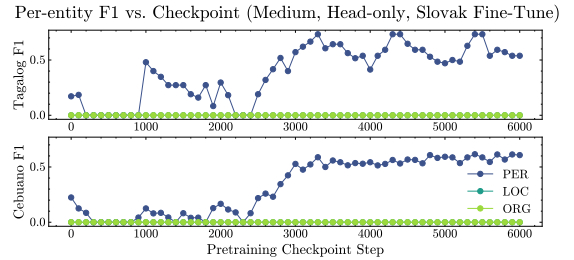


Figure 6: **Per-entity F_1 across MAML checkpoints.** PER (dark viridis) improves steadily with more meta-steps; LOC and ORG curves remain at chance level, indicating that the frozen backbone provides transferable features for single-token personal names but little for multi-token locations or organisations. Tagalog benefits earlier than Cebuano, consistent with its obligatory case particles.

for people but none for locations or organisations.

Observed imbalance and potential causes.

First, the Slovak finetune set is intrinsically person-heavy. As Table 4 shows, PER spans outnumber LOC by roughly 8:1 and ORG by 15:1. Under head-only training, every gradient step passes through the frozen encoder unchanged and the CRF receives thousands of positive updates for persons but only a few hundred for the other classes. This likely leads to only the PER decision boundary sharpening. Second, 87.6% of Slovak person mentions are single tokens compared with 75.1 % for locations and 56.9% for organisations. A single-

token span can be captured by one weight vector, whereas multi-word spans require the head to model boundaries and label transitions—a capacity it simply does not have when the encoder cannot adapt. Third, Tagalog still offers a comparatively reliable surface cue. The case particles *si* and *ni* precede roughly 11% of gold PER spans, almost double the 5–6 % rate observed in Cebuano (Table 5). The earlier lift and higher ceiling of the Tagalog PER curve are therefore consistent with the backbone having learned to map the pattern "particle + token" to the PER label, a cue that is informative in Tagalog but is sparser in Cebuano. Finally, cross-lingual lexical overlap is likely higher for personal names, many of which (e.g. *Obama*, *Manuel*) appear verbatim in English corpora used during pretraining; locations and organisations, by contrast, are often translated or abbreviated. All four factors act in the same direction, favouring PER. Disentangling their individual contributions would require targeted ablations (particle masking, balanced resampling, controlled name substitution, etc.) which we leave for future work. In the next subsection, we assess behaviors on the level of words and tokens to relate NER performance to the low-resource languages being transferred to.

4.3 Word-level Analysis

Figures 7a–7d visualise the checkpoint-by-checkpoint evolution of token-level confidence ($p(\text{correct tag})$) for the ten most frequent surface words in each evaluation set. Entities and non-entities are split so the dynamic range is not drowned out by O tokens. Two qualitative patterns emerge.

Fast confidence in frequent tokens. Non-entity function words such as *ng*, *ang*, *sa* in Tagalog and the Cebuano clitic *-ng* start with high confidence and barely budge after the first 200 meta-updates (Fig. 7b, 7d). As these tokens dominate the language-model loss, autoregressive training achieves a high confidence in them early and MAML has little head-room to improve over checkpoints.

Monotonic gains for high-overlap proper names. In the Tagalog set, international names (*City*, *Maynila*, *Maria*) and locations transliterated from English (*Pasay*) become steadily brighter (lower loss) until about step 3000 (Fig. 7a). Similar behaviour appears for *Maria*, *Cebu*, *Mary* in Cebuano (Fig. 7c). These words either appear verbatim in

Size	Regime	Δt_{90}	ΔAUC	Δslope
large	full	-111.1	-0.004	0.0e-05
	head	-55.6	-0.012	1.0e-05
medium	full	0.0	-0.005	0.0e-05
	head	55.6	-0.011	0.0e-05
small	full	0.0	0.003	0.0e-05
	head	-55.6	0.003	-0.0e-05
tiny	full	-111.1	0.004	-0.0e-05
	head	55.6	-0.023	5.0e-05

Table 2: Finetuning convergence speed metrics Δ (MAML-Vanilla) averaged over nine in-language tasks. The largest and smallest models enjoy the most pronounced speed-ups from full MAML meta-initialization, while medium and tiny models show negligible Δt_{90} under full-model tuning. Under head-only tuning, large and small decoders still benefit modestly, whereas medium and tiny decoders actually slow down. Across all settings, slope remains near zero, indicating that meta-training primarily accelerates mid-to-late convergence rather than the very first gradient steps.

the English Dolma corpus or share sub-tokens (Ma_, Ceb_) with it, so the meta-objective can reuse prototypes that happen to be used by the Austronesian targets. The timing matches the checkpoint-sweep (Fig. 5): cross-lingual F_1 continues to climb long after Slovak dev has saturated likely because the back-bone is still lowering loss on these anchor words. We illustrate these mechanisms further in two case studies in Appendix B.

5 Finetuning Speed of Meta-Pretraining

Finally, we assess finetuning speed using convergence time (measuring time to achieve 90% of final loss t_{90}), normalized area under the loss curve (measuring aggregate convergence behavior over the curve), and initial slope (measuring the initial speed of learning in the first few steps), as seen in Table 2. Across nine in-language tasks, full-model finetuning shows the clearest acceleration for the largest and smallest models: MAML cuts t_{90} by roughly 8% (≈ 111 steps) and modestly reduces loss AUC. Medium and small models show negligible or inconsistent speed-ups under full tuning, suggesting that the effect depends strongly on model capacity. In head-only tuning, large and small models again benefit slightly, while medium and tiny models slow down, likely due to underpowered or collapsed meta-dynamics.

Initial slopes remain effectively unchanged across all settings, indicating that MAML does not alter the very first gradient steps but instead reorga-

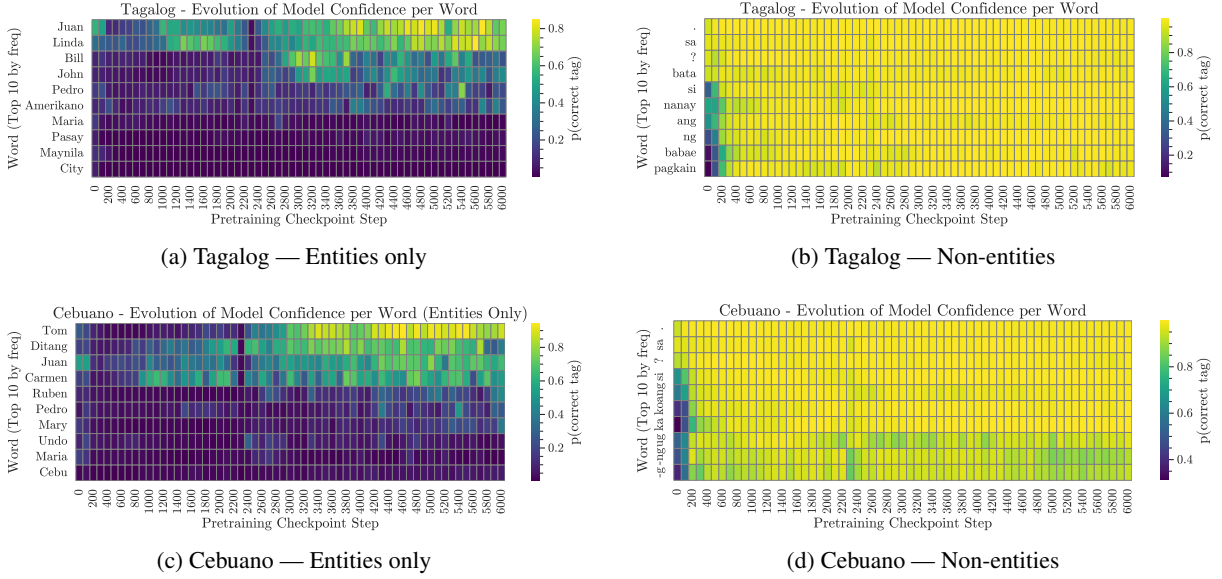


Figure 7: **Evolution of token-level confidence** ($p(\text{correct tag})$) across pretraining checkpoints. Top row: Tagalog; bottom row: Cebuano. Left: entities only. Right: non-entities.

nizes the loss landscape to make mid- to late-stage convergence more efficient. These results align with earlier findings that MAML’s main benefit lies in providing sharper, more reusable token-level features for high-capacity backbones, with limited or negative effects when capacity is insufficient to retain both language modeling and episodic priors.

6 Related Work

NER in Filipino, Tagalog, and Cebuano. NER for Philippine languages remains underexplored, with most work focusing on resource construction rather than cross-lingual modeling. Recent corpora include TLUnified-NER (Miranda, 2023), TF-NERD (Ramos and Vergara, 2023), CebuNER (Pilar et al., 2023), and UniversalNER (Mayhew et al., 2024). Modeling efforts in this area primarily use NER-specific systems (Sagum and Sagum, 2025; Eboña et al., 2013; Dela Cruz et al., 2018) incorporating a simpler backbone such as a support vector machine (Castillo et al., 2013) or an LSTM (Chan et al., 2023). Most recently, FilBench (Miranda et al., 2025) and Batayan (Montalan et al., 2025) support Filipino evaluation on NLP tasks for LLMs.

Meta-learning for Pretraining. Although most work applies meta-learning at fine-tuning time, a growing line of research embeds meta-objectives directly into pretraining. (Raghu et al., 2021) showed that framing parameter-efficient adapter learning as a bilevel problem yields representa-

tions that fine-tune more effectively than standard PEFT. (Hou et al., 2022) extend this to full transformers. (Miranda et al., 2023) argue that explicit MAML objectives can outperform fixed pretraining on highly diverse task distributions. (Ke et al., 2021) integrate a MAML-style inner loop into a multi-criteria Chinese Word Segmentation pretraining task.

7 Conclusion

This paper shows that MAML-based meta-pretraining, even when applied to small decoder-only language models, can meaningfully improve zero-shot transfer to low-resource languages, as demonstrated on Tagalog and Cebuano NER. The gains are most pronounced for person entities and head-only finetuning, and scale best with larger model capacities. Our qualitative and word-level analyses reveal that the mechanism of improvement centers on the sharpening of lexical prototypes and better anchoring to surface cues like Tagalog case particles. Hence, we do not expect these improvements to fully generalize to multi-token or highly contextual entity types.

These findings suggest that meta-learning can provide a principled route to more adaptable small models, but also highlight key limitations: the benefits are capacity- and task-dependent, and the current approach struggles with richer entity structures. Future work should explore alternative meta-learning objectives, extend to more diverse tasks

and languages, and investigate the dynamics of prototype formation in even lower-resource settings.

Limitations

The gains are most pronounced for person entities and head-only finetuning, and scale best with larger model capacities. All training runs stop at exactly six thousand outer steps, a horizon that may be too short for the largest model, so the conclusions derived only cover a fraction of the training budget a corporate setup might have. A more diverse and multilingual corpus may alter both quantitative and qualitative conclusions, and varying languages in the meta-task is a natural way to extend this work. Qualitative analysis was conducted on a single configuration and single seed due to cost and GPU constraints. Qualitative analysis was conducted by a native Tagalog speaker with a register typical of Manila, and a wide variety of perspectives would improve the robustness of the analysis. Finally (and most naturally), our focus on only two Austronesian languages controls for certain lexical and syntactic divergences but limits the generality of the typological conclusions; extending to a broader set of Philippine and Malayo-Polynesian languages is a natural next step.

Acknowledgments

This work was supported by a grant from the Accelerate Programme for Scientific Discovery, made possible by a donation from Schmidt Futures. David Demitri Africa is supported by the Cambridge Trust and the Jardine Foundation. Suchir Salhan is supported by Cambridge University Press & Assessment. Richard Diehl Martinez is supported by the Gates Cambridge Trust (grant OPP1144 from the Bill & Melinda Gates Foundation). It was performed using resources provided by the Cambridge Service for Data Driven Discovery (CSD3) operated by the University of Cambridge Research Computing Service, provided by Dell EMC and Intel using Tier-2 funding from the Engineering and Physical Sciences Research Council (capital grant EP/T022159/1), and DiRAC funding from the Science and Technology Facilities Council.

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A NER-Relevant Typological Features of Cebuano and Tagalog

This extended table highlights how morphosyntactic and discourse-level differences between the two languages interact with the challenges of named entity recognition (NER). We lay out feature-by-feature contrasts to illustrate that even closely related Philippine languages present distinct hurdles for tasks like NER. The table emphasizes that while Tagalog offers overt morphosyntactic cues (e.g., case particles, topic marking), Cebuano relies more heavily on discourse inference, thereby requiring different modeling strategies for effective NER.

Typological Feature	Tagalog	Cebuano	Challenge for NER
Voice system	Four-way actor/non-actor voice paradigm	Reduced two-way system	Tagalog’s rich voice alternations encode argument roles morphologically, complicating alignment of entities with semantic roles. Cebuano’s reduced system lowers redundancy, making cues for role identification less explicit.
Case marking	Obligatory case particles (si, ni, ang, ng, sa)	Case particles often dropped or fused	Tagalog provides reliable morphosyntactic signals for entity boundaries/roles. Cebuano forces reliance on discourse, requiring coreference and contextual inference.
Lexical borrowing / code-switching	High density of Spanish loans and English code-switching	More conservative Austronesian lexicon	Tagalog NER must cope with OOV issues, language-mixing, and orthographic variation. Cebuano NER must handle morphologically complex Austronesian stems, underrepresented in multilingual embeddings.
Morphological richness	Productive affixation (focus, aspect, causatives)	Similarly rich, but slightly more regular	Surface forms for named entities may be inflected or derivationally complex, increasing sparsity for training data.
Word order flexibility	Relatively free (voice and particles constrain roles)	Even freer, especially without explicit case markers	Named entities may appear in non-canonical positions, reducing the utility of positional cues.
Pronominal systems	Rich system of clitic pronouns that attach to verbs or particles	Similar system but with different distributions	Entities can be referred to obliquely or dropped entirely; clitic attachment blurs tokenization boundaries, confusing NER pipelines.
Reduplication	Common for aspect, plurality, intensification	Widespread and productive	Reduplicated forms of named entities (nicknames, reduplicated roots) may not be recognized as related to the canonical form.
Orthography & variation	Spanish-influenced orthography, multiple spelling conventions	More phonologically consistent, but dialectal spelling variation persists	Orthographic inconsistency makes lexicon-based NER brittle, especially in noisy social media text.
Discourse prominence / topic marking	Ang-marked topic influences salience	Topic is often inferred from discourse, less explicit marking	Tagalog gives overt topic marking, aiding salience detection; Cebuano relies on pragmatics, requiring discourse-level modeling.

Table 3: Detailed typological contrasts between Tagalog and Cebuano and their implications for NER.

<i>Tag.</i>	Pumunta	si	Maria	sa	Cebu.
Gloss	go.PFV	NOM	Maria	OBL	Cebu
NER	O	O	B-PER	O	B-LOC
<i>Ceb. (with marker)</i>	Miadto	si	Juan	sa	Sugbo.
Gloss	go.PST	NOM	Juan	OBL	Cebu
NER	O	O	B-PER	O	B-LOC
<i>Ceb. (zero-marked)</i>	Miadto	Juan	sa	Sugbo.	
Gloss	go.PST	Juan	OBL	Cebu	
NER	O	B-PER	O	B-LOC	

Figure 8: Surface cues for named entities. Tagalog typically provides an overt personal article (*si/ni*) before names; Cebuano may show the same article, but zero-marked variants also occur in some registers/contexts, reducing overt anchors.

B Case Studies

To illustrate the mechanisms underlying MAML’s improvements, we present two contrasting examples that demonstrate how meta-pretraining affects different types of linguistic patterns in Tagalog NER. We measure $\Delta \log\text{-prob}$ as the change in surprisal ($-\log p$) for the gold label between the vanilla and MAML model. A negative Δ means the model is more confident after MAML; a positive Δ means less confident.

Case 1: Prototype Amplification. Sentence: “Inahit ni John ang sarili niya.” (Gloss: “John shaved himself.”)

The first case study demonstrates how MAML strengthens recognition of cross-linguistically common proper names. In this example, MAML sharply reduces surprisal on “John,” indicating stronger prototype activation.

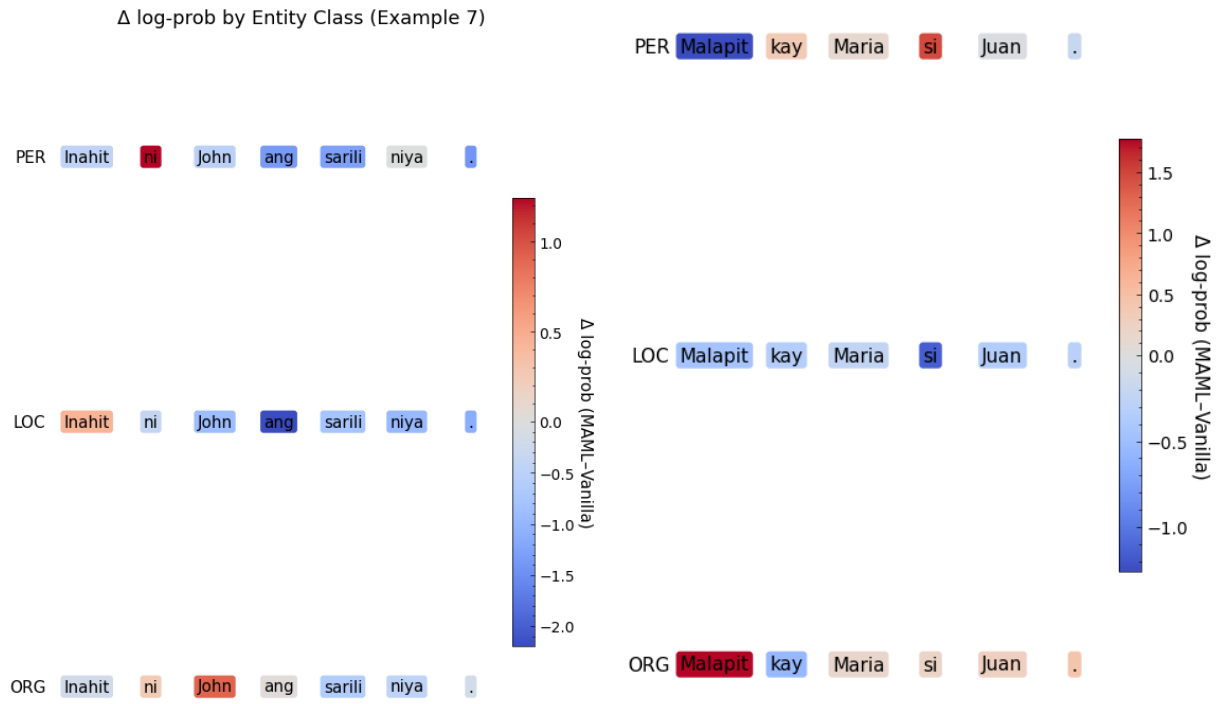
We suspect improvement operates at two levels: (1) lexical level, in the sense that the token “John” becomes more strongly associated with person entities through meta-learning’s emphasis on rapid adaptation to new entities, and (2) contextual level, in the sense that the *ni* + proper-name pattern gets reinforced as a reliable PER indicator during meta-training episodes.

Case 2: Contextual Suppression (Loss). Sentence: “Malapit kay Maria si Juan.” (Gloss: “Juan is close to Maria.”)

The second case study reveals MAML’s limitations with complex multi-token constructions. Here, Δ is positive for key tokens, showing that MAML reduces confidence in the correct label. In “Malapit kay Maria si Juan” (Juan is close to Maria), both the locative adverb “Malapit” (close/near) and the oblique case marker “kay” show substantially decreased confidence for location labeling under MAML (combined decrease of approximately -3.3 log-probability points).

We suspect this occurs due to: (1) capacity constraints, in the sense that the frozen backbone has limited representational capacity, and strengthening PER features may crowd out LOC/ORG representations, and (2) training signal imbalance, in the sense that finetuning contained more person-like entities than complex locative expressions, biasing the learned representations toward single-token person recognition.

$\Delta \log\text{-prob}$ by Entity Class (Example 4)



(a) Prototype Amplification.

(b) Contextual Suppression.

Figure 9: MAML’s impact on (a) single-token prototype confidence and (b) multi-token contextual cue sensitivity.

C Pseudocode

Below is the pseudocode for the MAML and vanilla pretraining setup.

Distributed Subset Masked Language Modeling Tasks (SMLMT) Training

Algorithm 1 Distributed SMLMT Loop

```

1: // Initialization: same as Alg. 2, plus
2: initialize inner-optimizer SGD on head  $h_\phi$ 
3: step  $\leftarrow 0$ 
4: for each sub_batch in dataloader do
5:   // gather across GPUs
6:    $X \leftarrow \text{fabric.all\_gather}(\text{sub\_batch}["\text{input\_ids}"])$ 
7:   // sync random branch decision
8:    $r \leftarrow \text{Uniform}(0, 1)$ ;  $r \leftarrow \text{fabric.broadcast}(r)$ 
9:   if  $r < \rho$  then
10:    // Meta-learning episode
11:     $(S, Q), \text{labels}_S, \text{labels}_Q \leftarrow \text{mask\_tokens}(X)$ 
12:     $\phi_0 \leftarrow \phi$  ▷ snapshot head params
13:    for  $t = 1$  to  $T_{\text{inner}}$  do
14:       $\ell_S \leftarrow \text{CE}(h_{\phi_{t-1}}(f_\theta(S)), \text{labels}_S)$ 
15:       $\phi_t \leftarrow \phi_{t-1} - \alpha \bullet \ell_S$  ▷ inner SGD
16:    end for
17:     $\ell_Q \leftarrow \text{CE}(h_{\phi_T}(f_\theta(Q)), \text{labels}_Q)$ 
18:     $\phi \leftarrow \phi_0$  ▷ restore head
19:    fabric.backward( $\ell_Q / \text{accum\_steps}$ )
20:  else
21:    // Standard AR
22:     $X_{\text{in}}, Y \leftarrow X[:, :-1], X[:, 1:]$ 
23:     $\ell_{\text{AR}} \leftarrow \text{CE}(f_\theta(X_{\text{in}}), Y)$ 
24:    fabric.backward( $\ell_{\text{AR}} / \text{accum\_steps}$ )
25:  end if
26:  // outer-step and logging
27:  if (step+1) % accum_steps == 0 then
28:    opt.step(); scheduler.step(); opt.zero_grad()
29:    // aggregate metrics across GPUs
30:    log_loss  $\leftarrow \text{fabric.all\_reduce}(\ell)$ 
31:    fabric.log(...)
32:    fabric.barrier()
33:  end if
34:  step += 1
35: end for

```

Distributed Autoregressive (AR) Training

Algorithm 2 Distributed AR Loop

```
1: // Initialization (in Trainer.__init__):
2: Load configs; initialize Fabric, tokenizer, model  $f_\theta$ 
3: (model, opt)  $\leftarrow$  fabric.setup( $f_\theta$ , AdamW)
4: dl  $\leftarrow$  base dataloader; dl  $\leftarrow$  fabric.setup_data loaders(dl)
5: step  $\leftarrow$  0; zero gradients
6: for each sub_batch in dl do
7:   // Gather full batch across GPUs if needed:
8:    $X \leftarrow$  fabric.all_gather(sub_batch["input_ids"])
9:    $X_{\text{in}}, Y \leftarrow X[:, :-1], X[:, 1:]$ 
10:  // forward + loss
11:   $\ell \leftarrow \text{CE}(f_\theta(X_{\text{in}}), Y)$ 
12:  // backward (handles synchronization)
13:  fabric.backward( $\ell/\text{accum\_steps}$ )
14:  // outer-step when accumulated
15:  if (step+1) % accum_steps == 0 then
16:    opt.step(); scheduler.step(); opt.zero_grad()
17:    // optional barrier
18:    fabric.barrier()
19:  end if
20:  step + = 1
21: end for
```

C.1 Multi-GPU processing

Pico already uses Lightning-Fabric data parallelism but meta-learning introduces various demands that make multi-GPU processing complicated. A Bernoulli draw is done on one GPU and broadcast so all ranks choose the same objective. Support and query tensors are constructed on rank 0 then scattered, because per-rank random masks would destroy gradient equivalence. Every GPU performs the same ten head updates before any gradient is communicated. A stray early `all_reduce` would mix gradients from different inner steps, so we place an explicit barrier between inner and outer phases.

D Universal NER Datasets

To comprehensively evaluate the pretraining method, each permutation of finetuning setup ({head-only, full}, finetuning dataset ({da_ddt, ..., zh_gsdsimp, all}) (where all consists of all available training sets), model size ({tiny, small, medium, large}), and pretraining setup ({vanilla, MAML}) is evaluated, for a total of 160 evaluation runs.

- **Publicly Available In-language treebanks** (9 langs): full train/dev/test splits, identical to the official UD partitions.
 - da_ddt, en_ewt, hr_set, pt_bosque, sk_snk, sr_set, sv_talbanken, zh_gsd, zh_gsdsimp
- **Parallel UD (PUD) evaluation** (6 langs): single test.txt files, all sentence-aligned across German, English, Portuguese, Russian, Swedish and Chinese.
 - de_pud, en_pud, pt_pud, ru_pud, sv_pud, zh_pud
- **Other eval-only sets** (3 langs): small test splits for low-resource languages.
 - ceb_gja (Cebuano), tl_trg (Tagalog TRG), tl_ugnayan (Tagalog Ugnayan)

D.1 Slovak Fine-Tune Token Statistics

Entity	# spans	% single-token
PER	2 277	87.6 %
LOC	277	75.1 %
ORG	153	56.9 %

Table 4: Span statistics for the Slovak finetune set (sk_snk train). The data are strongly person-heavy and person spans are almost always single words, whereas locations and organisations are both rarer and more often multi-token.

D.2 Tagalog and Cebuano Particle and Out-of-Vocabulary Statistics

Language	Particle recall	OOV rate
Tagalog	0.113 \pm 0.000	0.523 \pm 0.000
Cebuano	0.058 \pm 0.000	0.534 \pm 0.000

Table 5: Mean (\pm s.d. across checkpoints) of particle–preceding-span recall and token out-of-vocabulary rate, measured on the zero-shot evaluation sets after Slovak head-only tuning. “Particle recall” is the fraction of gold PER entities whose left context token is a Filipino case particle recognised by the model.

E Pretraining Results

We present the unedited pretraining indicators for each pico-maml-decoder model below, as logged on WandB.

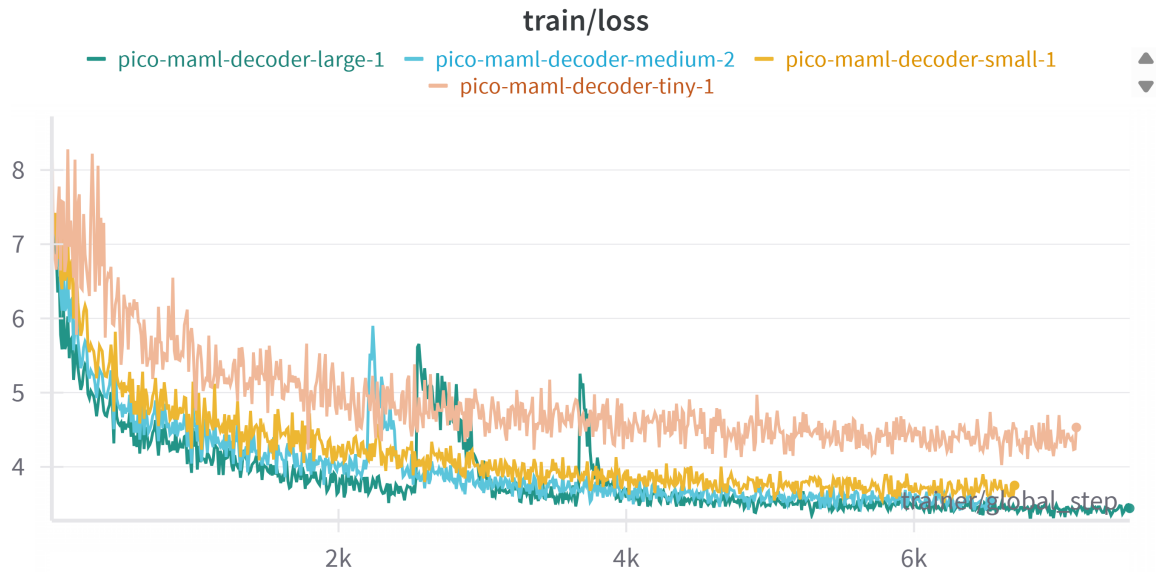


Figure 10: Pretraining training loss curve.

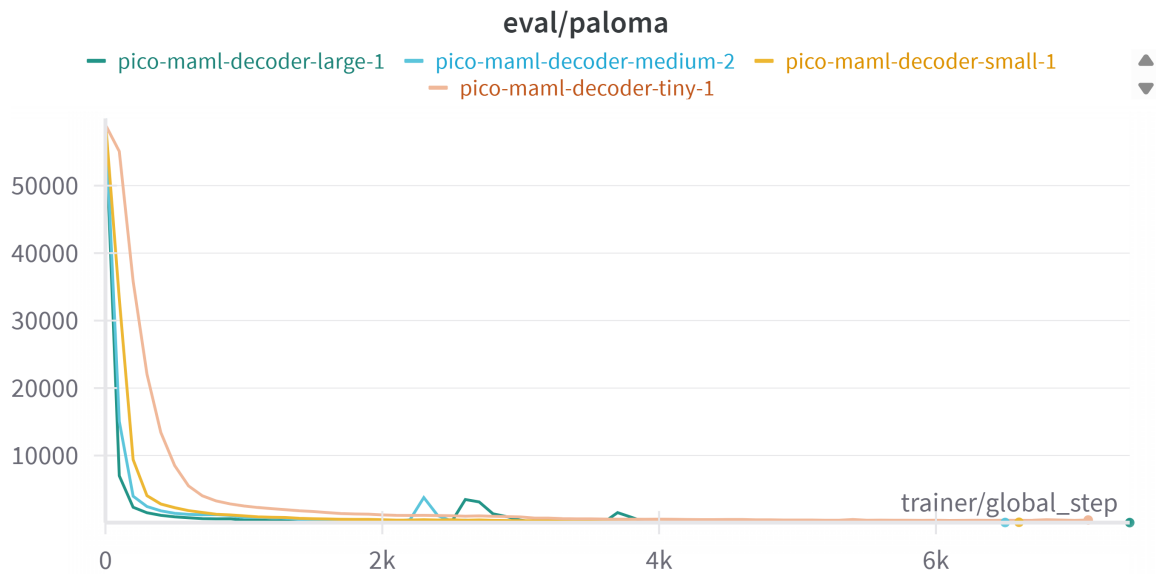


Figure 11: PALOMA score over pretraining steps.

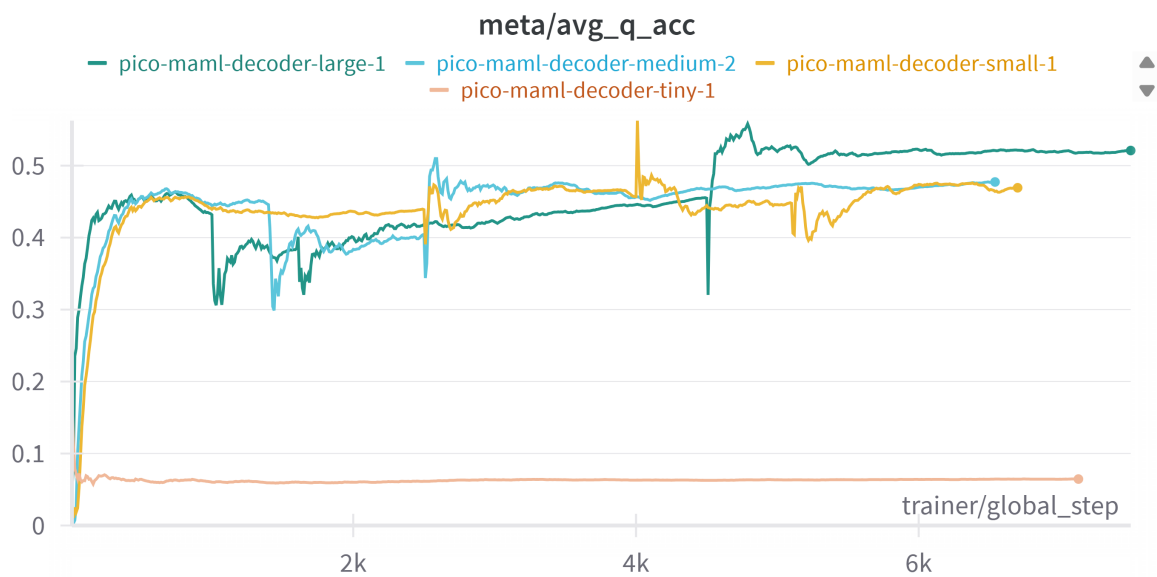


Figure 12: Query accuracy during pretraining.

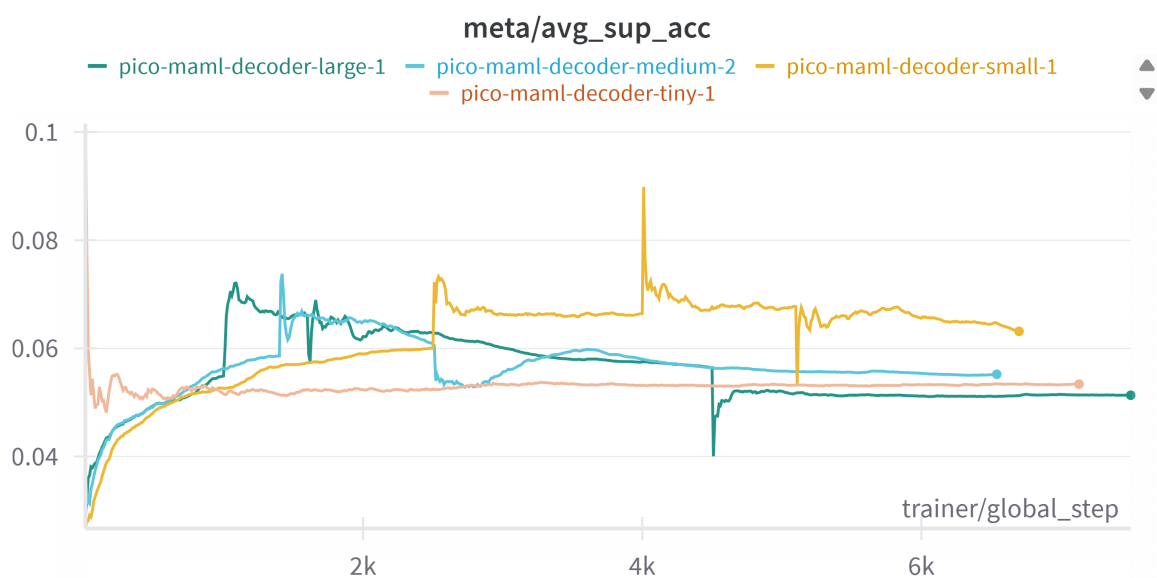


Figure 13: Support accuracy over pretraining.

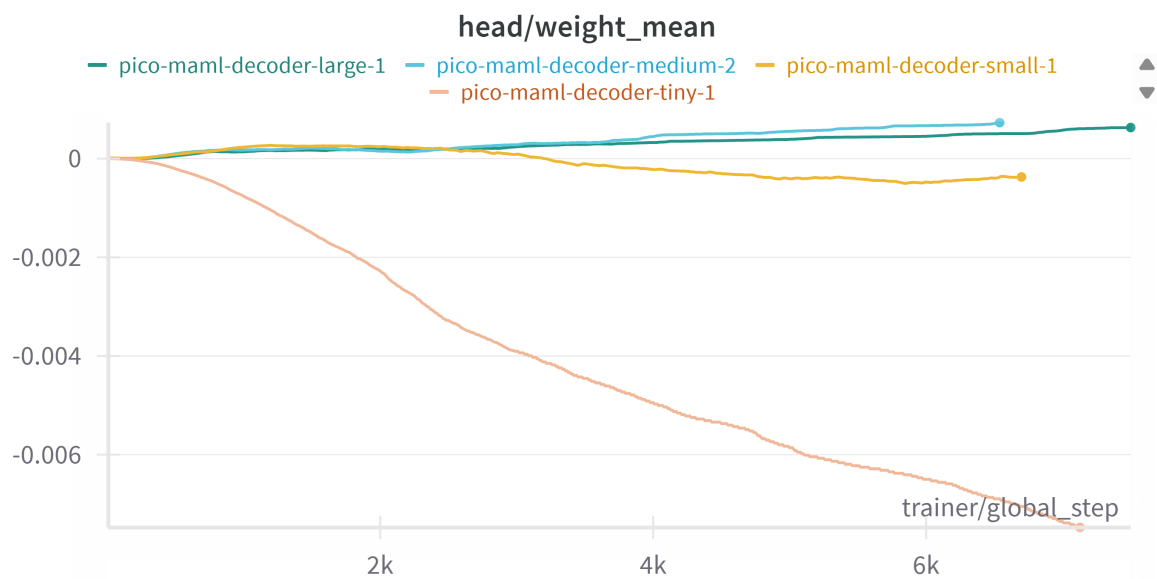


Figure 14: Mean of weights in classifier head over pretraining.

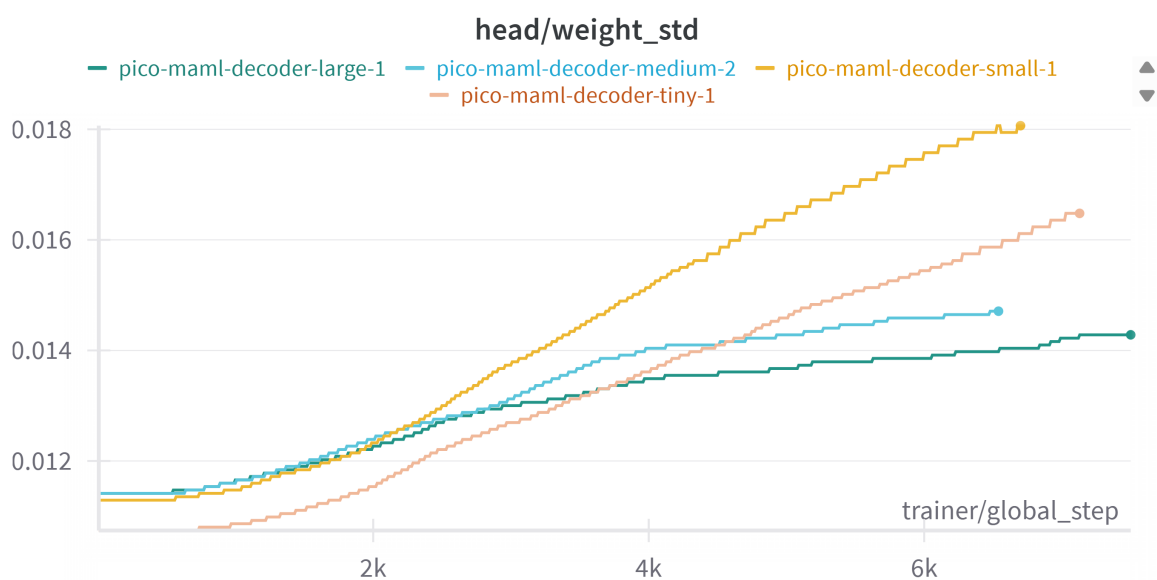


Figure 15: Standard deviation of weights in classifier head over pretraining.

F Default pico-maml-train Configurations


Category	Parameter	Default Value
Model	Model Type	pico_decoder
	Hidden Dimension (d_{model})	768
	Number of Layers (n_{layers})	12
	Vocabulary Size	50,304
	Sequence Length	2,048
	Attention Heads	12
	Key/Value Heads	4
	Activation Hidden Dim	3,072
	Normalization Epsilon	1×10^{-6}
	Positional Embedding Theta	10,000.0
Training	Optimizer	AdamW
	Learning Rate	3×10^{-4}
	LR Scheduler	Linear w/ Warmup
	Warmup Steps	2,500
	Gradient Accumulation Steps	128
	Max Training Steps	200,000
	Precision	BF16 Mixed
Data	Dataset Name	pico-lm/pretokenized-dolma
	Batch Size	1,024
	Tokenizer	allenai/OLMo-7B-0724-hf
Checkpointing	Auto Resume	True
	Save Every N Steps	100
Checkpointing	Learning Dynamics Layers	"attention.v_proj", "attention.o_proj", "swiglu.w_2"
	Learning Dynamics Eval Data	pico-lm/pretokenized-paloma-tinsy
Evaluation	Metrics	["paloma"]
	Paloma Dataset Name	pico-lm/pretokenized-paloma-tinsy
	Eval Batch Size	16
Monitoring	Logging Level	INFO
	Log Every N Steps	100
Meta-Learning	Enabled	True
	Hybrid Ratio	0.5
	Inner Steps (k)	10
	Inner Learning Rate	0.001
	Support Shots (k)	4
	Query Ways (n)	32
	Classifier Head Layers	4
	Classifier Head Hidden Dim	128
	Classifier Head Dropout	0.1
	Classifier Head Init Method	xavier
Monitoring	Logging Level	INFO
	Log Every N Steps	100


Table 6: Default configuration settings used in pico-maml-train.


Pico-MAML-Decoder Model Comparison				
Attribute	tiny	small	medium	large
Parameter Count	11M	65M	181M	570M
Hidden Dimension (d_{model})	96	384	768	1536
Feed-forward Dim	384	1536	3072	6144
Training Time (6k steps)	10h	15h	16h	25h

Table 7: Comparison of pico-maml-decoder model variants trained with default pico-maml-train configurations. Except for hidden and feed-forward dimension, all models share the training settings detailed in 6. Models were trained for 6000 training steps on 4 NVIDIA A100-SXM4-80GB GPUs; the listed training times correspond to the initial 6000 steps.

"Linguistic Universals": Emergent Shared Features in Independent Monolingual Language Models via Sparse Autoencoders

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1 Introduction

Whether certain structural patterns are shared across all natural languages, despite surface-level differences, has long been a topic of debate in linguistics. In Natural Language Processing, studies have shown that multilingual language models possess semantically aligned capabilities across languages even without explicit parallel supervision (Pires et al., 2019; Conneau et al., 2020; Tang et al., 2024). This suggests that machine-learned representations capture crosslinguistic regularities, but it should be noted that this alignment is aided by shared vocabularies and parameters (Dufter and Schütze, 2020; Philippy et al., 2023).

A more fundamental question remains: can independently trained monolingual LMs – which share no parameters nor vocabulary – nonetheless converge on analogous high-level features? If so, this would suggest that certain structural principles of language emerge robustly in machine learning, even when models are trained in isolation. Goldfish (Chang et al., 2024) provides us with a suite of monolingual GPT-style models covering 350 languages. These models have identical architectures and training budgets but were each trained with strictly monolingual corpora. They thus form a controlled testbed for crosslinguistic comparison.

A key technical challenge is how to identify and compare high-level features across different models. To overcome this, we adopt sparse autoencoders (SAEs) as an analysis tool. Recent work (Cunningham et al., 2023) showed that training a single-layer SAE on a model’s activations yields a set of sparsely activating features that are far more interpretable and monosemantic than the original neuron basis. In essence, the SAE “discovers” a dictionary of latent feature directions in activation space, each corresponding to a distinct concept

or pattern in the data. Brinkmann et al. (2025) demonstrated that SAEs trained on multilingual LLMs uncover both monolingual and multilingual features. Notably, Lan et al. (2025) recently employed SAEs to compare features across different English LLMs. They hypothesized that the spaces spanned by SAE features are similar, such that one SAE space is similar to another SAE space under rotation-invariant transformations, and found high similarities for SAE feature spaces across various LLMs, providing evidence for feature space universality. We build on this approach in a novel crosslinguistic setting. Our research questions are framed as follows:

- RQ1:** Can SAE features trained on independently trained monolingual LMs be matched across languages? After matching, do they show non-trivial (above baseline) convergence (i.e., have higher alignment score)?
- RQ2:** At which model depths (layers) is feature alignment strongest across languages?
- RQ3:** Does the degree of alignment correlate systematically with linguistic relatedness (e.g., typological or genealogical distance)?
- RQ4:** Are there features that emerge universally across languages, and can they be interpreted (e.g., punctuation, numerals, structural delimiters)? How prevalent are such features?

2 Methodology

2.1 SAE Training

For each monolingual model, we collect hidden activations from each layer using held-out text sampled from the same monolingual training corpus used in Goldfish (5MB–1GB per language, depending on availability). Given these activations, we train an SAE to learn a set of latent features that can reconstruct the activations. Each SAE

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is a one-hidden-layer autoencoder with tied encoder–decoder weights, a linear hidden layer, and an ℓ_1 sparsity penalty to encourage most feature units to remain off for any given input. We train separate SAEs for each language model’s each layers.

2.2 SAE Feature Activations (Data Matrix)

For each language ℓ and layer h , we construct an activation matrix $\mathbf{A}^{(\ell,h)} \in \mathbb{R}^{N \times K}$ by feeding N parallel sentences from FLORES-200 (NLLB Team, 2022) through the monolingual model and recording the activations of its K SAE features (z-scored per feature across sentences).

2.3 Pairwise Feature Matching

Given two languages (ℓ_1, ℓ_2) at layer h , we compute the $K \times K$ correlation matrix $\mathbf{C}^{(\ell_1, \ell_2, h)}$ with entries $C_{ij} = \text{corr}(\mathbf{A}_{\cdot i}^{(\ell_1, h)}, \mathbf{A}_{\cdot j}^{(\ell_2, h)})$ (Pearson over the shared FLORES sentences). We obtain a one-to-one alignment via maximum-weight bipartite matching (Hungarian algorithm) on $\mathbf{C}^{(\ell_1, \ell_2, h)}$.

2.4 Pairwise Alignment Score

For each pair (ℓ_1, ℓ_2, h) , the alignment score is the mean correlation of matched pairs:

$$\text{Align}(\ell_1, \ell_2, h) = \frac{1}{K} \sum_{(i,j) \in \mathcal{M}^{(\ell_1, \ell_2, h)}} C_{ij}.$$

We visualize the matrix of $\text{Align}(\ell_1, \ell_2, h)$ across all language pairs as a heat map.

3 Analysis

3.1 Alignment Against Baselines

To ensure the alignment is non-trivial, we compare against: (i) **random feature assignment**—shuffle columns of $\mathbf{A}^{(\ell_2, h)}$ before matching, (ii) **row-shuffled sentences**—independently permute rows of $\mathbf{A}^{(\ell_2, h)}$ (breaks sentence-level correspondence), and (iii) **within-model shuffle**—match ℓ_1 to a copy of itself with feature order shuffled. We report Δ over baseline (absolute and percentage), with 95% CIs from bootstrap over sentences.

3.2 Layer-wise Analysis

We aggregate $\text{Align}(\ell_1, \ell_2, h)$ over language pairs for each layer h to obtain layer-wise trends. We test for a peak layer via a mixed-effects model with random intercepts for language pairs and fixed effect for layer, or via paired non-parametric tests across layers.

3.3 Language-Distance Analysis

Given the Pairwise Alignment Score, a natural question—and our hypothesis—is whether more closely related (genealogically or typologically) languages share more emergent features, i.e., exhibit higher pairwise alignment score. We correlate alignment strength with linguistic distance. For each pair (ℓ_1, ℓ_2) we compute: (i) genealogical family match (binary), (ii) typological distance (e.g., URIEL/WALS features), and (iii) script match (binary). We fit $\text{Align}(\ell_1, \ell_2, h) \sim \text{distance metrics} + \text{layer}$ and report standardized coefficients. We also stratify heat maps by family/script to visualize systematic variation.

4 Universal Features

After aligning features between each pair of languages, we ask if these features are universal across all languages.

Definition. A feature cluster is *universal* at layer h if it contains aligned features from at least $p\%$ of languages (we choose $p \in \{50, 75, 90\}$).

Construction. We build a graph whose nodes are (language, feature) and whose edges connect matched pairs from Section 2.3 (weight = C_{ij}). Connected components (or communities via Louvain) define crosslinguistic clusters. For each cluster we report: coverage (fraction of languages present), mean within-cluster correlation, and stability across bootstrap resamples. Preliminary expectations are that a non-trivial fraction of the learned features – especially those capturing very general patterns – will be universal. For instance, we anticipate discovering features related to punctuation, numerals, and structural delimiters that appear in every model.

Interpretability. For each universal cluster, we list top activating n-grams/tokens per language and show cross-language trigger sets (digits, punctuation, brackets, etc.). We include exemplar sentences and activation traces for qualitative validation. We hope that uncovering such crosslinguistic universal features will shed light on whether machine-learned representations mirror long-standing hypotheses in linguistic theory, and may even provide a complementary empirical perspective to the study of linguistic universals in human languages.

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The Unreasonable Effectiveness of Model Merging for Cross-Lingual Transfer in LLMs

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Abstract

Large language models (LLMs) still struggle across tasks outside of high-resource languages. In this work, we investigate cross-lingual transfer to lower-resource languages where task-specific post-training data is scarce. Building on prior work, we first validate that the subsets of model parameters that matter most for mathematical reasoning and multilingual capabilities are distinctly non-overlapping. To exploit this implicit separability between task and target language parameterization, we develop and analyze numerous *modular* frameworks to improve the *composition* of the two during fine-tuning. These methods generally employ freezing parameters or post hoc model merging to assign math and language improvement to different key parts of the LLM. In the absence of in-language math data, we demonstrate that the modular approaches successfully improve upon baselines across three languages, four models, and two fine-tuning paradigms (full and LoRA). Furthermore, we identify the most consistently successful modular method to be fine-tuning separate language and math experts and model merging via Layer-Swapping (Bandarkar et al., 2025a), somewhat surprisingly. We offer possible explanations for this result via recent works on the linearity of task vectors. We further explain this by empirically showing that reverting less useful fine-tuning updates after training often outperforms freezing them from the start.

1 Introduction

Post-training large language models (LLMs) on labeled text data is a critical step in developing models for real-world applications. However, when these LLMs are fine-tuned for lower-resource languages, significant challenges arise due to the pre-trained model’s limited capabilities. Although in recent years the broader scaling of pretraining and increased investment in additional languages (Dang

et al., 2024b; Llama et al., 2024) have led to major improvements, pretrained LLMs still struggle to understand and generate text in all but a few languages (Romanou et al., 2025; Qin et al., 2025).

This pretraining disparity is further exacerbated by the lack of available high-quality multilingual fine-tuning data (Singh et al., 2024) and the significant cost to procure such annotated data (even through machine translation). For many of the capabilities developers target during post-training (e.g., instruction-following, reasoning, or safety) there are only sufficient open-source data available in English, Chinese, and a handful of other languages. This motivates the need for better cross-lingual transfer: the generalization of learned capacities from high-resource languages to lower-resource ones (Hu et al., 2020; Philippy et al., 2023).

Despite recent releases of massive mixture-of-expert LLMs (Team, 2024b; DeepSeek-AI et al., 2025; Team, 2025), a large majority of modern LLMs are *dense*, meaning that all parameters are active during training and inference. However, even within dense LLMs, recent works have found separability in where and how varying capabilities are represented (Yin et al., 2024; Yao et al., 2024). For example, multilingual capabilities are typically concentrated in the top and bottom transformer layers and multi-head attention parameters of an LLM (Chang et al., 2022; Choenni et al., 2024). This notably contrasts mathematical reasoning capabilities being encoded mainly in the middle transformer layers (Hanna et al., 2023; Stolfo et al., 2023). In the context of cross-lingual transfer, this functional separation motivates *modular* approaches to fine-tuning, which distinct model components can be trained, swapped, or merged (Bengio et al., 2020; Pfeiffer et al., 2023) for efficient and flexible multi-objective optimization.

In this work, we explore several modular approaches for composing target task and target language capabilities in off-the-shelf dense LLMs.

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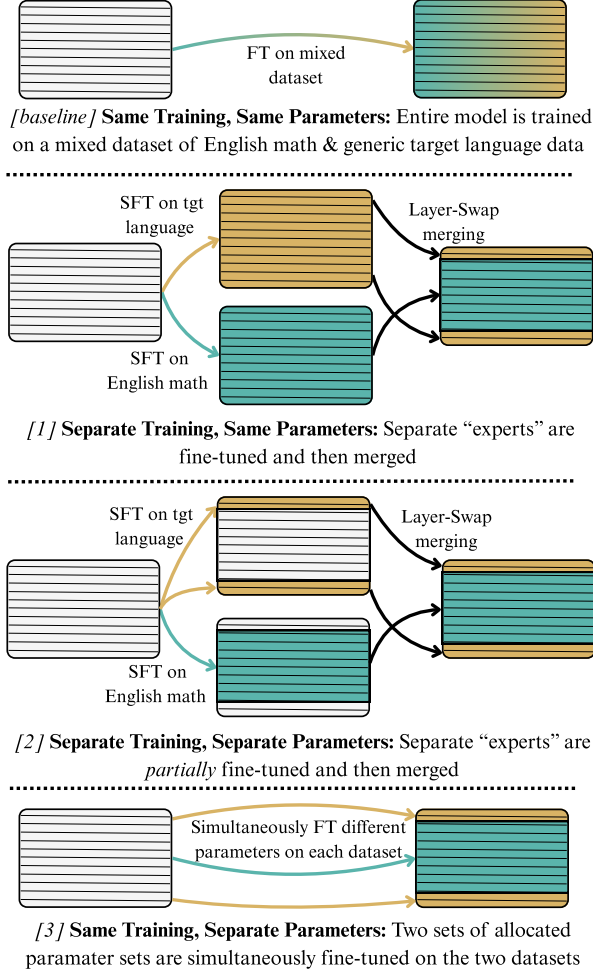


Figure 1: Illustration of the three methods that induce modularity by imposing target language capabilities (brown) and mathematical reasoning (blue) on separate LLM parameters. [1] is from [Bandarkar et al. \(2025a\)](#)

Our goal is to induce modularity by exploiting the differences in parameters that are most relevant to mathematical reasoning versus multilingual capabilities. We focus on the prevalent scenario where task-specific data is scarce in the target language but readily available in English. We address this by working with two datasets; one English math dataset for supervised fine-tuning (SFT) and one general, multi-task SFT dataset in the target language. Using the target languages of Bengali, Swahili, and Telugu, we evaluate the methods on the multilingual math benchmark, MGSM ([Shi et al., 2023](#)).

With these datasets, we evaluate numerous training paradigms that incentivize the model, to varying degrees, to learn multilingual or math capabilities in specific parameters. We organize the settings along two axes: (1) whether the models are optimized separately or together over the two

SFT datasets and (2) whether the same or separate model parameters are trained on the datasets. When the models are trained separately, we combine the learned capabilities using model merging methods such as variants of Layer-Swapping ([Bandarkar et al., 2025a](#)). To train separate model parameters, we start by dividing all parameters into two partitions according to prior work: (1) one set allocated to target language training and (2) one set to English math. Only allocated parameters are fine-tuned, while the opposite partition is frozen. We additionally develop a method to train separate parameters in a single, joint training by frequently freezing and unfreezing parameters to simulate simultaneous training.

Despite the strong starting capabilities of the four LLMs and the data-constrained setting, our experimental results show that all of the modular solutions outperform our baselines, despite being subject to varying training constraints. This implies that intentional separation of parameters and/or training improves the *compositionality* of task and language capabilities.

Amongst our modular solutions, we surprisingly find that post hoc model merging via Layer-Swapping outperforms more coordinated multi-task fine-tuning approaches. To contextualize this counterintuitive result, we explore recent academic literature that help explain the phenomenon. We provide empirical evidence for training all model parameters, even if large portions will be discarded during Layer-Swapping. While these subsets of task vectors are unproductive, freezing them during fine-tuning leads to less optimal updates to the target parameters. Notably, we rationalize that the fine-tuning task vectors (Δ s) are quite linear within individual parameter blocks ([Dai et al., 2025](#)), meaning they can be added, scaled, or interpolated as linear components ([Adilova et al., 2024](#)).

Overall, we enumerate the following principal contributions of this work:

- We develop and synthesize a number of modular solutions that *each* increase compositionality for cross-lingual transfer compared to non-modular baselines, demonstrated through extensive experiments.
- Of the modular methods, we find that fine-tuning all parameters and then merging via Layer-Swapping performs best on average.
- We provide a mix of theoretical and empirical explanations to explain the surprising success of Layer-Swapping relative to alternatives.

2 Background

2.1 Cross-Lingual Transfer

The relative abundance of textual data available in English in comparison to other languages has long motivated research in developing methods to efficiently transfer learned capabilities across languages (Koehn and Knight, 2002). Typically, some capabilities transfer naturally across languages, as evidenced by the superior performance of multilingual models on low-resource languages compared to monolingual models (Firat et al., 2016; Pires et al., 2019; Artetxe et al., 2020). In encoder models, the text embedding could be aligned across languages to improve transfer using methods such as contrastive learning (Mikolov et al., 2013; Artetxe et al., 2018; Muller et al., 2021).

However, cross-lingual alignment in more modern decoder-only models has become less methodical because of the lack of universal embedding (Kargaran et al., 2025). Since most popular LLMs have been trained on a majority English corpora, recent works have examined how much intrinsic cross-lingual transfer occurs at different training stages (Choenni et al., 2023; Wang et al., 2024). These large models have broader generalization and robustness, but still fail to transfer much of their capabilities across languages (Philippy et al., 2023). Recent works have identified prompting methods (Shi et al., 2023; Zhang et al., 2024) or post-training data augmentation (Dang et al., 2024a; She et al., 2024; Lai et al., 2024) to help generalization.

2.2 Modularity in Multilingual NLP

A major constraint for models being able to process many languages has been the number of parameters available to represent them. As a result, improving a language model in one language risks undermining its knowledge of another, termed the *curse of multilinguality* (Conneau et al., 2020; Pfeiffer et al., 2022). Naturally, numerous methods have been proposed to increase the model’s parametric capacity without increasing the inference cost, such as mixture-of-expert architectures (Fedus et al., 2022) that route tokens according to their language (NLLB et al., 2022). Methods that leverage modular parameters were developed to compose capabilities for transfer learning by inserting trainable adapters within model layers (Houlsby et al., 2019; Pfeiffer et al., 2021). These methods were modified for multilinguality by allocating adapters for particular languages and switching them in or out

depending on the input (Bapna and Firat, 2019; Pfeiffer et al., 2020). Pfeiffer et al. (2022) extended these methods by pretraining an adapter-based multilingual model from scratch. In decoder models, cross-lingual adapters have also been proposed at the token embedding level (Jiang et al., 2025).

Even in dense LLMs, however, interpretability research has identified the emergence of effective modularity (Csordás et al., 2021) as LLM parameters scale (Zhang et al., 2022; Qiu et al., 2024; Chen et al., 2025). Principally, numerous recent works have identified that just a few transformer layers at the top and bottom of English-centric LLMs are responsible for multilingual capabilities, notably by mapping input and output into a universal representation (Kojima et al., 2024; Wendler et al., 2024; Tang et al., 2024b; Alabi et al., 2024; Wu et al., 2025). Similar patterns are observed in modern sparse mixture-of-experts LLMs, where it is also observed that language-specialized experts are completely distinct from task/domain-specialized ones (Bandarkar et al., 2025b).

2.3 Model Merging

Model merging is the practice of combining the weights of multiple checkpoints of the same model architecture into a singular model. While averaging models is a fundamental machine learning approach to increase statistical robustness (Breiman, 1996), the averaging of model checkpoints, dubbed a model soup by Wortsman et al. (2022), has re-emerged in large-scale LLMs as a method to increase model robustness. More importantly, it also increases the search space of valid model variants at any given training step without additional costly training runs (Llama et al., 2024). However, simple weight averaging is vulnerable to negative transfer, or interference, between checkpoints so numerous methods have been presented to selectively merge parameters (Ilharco et al., 2023a; Yadav et al., 2023; Yu et al., 2024a). Surprisingly, training models on separate data and then merging can often outperform a single training run on mixed data (Tang et al., 2024a; Aakanksha et al., 2024) and has shown to be highly effective in large-scale multilingual pretraining (Dang et al., 2024b). For cross-lingual transfer in particular, Ansell et al. (2022) showed that sparse fine-tuning can lead to better composition. Bandarkar et al. (2025a) extended this by notably identifying that mathematical reasoning was concentrated in parameters different from multilingual capabilities. As a result, model

Training Description	Base Model	Partial LoRA	Partial SFT	LoRA	Full SFT
Math-only	19.0%	18.0%	19.5%	18.9%	19.6%
Language-only	19.0%	19.2%	19.8%	19.7%	20.3%
Data mixing	19.0%	-	-	19.7%	20.4%
Simultaneous SFT	19.0%	20.4%	21.0%	-	-
Layer-Swapping	19.0%	20.0%	20.4%	20.8%	21.5%

Table 1: Summary Table of Results. Each value represents *the average across four models, three languages, and multiple training runs* on MGSM in 2-shot evaluations. The last row represents “Separate Training” while the “Partial” trainings correspond to “Separate Parameters” trainings. All results shown here and in all other tables of this paper display exact-match (EM) accuracy (\uparrow) as a percentage.

variants trained on English math data and multilingual data can be combined by Layer-Swapping, or swapping the transformer layers most important to each.

3 Experimental Setup

3.1 Evaluation

Limited by the lack of task-specific benchmarks for medium- and low-resource languages, we focus on MGSM (Shi et al., 2023) as the target task of this project. MGSM is a mathematical reasoning benchmark parallel across 10 languages as a result of high quality translations from the popular English benchmark, GSM8K (Cobbe et al., 2021). For MGSM, we report exact match accuracy in two-shot, as one- and zero-shot led to inconsistent results. More few-shot examples did not display substantial gain. For target languages, we choose the languages in MGSM where the four LLMs perform the worst: Bengali, Telugu, and Swahili. In addition, the lack of open-source math SFT data available in these languages motivates the need for more effective cross-lingual transfer. For a given fine-tuned model, we also evaluate the two-shot MGSM performance in English to evaluate its math performance irrespective of target language capability. Conversely, we use the multilingual MCQA benchmarks GLOBAL MMLU (Singh et al., 2025) and BELEBELE (Bandarkar et al., 2024) as pure language understanding signals, independent of math.

3.2 Models

We run experiments on four state-of-the-art instruction-finetuned LLMs: FALCON 3 7B (Team, 2024a), QWEN2.5 7B Instruct (Yang et al., 2024), LLAMA 3.1 8B Instruct (Llama et al., 2024), and AYA Expanse 8B (Dang et al., 2024b). All have similarly high performance on MGSM in English.

LLAMA 3.1 and FALCON 3 are English-centric, QWEN2.5 bilingual with Chinese, and AYA Expanse explicitly multilingual. However, all officially cover numerous other languages (up to 23 for AYA) and perform reasonably on such languages, which we verify using BELEBELE and GLOBAL MMLU. Bengali, Swahili, and Telugu are amongst the official languages for none of these models. As a result, the four models are all low-scoring in MGSM in these languages, with the exception of LLAMA on Swahili (See Appendix A.8).

3.3 Parameter Allocation

To determine which parameters to “allocate” to each capability, we rely on a mix of interpretability papers and small-scale empirical tests. As mentioned in Section 2.2, numerous papers have identified the most important parameters for multilingual capabilities to be the first few and last few transformer layers of LLMs. These works, however, typically discuss mostly English-centric models (such as LLAMA 3.1 and FALCON 3). We therefore need to evaluate this for bilingual and multilingual models like QWEN2.5 and AYA Expanse. For mathematical reasoning, we note that Bandarkar et al. (2025a) identifies the middle and late-middle transformer layers as being the most important. This work, and numerous others (Voita et al., 2019; Ma et al., 2021; Zhao et al., 2024), similarly identifies multi-head attention parameters as critical to multilingual capabilities, as opposed to multi-layer perceptron parameters.

To empirically verify these assumptions on our selected models, we run SFT over our datasets with different subsets frozen. We evaluated numerous ways to partition the parameters and find a number of splits that enable improvements on English math and on language-specific signals (e.g. BELEBELE). To validate that the good performance when freez-

Parameters that are frozen or reset	Frozen during	Reset after
base (no SFT)	78.4%	78.4%
[Z] only top-4 and bottom-8 layers (inverse of intuition)	78.2%	78.9%
[A] all MHA parameters + MLP parameters in top-2 and bottom-6 layers	79.4%	79.8%
[B] only top-4 and bottom-8 layers	79.8%	79.8%
[C] only top-2 and bottom-6 layers	79.7%	80.0%
None	80.1%	80.1%

Table 2: MGSM 2-shot results (\uparrow) on the *English* split after SFT on the English math data averaged across four models. These results (1) validate that our intuition leading to our parameter allocations [A, B, C] is reasonable seeing as results are close to full fine-tuning and are significantly higher than the inverse allocation [Z]. Additionally, (2) these results demonstrate that full fine-tuning then reverting parameters (second column) is more effective than freezing those parameters from the start (first column).

ing parameters is because the trainable parameters are particularly useful for a target task, we also run experiments with the *opposite* allocation (e.g. middle layers frozen during mathematical reasoning training) and find that it works poorly.

While the search space of which parameters to freeze is large, we settle on three partitions that show sufficient empirical success:

- [A] All multi-head attention parameters allocated to the target language. Then, amongst the multi-layer perceptron parameters, those in the first six and last two transformer layers still allocated to language, while those in the rest of the 32- or 36-layer LLM for math.
- [B] The first eight and last four transformer layers allocated to language, the rest for math.
- [C] The first six and last two transformer layers allocated to language, the rest for math.

In these three settings, both mathematical reasoning and target language capabilities improve similarly to full SFT with a fraction of trainable parameters (See Table 2 for results for math). We evaluate the three for each of our experimental settings and, unless noted, report the highest scoring.

3.4 Training

For SFT data, we create four datasets, one for math in English and one instruction dataset for each of the three target languages. The math instruction dataset consists of English math word problems from the Orca-Math synthetic dataset (Mitra et al., 2024). For the language datasets, we replicate the creation of “generic” instruction fine-tuning datasets from Bandarkar et al. (2025a) by combining samples from open-source instruction and task-specific datasets. Importantly, there are no math samples in these multi-task language datasets. We provide specific details and citations for these data collections in Appendix A.6.

Due to constraints on the amount of verifiable-quality data available in each of the target languages, our datasets are controlled at 80k samples, 2k of which is reserved for validation. Because of significantly diminishing returns exhibited by the validation loss and downstream evaluations, we only train for one epoch for each of our settings.

We additionally duplicate all experiments using Low-Rank Adapters (LoRA) (Hu et al., 2022). Specifically, we use rank-stabilized LoRA (Kala-jdziewski, 2023) applied to both multi-layer perceptron and multi-head attention parameters. In general, the adjustments of our methods to be compatible with LoRA were minor unless noted otherwise. With four models, three languages, and two fine-tuning approaches (full and LoRA), we have a total of 24 experimental settings. For each, we do hyperparameter search over several runs to ensure comparability (See Appendix A.4 for details).

4 Experiments

We describe numerous methods that modularize off-the-shelf, dense LLMs in different ways. We describe *separate training* as when we conduct separate SFT runs on different datasets, albeit starting from the same off-the-shelf model. As previously mentioned, the separately trained checkpoints are then merged via Layer-Swapping. *Separate parameters* implies that only the partition of parameters *allocated* (See Section 3.3) to that dataset are trained while the rest remain frozen.

4.1 Baselines (Math-only and Language-only)

For comparison, we evaluate a number of straightforward SFT setups to serve as baselines. We do full-parameter training runs for each of the target language generic SFT datasets and the English

math SFT dataset. For further baselines, we re-run the above when leaving only parameters *allocated* to that capability trainable, and the rest are frozen. In addition, we replicate both full training and partial training in LoRA, where parameters are “frozen” if no adapter is added for that parameter.

4.2 Data Mixing (Same Training, Same Parameters)

As an additional baseline, we randomly mix the two datasets together and jointly optimize over the two disjoint tasks with all parameters left trainable.

4.3 Layer-Swapping (Separate Training, Same Parameters)

For this setting, we exactly recreate the method presented by [Bandarkar et al. \(2025a\)](#). Starting from the same base model, separate variants are trained on different tasks, dubbed “experts”. Concretely, one expert has been trained on the English math data, and the other on the target language instruction dataset. To recompose a single model, the top and bottom transformer layers from the target language expert replace those in the math expert, while the math experts’ middle layers remain. We additionally implement the equivalent of this methodology with LoRA, where the set of adapters is merged by combining the adapters corresponding to parameters that would be swapped. Note that we do not retrain these experts and simply use the checkpoints from our baseline trainings.

4.4 Layer-Swapping with Partial SFT (Separate Training, Separate Parameters)

We modify Layer-Swapping so that only the parameters involved in the model merging are trained, and all those eventually ignored are kept frozen during training. The idea for this is that no parameters are unnecessarily trained and we can incentivize the training to focus the learned capabilities into the desired parameters. Similar to above, we do not retrain experts and simply merge checkpoints from our frozen parameter baselines.

4.5 Simultaneous Partition SFT (Same Training, Separate Parameters)

We design a methodology to “simultaneously” fine-tune two partitions of LLM parameters on two different datasets. To do so, we apply a gradient step on a batch from one dataset on the corresponding partition of parameters. Then, we switch which parameters are frozen and sample a batch from

the other dataset for the next gradient step. This frequent back-and-forth is intended to ensure the coordination of parameter updates during multi-task optimization. The validation set contains an equal amount from each datasets.

Switching We default to a single step before switching to best simulate fully simultaneous training, but additionally experiment with more steps between. We set the effective batch size¹ to 64. At the end of each step, all parameters just updated are frozen for the next step and conversely, all frozen parameters are unfrozen. In addition, a flag for the data iterator is switched to ensure the next batch of data will be sampled from the appropriate dataset. For LoRA training, the same logic is implemented.

Optimizer We consider numerous approaches to adapt the AdamW optimizer ([Loshchilov and Hutter, 2019](#)) used in all previous experiments. Although we technically employ a single optimizer initialized on all parameters during training, we configure it to function as two independent optimizers, each exclusively managing its own separate subset of parameters. Namely, when a subset of parameters A is frozen, the corresponding AdamW optimizer states Ω_A (momentum and variance estimates) are also frozen in time. As a result, when the parameters in A are unfrozen, the corresponding momentum and variance estimates of Ω_A still reflect only the gradients steps previously applied to A . However, the other parameters A^c have been updated in the meantime, meaning Ω_A risks being outdated given the modified loss landscape. To test the impact of this inconsistency, we ablate over different numbers of steps between switches and find that the differences are very negligible (See Appendix A.3). We conclude that the optimizer restarting on an outdated loss landscape is of minimal concern, presumably because of the smoothness of the loss topology. Since there is a single optimizer, the learning rate schedule is the same for all (constant with warmup). And while the gradients tend to be larger for the multilingual data, we set a maximum gradient norm of 1.0 for clipping.

5 Results

Our experimental setting was designed to replicate a real-world scenario where multilingual LLM developers would take a post-trained LLM and are

¹Effective batch size is the product of the batch size per GPU, number of GPUs, and gradient accumulation steps.

Performance Comparison of Modular Solutions								
SFT Type	Base	Full	Simultaneous SFT		Layer-Swapping			
			Full	LoRA	Full SFT	LoRA	Part. SFT	Part. LoRA
Swahili	23.5%	25.1%	25.9%	25.2%	26.7%	25.8%	25.1%	24.8%
Bengali	25.6%	27.9%	27.9%	26.9%	28.7%	27.5%	27.0%	26.7%
Telugu	7.9%	8.2%	9.3%	9.0%	9.2%	9.2%	9.0%	8.6%
English	78.4%	80.4%	81.8%	80.5%	80.9%	80.8%	79.9%	80.0%
sw,bn,te AVG	19.0%	20.4%	21.0%	20.4%	21.5%	20.8%	20.4%	20.0%

Table 3: All values presented above are MGSM 2-shot EM accuracy (\uparrow), averaged across four models. The baseline presented for comparison in the 3rd column is the full SFT on the mix of the two datasets.

limited by the amount of in-language post-training data. This constrained scenario means only modest improvements are achievable. However, we do observe several conclusive patterns. Across our different four models and three languages (12 conditions), we can summarize into 6 *treatments* discussed in Sections 4.1 to 4.5. Despite the small magnitude of differences, the rank-based Friedman test (non-parametric) shows statistically significant differences between the *treatments* at the 0.05 significance level.

In our setting, we find that only training on the language dataset is more effective in improving the target language MGSM score than only on the math dataset (details in Appendix A.1). This implies, perhaps, that what our four models need most, is improved Swahili, Bengali, or Telugu abilities as opposed to math improvement.

We validate the lack of need for full-parameter training when doing both language adaptation and math SFT. Once the most useful parameters have been identified for such a skill, as discussed in Section 3.3, comparable performance to full SFT can be achieved with a fraction of the trainable parameters. Beyond potentially contributing to compositionality, this leads to faster and more memory-efficient training. More details on these baselines can be seen in Appendix A.1. We do note, however, that in the absence of resource limitations, SFT with less trainable parameters converged a bit slower and full fine-tuning still performed best. This is also true for LoRA, which has much less trainable parameters by nature.

A significant result is that all our modular solutions perform statistically-significantly better than the non-modular baselines, as can be seen in Table 1. This is strongly the case for Telugu and

Swahili in the displayed four-model averages, but varies more by specific modular method for Bengali in comparison to the top baseline (data mixing) (See Appendix A.5 for per-language results).

Within our modular solutions, however, we find numerous surprising results. First, freezing the unused parameters in training experts before Layer-Swapping does not improve upon full training. As detailed in the last four columns of Table 3, the difference in performance is better when all modules are being finetuned for both LoRA and full-parameter SFT (statistically significant). This is counter-intuitive because the layers eventually merged are potentially dependent on parameter changes that are being replaced. Second, Layer-Swapping surprisingly outperforms the simultaneous SFT. This is surprising because in our simultaneous SFT, the modularity is being imposed cohesively as opposed to the ad hoc merging of layers from separate training runs. We note, however, that the simultaneous SFT performs second-best.

To validate results further, we also evaluate more expensive Continual Pretraining (CPT) for QWEN2.5 in Bengali across the experimental designs and find agreement with our SFT results (See details in Appendix A.2, A.7). However, we limit discussion of these results because of the small scale of experimental results.

We additionally analyze the composability of individual experts under Layer-Swapping. We define a good merging indicator as an evaluation signal of *an expert* that correlates with the performance of the merged model. We find that performance on general NLU benchmarks—BELEBELE and GLOBAL MMLU—is a stronger indicator of a *language* expert’s merge quality than MGSM results in the target language. Similarly, MGSM

performance in English is a better predictor for a *math* expert than MGSM in the target language. This is notable because MGSM in the target language is the target task of course, yet results more directly related to the training data tends to be more important for proper task composition.

6 Discussion

Given the rejection of our hypothesis that simultaneous fine-tuning would most effectively compose task and language capabilities, we discuss potential explanations for this outcome.

Train-then-Revert vs. Freeze-then-Train Intuition may dictate that fine-tuning parameters and then later reverting part of them should be less effective than simply freezing those parameters from the start. In the former, the fine-tuning is unaware of future edits while the latter provides hard constraints during optimization. However, empirically, we find that across models, training-then-resetting outperforms freezing-then-resetting. We display this for our English math fine-tuning in Table 3.3. This explains why Layer-Swapping with full training (Section 4.3) may be preferential to solutions involving freezing parameters. We conclude that while a large portion of fine-tuning weight updates are not needed in the end, either because they are noisy or redundant (Yu et al., 2024b), they enable optimization in a very high-dimensional space. This is analogous to recent papers discussing the Lottery Ticket Hypothesis (Frankle and Carbin, 2019), where it has been concluded that training a full neural network and then pruning it leads to stronger models than the same pruning before training (Frankle et al., 2021).

Concatenating Components in Layer-Swapping

We seek to explain why concatenating transformer layers from separately fine-tuned “experts” is so seamless. Task vectors (Ilharco et al., 2023b) are the Δ s that result from fine-tuning (i.e., $\theta_{FT} - \theta_0$). Task vector *linearity* refers to the property that linear combinations of such task vectors form a coherent, effective model. Ortiz-Jimenez et al. (2023) identifies that linearized task vectors exhibit better mergeability. Meanwhile, when fine-tuning heavily post-trained models like those used in our experiments, recent works show that updates to individual model layers exhibit significant linearity (Zhou et al., 2024; Razzhigaev et al., 2024; Dai et al., 2025). Furthermore, research on mode connectivity

(Frankle et al., 2020; Garipov et al., 2018) shows individual transformer layers can be smoothly interpolated (Zhou et al., 2023; Adilova et al., 2024). These works provide explanation for why ad hoc Layer-Swapping is not more degradative.

Further Considerations We note that model merging is convenient because the configuration (e.g., what parameters to swap), can be determined after training. This enables fast iteration through configurations without retraining. This flexibility is sacrificed for our “separate parameters” methods, which require fixing parameter allocations. However, an inconvenience of merging methods is the need to train two experts, potentially doubling the amount of training runs for hyperparameter search.

7 Conclusions

Our results demonstrate that imposing modularity into dense LLMs for cross-lingual transfer is quite effective in low-data scenarios. We empirically validate this with numerous ways to impose such modularity through fine-tuning with frozen parameters or model merging, all of which prove more effective than non-modular baselines. Furthermore, we discover the surprising success of Layer-Swapping over other modular methods that fine-tune task and language together or do not ad hoc revert parameter updates. We conjecture that the success of this ad hoc merging method is because the math and language experts, when represented as task vectors, exhibit a high degree of linearity. As a result, this method benefits from more robust training over all parameters while also leading to effective compositionality. We also empirically demonstrate that the success of Layer-Swapping is in part due to frozen-parameter fine-tunings underperforming full fine-tunings followed by parameter resets.

8 Future Work

We encourage further work in multilingual NLP that leverages implicit modularity in LLMs, induces it during training, or designs explicitly modular architectures. Our parameter allocation strategy relied on previous interpretability work and limited empirical evidence, and the search space of modular configurations is largely unexplored. With post hoc model merging, iterating through many ablations can be quick. Although we focused on mathematical reasoning—due to limited multilingual task-specific datasets—future work should examine other tasks that may warrant different parameter

allocations. More broadly, these results underscore the importance of improving interpretability around how capabilities are parameterized in LLMs, such as multilinguality. If we can better localize and separate parameters by function, our findings suggest that modularization may yield significant improvements.

Limitations

Small Δ s Our decision to use the instruction fine-tuned version of each of the open-source LLMs for our experiments was a conscious one that came with many considerations. We prioritized replicating a real-life practical scenario, where model developers would start from already fine-tuned LLM versions because of their broader capabilities. However, as a result, this meant that our fine-tuning experiments only led to relatively small performance improvements with respect to the starting checkpoint. Such checkpoints have undergone extensive post-training, notably with significant mathematical reasoning samples and varying amounts of multilingual samples. Therefore, possible model improvements with these small datasets were small, risking results that were not statistically significant. Nevertheless, this allowed us to control for the amount of improvement on benchmarks that was simply a result of the LLMs’ improved ability to follow instructions after SFT, in addition to reflecting a more practical setting.

Acknowledgement

The authors acknowledge the support provided by Tanmay Parekh and Mohsen Fayyaz for this project.

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A Appendix

A.1 Detailed Baseline Results

Detailed Performance of Non-Modular Baselines									
SFT Dataset SFT Type	None Base	Data-Mixing		Math-Only			Language-Only		
		Full	LoRA	Full	LoRA	Part. FT	Full	LoRA	Part. FT
Swahili	23.5%	25.1%	24.8%	25.2%	24.4%	25.0%	24.8%	23.8%	24.3%
Bengali	25.6%	27.9%	26.0%	26.1%	24.8%	25.6%	28.3%	26.6%	26.9%
Telugu	7.9%	8.2%	8.4%	7.4%	7.4%	8.0%	7.9%	8.6%	8.2%
English	78.4%	80.4%	80.0%	81.3%	81.0%	80.6%	79.9%	78.8%	79.0%
sw,bn,te AVG	19.0%	20.4%	19.7%	19.6%	18.9%	19.5%	20.3%	19.7%	19.8%

Table 4: All values presented above are MGSM 2-shot EM accuracy (\uparrow), averaged across four models. Generally, we find that data mixing is the most effective, but with very small difference in comparison to language-only SFT. We exclude Partial LoRA results for space considerations, but report here that the results were for all numbers, 0-1% lower than LoRA results.

A.2 CPT Results for QWEN2.5 in Bengali

Detailed Performance of CPT Experiments									
SFT Dataset SFT Type	None Base	Mix Full	Math-Only		Lang-Only		Simult. Part.FT	Layer-Swapping	
			Full	Part.FT	Full	Part.FT		Full	Part.FT
Bengali	37.6%	38.2%	33.2%	34.2%	37.6%	37.8%	38.8%	39.4%	38.8%
English	76.8%	77.6%	80.0%	79.8%	74.0%	73.8%	80.2%	79.2%	79.6%

Table 5: All values presented above are MGSM 2-shot EM accuracy (\uparrow), averaged across two runs. We find that our main results from SFT mostly stand, but limit our conclusions as the small number of runs prevent the findings from being statistically significant. We note that CPT trainings more substantially degrade performance in the *opposite* capability than SFT. "Mix" is "Data-Mixing" and "Simult." is "Simultaneous FT", shortened for space.

A.3 Number of Gradient Steps Between Switches

Table 6: Ablation over the number of gradient steps to do on a single dataset and single partition of model parameters before switching back to the other data and parameters. All runs were controlled to have the same exact hyperparameter settings on QWEN2.5 7B Instruct with the target language Swahili. Four upper layers and eight lower layers were allocated for the target language, and a learning rate $1.2e^{-06}$

Gradient Steps per Switch	Starting Validation Loss	Ending Validation Loss	Δ for MGSM, Swahili
1	2.301	1.605	+3.2%
5	2.301	1.612	+2.4%
10	2.301	1.613	+2.8%
50	2.301	1.613	+2.0%
200	2.301	1.602	+0.8%
500	2.301	1.565	+1.2%
1171	2.301	1.536	-1.2%

These results indicate no negligible differences between the tested step counts. This implies the concern discussed in Section 4.5 of the optimizer unfreezing with an outdated loss landscape is minimal. Or at least, it implies that the ability to do numerous steps without interruption in the same setting outweighs this concern. And while increasing the gradient steps per switch does provide no negligible difference on the validation loss, intuitively it leads to a training paradigm farther from a truly simultaneous training. We find that on the target task, MGSM in Swahili, performance goes down progressively as the gradient steps per switch is increased. This implies the composition of math and Swahili capabilities are working less effectively.

A.4 Details for Reproducibility

For reproducibility, we detail our implementation and hyperparameters for training. The datasets themselves are outlined in Sections A.6 and A.7.

- Training is run on a single cluster of A100s, typically with only one GPU per training run.
- Training methods are developed using the trl python package (von Werra et al., 2020) and models accessed via HuggingFace.
- Learning rate ranged across training runs, but was typically in the range $[1.0, 2.0] \times 10^{-6}$.
- For LoRA, it ranged from $[4.0, 9.0] \times 10^{-6}$. Rank and Alpha parameters were either (64, 16) or (32, 8).
- Sequence length was either 512 or 1024. Effective batch size was typically 32, except for effective batch size of 64 for simultaneous training, as described in Section 4.5.
- Evaluation is performed using the Language Model Evaluation Harness (Gao et al., 2024).

A.5 Bar Graph of Per-Language Results

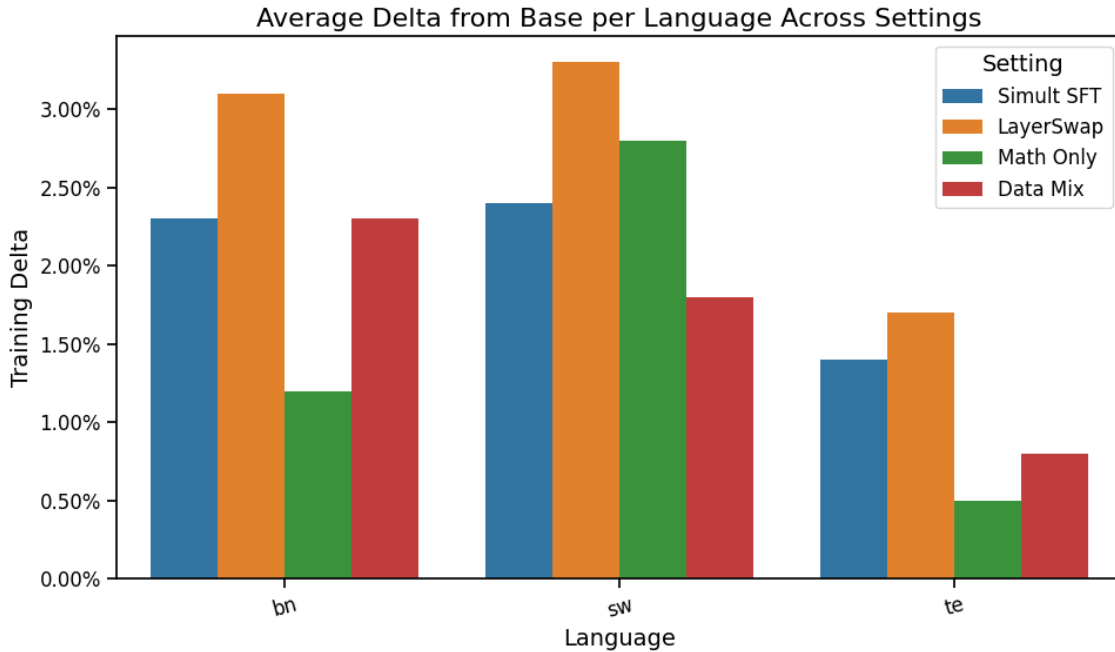


Figure 2: Per-language breakdown of the average performance gain seen during our different types of training, averaged across four models. We see that while math-only SFT (green) does well for Swahili and mixed-data SFT (red) does well for Bengali, our two modular solutions work consistently well across the three languages. Note: the y-axis is a percentage because the evaluation score is accuracy, *not* because this table displays percent change.

A.6 SFT Datasets

Table 7: Datasets used for supervised-fine-tuning (SFT) in this project

Category	Datasets	URL
Math	Orca Math word problems dataset from Microsoft (Mitra et al., 2024)	https://huggingface.co/datasets/microsoft/orca-math-word-problems-200k
Telugu	Aya Dataset from Cohere for AI (Singh et al., 2024)	https://huggingface.co/datasets/CohereForAI/aya_dataset
	NLLB English-Telugu translation data from FAIR (NLLB et al., 2022)	https://huggingface.co/datasets/allenai/nllb
	Synthetic English instruction dataset, machine translated to Telugu by Telugu-LLM-Labs	https://huggingface.co/collections/Telugu-LLM-Labs/indic-alpaca-datasets-65f2a3687d5cdbce8880c581
Bengali	Aya Dataset by Cohere for AI (Singh et al., 2024)	https://huggingface.co/datasets/CohereForAI/aya_dataset
	NLLB English-Bengali translation data from FAIR (NLLB et al., 2022)	https://huggingface.co/datasets/allenai/nllb
	IndicShareLlama dataset from AI4Bharat (Khan et al., 2024)	https://huggingface.co/datasets/ai4bharat/indic-align
	BongChat dataset from Lumatic AI	https://huggingface.co/datasets/lumatic-ai/BongChat-v1-253k
Swahili	Aya Dataset by Cohere for AI (Singh et al., 2024)	https://huggingface.co/datasets/CohereForAI/aya_dataset
	NLLB English-Swahili translation data from FAIR (NLLB et al., 2022)	https://huggingface.co/datasets/allenai/nllb
	Inkuba dataset from Lelapa (Tonja et al., 2024)	https://huggingface.co/datasets/lelapa/Inkuba-instruct
	xP3 MT dataset from BigScience, with FLORES samples removed (Muenighoff et al., 2023)	https://huggingface.co/datasets/bigscience/xP3mt

All datasets listed above were verified to be used in compliance with their respective licenses. Each dataset was properly attributed according to its license requirements.

A.7 CPT Datasets

Table 8: Datasets used for continual pretraining (CPT) in this project

Category	Datasets	URL
Math	Open Web mathematical texts collected by the University of Toronto and Cambridge (Paster et al., 2024)	https://huggingface.co/datasets/open-web-math/open-web-math
Bengali	The ROOTS corpus subset of Bengali Wikipedia from BigScience (Laurençon et al., 2022)	https://huggingface.co/datasets/bigscience-data/roots_indic-bn_wikisource

All datasets listed above were verified to be used in compliance with their respective licenses. Each dataset was properly attributed according to its license requirements.

A.8 Off-the-shelf Model Results

To motivate the use of our four models and the three target languages, we provide preliminary results of these models prior to any fine-tuning.

Model	Size	MGSM				BELEBELE			
		EN	SW	BN	TE	EN	SW	BN	TE
LLAMA 3.1	8B	79.6%	52.0%	32.8%	11.2%	88.6%	56.1%	59.3%	53.6%
QWEN2.5	7B	76.8%	12.8%	37.6%	13.6%	91.1%	37.2%	64.7%	41.3%
AYA Expanse	8B	78.8%	10.8%	21.6%	3.2%	81.6%	32.3%	42.3%	29.9%
FALCON 3	7B	78.4%	14.4%	10.4%	3.6%	85.9%	36.3%	34.8%	30.1%

Table 9: The results on the MGSM (2-shot, EM accuracy (\uparrow)) and BELEBELE (0-shot accuracy (\uparrow)) benchmarks for the four models used in our experiments. We note that for all models, we use the instruction-finetuned version.

Reassessing Speech Translation for Low-Resource Languages: Do LLMs Redefine the State-of-the-Art Against Cascaded Models?

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Abstract

Automatic speech translation (AST) promotes seamless communication among speakers of different languages. While current state-of-the-art models excel with high-resource languages, their performance on low-resource languages (LRLs) is not well-established. We investigate this by evaluating state-of-the-art models on 10 LRLs with varying data amounts (10-30+ hours). Through six finetuning strategies and experimenting with three main AST paradigms, we observe that: (1) The latest Large Language Models (LLMs) may struggle with LRLs. (2) Comprehensive experiments suggest that for LRLs, more AST finetuning data is not always beneficial. (3) Our 2-Stage with ASR corrector finetuning recipe can substantially improve AST performance on LRLs, achieving up to a 5.8x BLEU score boost on translating related languages to English, while on par with the best monolingual finetuning in BLEU score when translating the target language to English. (4) We share our effective engineering practices, including how to effectively adapt AST models to unseen languages.

1 Introduction

Automatic speech translation directly converts speech from a source language into text or speech in a target language. The field has recently advanced at a rapid pace, driven by new paradigms like large-scale pre-training (Babu et al., 2021; Baevski et al., 2020; Conneau et al., 2020), large speech models, *e.g.* SeamlessM4T (Communication et al., 2023); Large Language Models (LLMs), *e.g.* ChatGPT (OpenAI, 2023); and speech-native audio LLMs, *e.g.* GPT-4o AUDIO (OpenAI, 2024), Gemini 2.0 Flash (Google, 2025), etc. Despite these progresses, many AST research centered on high-resource languages like English, French, German (Di Gangi et al., 2019; Bahar et al.,

2019). Therefore, a most recent investigation of the novel modeling paradigms for the low-resource languages (LRLs) for AST is needed. AST for LRLs is constrained by scarce training data. Recent multilingual speech corpora like MuST-C (Di Gangi et al., 2019), CoVoST 2 (Wang et al., 2021), and FLEURS (Conneau et al., 2023) enable novel AST paradigms for these languages.

AST modeling paradigms fall into three categories: (1) **cascaded approaches** that apply automatic speech recognition (ASR) followed by machine translation (MT), (2) **multimodal MT approaches** like SeamlessM4T (Communication et al., 2023) that directly translate speech to text, and (3) multimodal **large language models** such as Gemini 2.0 Flash, which natively process text, speech and images, can perform direct speech-to-text translation (S2TT). Even for other LLMs which do not natively support audio input, mapping audio tokens to the token vocabulary (Wang et al., 2023; Ambilduke et al., 2025) can leverage MT capabilities, such as models like SALMONN (Tang et al., 2024), Qwen 2 Audio (Chu et al., 2024) and SPIRE (Ambilduke et al., 2025).

We investigate which approach works best for LRLs with small amounts of finetuning data. Specifically, *is the cascaded architecture superior with small data when compared to multimodal MT approaches like SeamlessM4T and Audio LLMs?* We experiment with ten LRLs from FLEURS (five Indic, five African) translating to English, choosing a translation direction $X \rightarrow \text{English}$ so that the multilingual capabilities of each method can be better assessed. We then compare performances across different AST paradigms against a high-resource language pair, *i.e.* $\text{French} \rightarrow \text{English}$.

For cascaded approach, we proposed various finetuning strategies for all the three main modeling paradigms of AST. Through comprehensive

experiments across 11 languages, we show that the best AST approach depends on the resource-level of the languages: For languages with slightly better data availability, such as all five Indic languages and Swahili, prompting Gemini-2.0 Flash LLM works best. While for extremely low-resource languages, such as Hausa and Yorùbá, finetuning from large MT models or sequentially finetuning ASR and MT models can be more effective. To summarize, our contributions include:

- A comprehensive evaluation of AST for low-resource languages, establishing a **generalizable and highly effective blueprint**, comparing three modeling paradigms across 11 languages with various finetuning recipes.
- A simple yet effective "2-stage with ASR correction" strategy, that reduces WER by **54.2% relative on average** for African languages and yields a **5.8 times** increase in BLEU and a **2.6 times** increase in BLEU for African and Indic language groups, respectively, without additional data or model architectural changes.
- Our best recipe performs well on the target language while preserving **balanced AST performance** across languages, avoiding over-optimization for a single language. This offers practical guidelines for adapting multilingual AST models.
- Through comprehensive experiments, we share the finding that for low-resource languages, more AST finetuning is **not always beneficial**, providing a nuanced perspective on common practices.

We ensure **full reproducibility** by using only publicly available data and APIs, and open-sourcing our code and recipes.¹

2 Related Work

The central challenge in AST is data scarcity (Xu et al., 2023) of high-quality paired (source speech, target text) data. Conventional AST thus uses cascaded approaches (Matusov, 2005) that first transcribe speech via ASR, then translate using MT. When it comes to the LRLs, the challenge of data scarcity is more severe. Multiple efforts address this challenge. Corpora like FLEURS and Common Voice (Ardila et al., 2019) enable

AST for LRLs, while NaijaVoices (Emezue et al., 2025) and BhasaAnuvaad (Jain et al., 2024) contribute data for African and Indian languages, respectively, although wide gaps persist compared to high-resource languages.

Recent speech foundation models like Wav2Vec2 (Baevski et al., 2020) and multimodal LLMs (Google, 2025) have transformed AST: Bansal et al. (2018) and Stoian et al. (2020) demonstrated the benefit of pre-training AST models on high-resource ASR data to improve performance for low-resource language pairs.

Popular parameter-efficient finetuning methods such as LoRA (Hu et al., 2021; Liang et al., 2025), lightweight adapter (Le et al., 2021), always require changing the model architecture. In contrast to these studies, our research concentrates on the curriculum design of finetuning, to uncover hidden factors within simple full finetuning methods.

Kocmi et al. (2024) concluded that despite the rise of LLMs, AST still requires significant improvement, particularly in low-resource scenarios.

Multimodal benchmarks like SUPERB (Yang et al., 2021) cover many speech tasks but exclude AST, while mSTEB (Beyene et al., 2025) analyzes AST only at the language-family level. OWLS (Chen et al., 2025) demonstrates scaling benefits for low-resource performance, which our Whisper findings echo. We focus on broadly effective finetuning recipes and provide detailed analysis for low-resource African and Indic languages, underexplored in prior surveys.

Multilingual finetuning on models like Whisper (ASR) and SeamlessM4T (Communication et al., 2023) (AST) often degrades non-target languages, especially with monolingual finetuning. We propose an effective 2-stage finetuning curriculum that reduces this shift without architectural changes, much simpler than multi-stage methods proposed in Thillainathan et al. (2025). We also apply LLM correction to ASR components, previously used mainly in ASR systems (Ruder et al., 2023; Ma et al., 2025).

Trade-offs between cascaded and end-to-end systems remain debated, with methods lacking systematic evaluation across diverse LRLs. Our work aims to complement these efforts by providing a unified, cross-paradigm evaluation across LRLs, comparing data efficiency and generalization across cascaded, multimodal MT, and audio-LLM systems.

¹<https://github.com/McGill-NLP/ast-lrl-speech>

3 Experimental Setup

3.1 Model Selection and Baselines

3.1.1 Cascaded approach

We employ OpenAI’s WHISPER LARGE V3 1.5B given its robust zero-shot performance across 98 non-English languages from 680 K hours of weakly supervised ASR data and 125 K hours of speech-to-English translation pairs (Radford et al., 2022). For MT, we integrate Meta’s NLLB-200 1.3B, trained on hundreds of billions of tokens spanning 200 languages (NLLB-Team, 2022). This setup strikes a balance between translation quality and computational efficiency. We evaluate WHISPER LARGE V3 on FLEURS test of 11 target languages to serve as a cascaded-approach baseline.

3.1.2 Multimodal machine translation

We evaluate Meta’s SEAMLESSM4T LARGE 1.6B, pretrained on 4.1 M hours of speech and text data over 100 languages. It enables direct speech-to-text and speech-to-speech translation without separate ASR/MT modules (Communication et al., 2023), serving as our end-to-end baseline.

3.1.3 Audio LLMs

We benchmark two SOTA audio LLMs: OpenAI’s GPT-4o AUDIO (GPT-4o backbone with audio pretraining), and Google’s GEMINI 2.0 FLASH, a multimodal model that supports text and audio. Both reflect SOTA AST via their incorporation of leading-edge modeling and web-scale training data.

3.2 Data

Training and Evaluation data: We used the FLEURS dataset for the initial training data. FLEURS contains n-way parallel speech and text in 102 typologically and geographically diverse languages drawn from the FLoRes-101 benchmark (Goyal et al., 2021), with approximately 12 hours of high-quality, human-read speech per language. Since 80% of these are low-resource languages, FLEURS is well-suited for evaluating AST paradigms in such settings.

Data for ablation: For our ablation studies on African languages, we added 20 hours of validated speech from Mozilla Common Voice² (Swahili and Luganda) and the Naija Voice corpus (Lee et al., 2022) (Igbo, Hausa, and Yorùbá). Common Voice

²https://huggingface.co/datasets/mozilla-foundation/common_voice_17_0

Model	Parameters	Used Capabilities	Unsupported Lang.
Whisper Large v3	1.5 B	ASR	Igbo, Luganda
NLLB-200 Large	1.3 B	MT	None
SeamlessM4T Large	1.6 B	Multimodal MT AST	Hausa
mT5-Base	580M	ASR correction (T2T)	Luganda
GPT-4o Audio	Unknown	End-to-End AST	Unknown
Gemini 2.0 Flash	Unknown	End-to-End AST	Unknown

Table 1: Model Information. Please refer to Section 3.1 for details.

lacked sufficient validated data³ for the Nigerian languages, whereas Naija Voice offers over 600 hours per language.

3.3 Model finetuning Strategies

We detail our finetuning recipes for adapting the ASR model of the *cascaded approach* and for the general finetuning of multimodal MT.

3.3.1 ASR model finetuning

We *finetuned* on the FLEURS training data of each of 11 spoken languages for 10 epochs by updating all the parameters. To ensure consistent evaluation across all methods, the best model was selected after 10 epochs without using a validation set. We also note that as Igbo and Luganda are not included in Whisper’s original language inventory, Whisper will reject any training examples tagged with an out-of-vocabulary language code. Therefore, we override the language identifier during finetuning by mapping languages to their closest relatives in the supported set based on phonology and lexical similarity. For instance, we map Igbo to Lingala and Luganda to Shona. Similar approach to fine-tune machine translation models for unseen languages has been mentioned in (Yang et al., 2021). We describe the different finetuning recipes below (all parameters were updated if not specified).

- **Monolingual finetuning** (“**Monolingual**” or “**S2**”): we independently finetuned ten separate WHISPER LARGE V3, where finetuning uses the entire FLEURS training data of the target language. The preprocessing pipeline and training hyperparameters are the same as the multilingual experiments.
- **Multilingual finetuning** (**S3**): we group our ten target languages into two regionally and typologically coherent subsets: “Indic” (Hindi, Punjabi, Tamil, Telugu, Malayalam), and

³Common Voice is volunteer-based, with recordings requiring validation for quality.

“African” (Swahili, Hausa, Yorùbá, Igbo, Luganda), We then finetuned two WHISPER LARGE V3 models on the combined data of all languages from each group, motivated by potential cross-language transfer (Conneau et al., 2020): *e.g.* African languages using a shared Latin script, while Indic languages use distinct writing systems but are similar in phonology.

- 2-stage FT (Multilingual + Monolingual, **S4**): to capture both cross-lingual transfer and language-specific specialization, we first conduct a multilingual finetuning with group data for 10 epochs, then continue finetuning on the target language only for 10 more epochs.
- ASR corrector (**S5** and **S6**): to explore how much text-only correction can reduce recognition errors beyond speech finetuning, we adopt the ASR correction strategy from XTREME-UP (Ruder et al., 2023), applying it to the optimal models finetuned by above recipes. We finetuned mT5-base (Xue et al., 2021) a Text-to-Text model for 20 epochs with earlystopping on ASR (finetuned WHISPER LARGE V3 **S3**) prediction-reference pairs from the FLEURS training set. This approach ensures no data leakage, as we leverage the same training data used in speech finetuning. Full training details are in Appendix A.

Once ASR transcribed input speech into text of source language, we used NLLB (NLLB-Team, 2022), an open-sourced large-scale machine translation model to translate text to the target language.

3.3.2 General MT finetuning

We finetuned SEAMLESSM4T LARGE model, which supports speech inputs, on Indic and African language groups separately, by updating all the parameters over 10 epochs. This method is a fully end-to-end approach of AST.

3.4 Evaluation metrics

We use BLEU to evaluate final performances of all machine translation systems. For cascaded systems, we also report ASR Word Error Rate (WER)⁴.

4 Results & Analysis

4.1 ASR Performance

Table 2 presents an overview of ASR baseline created by WHISPER LARGE V3, with the finetuning recipes described in Section 3.3.1. We observed:

Monolingual finetuning is most efficient while 2-Stage better maintains generalization. Given the same finetuning amounts of speech data, solely finetuning on target languages significantly reduced average baseline WER from 88.39% to 45.90%. Multilingual finetuning (S3) also significantly reduced WER for the single target languages, though slightly worse than the monolingual ones. Interestingly, continuing finetuning from the multilingual model (S3) on individual target languages, without using any additional data, S4 not only recovered the performance on each language but also resulted in slightly better performance than monolingual finetuning (S2). This might be because the design of the 2-stage FT (S4) recipe allows the model to better learn from the common acoustic-phonetic and lexical properties shared by related languages.

Multilingual + Monolingual + Corrector is most effective. The system consistently performed best in 9 of the 10 low-resource languages. The strategy did not introduce any additional speech data, but leverage reference transcripts in a more effective way. Specifically, the corrector models learned from paired (ASR transcript, reference transcript) training data, leading to an average 15.2% relative reduction in WER compared to the Multilingual (S3) baseline and a significant 54.2% reduction relative to the initial Baseline (S1) models, all without increasing the footprint of the multilingual finetuned ASR models.

Zero-shot evaluation might be enough for ASR of high-resource languages. We selected French, a high-resource language, to evaluate the off-the-shelf models’ performance and to understand the performance gap when compared against their performance on the low-resource languages we focus on in this paper. As shown in Table 2, by directly evaluating WHISPER LARGE V3 on French test data, the WER already achieved 12.73%; however, the simplest monolingual finetuning nearly doubled French WER to 24.72%. We hypothesize that, for languages with abundant data and well-optimized pre-training representations, aggressive monolingual adaptation can induce overfitting

⁴Adopted the implementation of <https://huggingface.co/spaces/evaluate-metric/wer>.

Language	Whisper ASR Baseline and Models finetuned from IT						$\Delta_{(S1,S6)}$ $\Delta_{(S3,S6)}$		FLEURS Training Hours
	Baseline (S1)	Mono. (S2)	Multi. (S3)	Multi. + Mono. (S4)	Multi. + ASR Corrector (S5)	S4 + ASR Corrector (S6)			
<i>French</i>	12.73%	24.72%	x	x	x	x	x	x	10.3
<i>Hindi</i>	46.67%	24.06%	25.00%	23.85%	23.12%	21.63%	-53.6%	-13.4%	6.6
<i>Punjabi</i>	84.46%	33.66%	33.91%	32.68%	40.70%	43.08%	-48.9%	+27.0%	6.3
<i>Tamil</i>	59.96%	45.33%	46.25%	44.40%	40.54%	38.58%	-35.6%	-16.5%	8.6
<i>Telugu</i>	78.12%	45.75%	46.03%	44.38%	39.46%	37.63%	-51.8%	-18.2%	7.9
<i>Malayalam</i>	138.91%	44.87%	46.20%	44.02%	43.45%	39.81%	-71.3%	-13.8%	10.0
<i>Swahili</i>	42.88%	33.11%	35.04%	33.26%	24.86%	22.85%	-46.7%	-34.8%	13.4
<i>Hausa</i>	112.78%	42.58%	49.27%	43.78%	40.07%	34.47%	-69.4%	-30.0%	13.6
<i>Yorùbá</i>	105.70%	68.67%	68.69%	66.36%	64.93%	61.92%	-41.4%	-9.8%	10.0
<i>Igbo</i>	106.56%*	59.26%	61.84%	56.98%	54.66%	50.93%	-52.2%	-17.6%	13.8
<i>Luganda</i>	107.90%*	61.68%	47.72%	60.46%	54.16%	53.26%	-50.6%	+11.6%	12.6
Average	88.39%	45.90%	47.72%	45.02%	42.59%	40.45%	-54.2%	-15.2%	10.3

^a Starred (*) WERs indicate that the target languages were unseen by the model. **Bolded WERs** indicate the best score across different finetuning strategies and baseline.

Table 2: Overview of **WER**(↓) for Whisper Large ASR models using different finetuning strategies (denoted as S2 – S6). We show $\Delta_{(S1,S6)}$, the relative changes obtained by S6 using S1 as baseline. Similar notation for $\Delta_{(S3,S6)}$. please refer to **Section 3.3.1** for definitions of finetuning strategies, and **Section 4.1** for detailed analysis.

or catastrophic forgetting of general acoustic patterns. When comparing the output transcripts from both models, we observed peculiar word hallucinations in the monolingual model (*e.g.* “Dans le climat chaud” was transcribed as “Dans le chuma-cho”). These phonetic hallucinations were similar to those seen in other languages, but unlike those instances, they were exacerbated rather than mitigated by monolingual finetuning. Such regression suggests more thoughts in the finetuning design to preserve the learned syntax while adapting large speech model to the target data domain.

Similar language serves as a good proxy when adapting to an unseen language. A key challenge in finetuning the Whisper ASR model for Igbo and Luganda was that they are not among the 98 languages Whisper supports. We notice that both the two *unseen* languages use Latin writing system, so we hypothesized that a similar language label could serve as a proxy. Specifically, we selected Lingala and Shona as the proxy language label for Igbo and Luganda respectively, considering their phonetic and regional similarities. Experimental results prove the method’s effectiveness, with relative improvements of up to 52.2% for Igbo and 50.6% for Luganda achieved by the best finetuning recipe. This success suggests a strong potential to expand Whisper’s coverage to 20+ additional low-resource languages beyond its current 98 non-English ones, with careful selection of proxy language: To verify the effect of proxy choices, we also conducted a comparative experiment by labeling Igbo as French: while both use Latin alphabet, they differ phonetically. The dramatic increase in WER indicates the importance of a proper proxy language.

4.2 Translation Quality

All three AST modeling paradigms, cascaded ASR+MT (with various finetuned ASR models), multimodal SeamlessM4T, and audio-centric LLMs (GPT-4o Audio and Gemini 2.0 Flash), have been evaluated in terms of BLEU in Table 4.

Gemini works best for Indic speech translation. For the five Indic languages (Hindi, Punjabi, Tamil, Telugu, Malayalam) and Swahili, Gemini 2.0 Flash achieves the highest BLEU in every case (*e.g.* 35.38 on Hindi, 30.78 on Telugu, and 31.91 on Swahili), outperforming both GPT-4o Audio and all cascaded or multimodal MT baselines.

Cascaded ASR+MT models and expert MT models seem more effective to finetune for under-represented languages. For lower-resource African languages (Hausa, Yorùbá, Igbo, Luganda), the best results are obtained by finetuned Whisper variants + NLLB and SeamlessM4T, rather than audio LLMs: Whisper Multi. + Mono. + ASR Corrector reaches 13.93 on Igbo and 20.05 on Hausa, and SeamlessM4T Multilingual peaks at 18.92 on Luganda – each exceeding Gemini 2.0 Flash’s corresponding 2.19, 16.29, and 11.93. When averaging across all languages except French, the cascaded Whisper Monolingual (21.26), Whisper Multilingual + ASR Corrector (21.82), and SeamlessM4T Multilingual (21.28) nearly match Gemini 2.0 Flash’s 22.09, while Whisper Multilingual + Monolingual + ASR Corrector (*i.e.* T6), actually outperforms Gemini with 22.24 BLEU, indicating targeted finetuning on low-resource corpora can rival SOTA audio LLMs in AST performance.

Zero-shot evaluation might be enough for the translation of high-resource languages. As stated

Source Language X	Monolingual		Multilingual + Monolingual		Monolingual		Multilingual + Monolingual	
	WER(X)	Average WER(Others)	WER(X)	Average WER(Others)	BLEU(X)	Average BLEU(Others)	BLEU(X)	Average BLEU(Others)
Hindi	24.06%	56.07%	23.85%	22.76%	31.18	14.81	30.90	23.86
Punjabi	33.66%	80.50%	32.68%	34.22%	26.59	3.42	26.68	19.50
Tamil	45.33%	74.32%	44.40%	40.25%	22.65	4.69	22.78	16.85
Telugu	45.75%	87.83%	44.38%	43.70%	25.12	2.96	25.15	18.32
Malayalam	44.87%	98.13%	44.02%	41.39%	27.07	1.77	27.68	20.66
Indic Group	38.73%	79.37%	37.87% (-2%)	36.46% (-54%)	26.52	5.53	26.64 (+0.5%)	19.84 (+259%)
Swahili	33.11%	76.52%	33.26%	30.33%	27.55	4.58	27.70	20.80
Hausa	42.58%	87.31%	43.78%	44.74%	18.45	0.61	18.34	12.22
Yorùbá	68.67%	80.75%	66.36%	62.80%	11.14	0.88	11.04	6.53
Igbo	59.26%	83.92%	56.98%	56.30%	11.46	1.03	11.60	7.05
Luganda	61.68%	117.59%	60.46%	53.78%	11.36	1.05	11.56	8.69
African Group	53.06%	89.22%	52.17% (-2%)	49.59% (-44%)	15.99	1.63	16.05 (+0.4%)	11.06 (+579%)

Table 3: A comparison of Monolingual and Multilingual+Monolingual models. The table displays **WER** (\downarrow) and **BLEU** scores (\uparrow) for various Indic and African languages. Highlighted cells show the performance for the grouped languages. “Others” refers to the other languages in the same group except target language X.

Language	ASR (Whisper) + MT (NLLB)						Multimodal Speech Translation		Audio LLMs	
	Cascaded Baseline (T1)	Cascaded Mono. (T2)	Cascaded Multi. (T3)	Cascaded Multi. + Mono. (T4)	Cascaded Multi. + ASR Corrector (T5)	T4 + ASR Corrector (T6)	SeamlessM4T Baseline	SeamlessM4T Multi.	GPT-4o audio	Gemini 2.0 Flash
<i>French</i>	38.30	31.49	x	x	x	x	33.77	x	37.49	36.16
<i>Hindi</i>	27.79	31.18	30.85	30.90	31.08	31.48	24.62	28.71	29.28	35.38
<i>Punjabi</i>	13.87	26.59	26.65	26.68	25.38	24.62	28.71	28.10	19.15	29.58
<i>Tamil</i>	19.53	22.65	22.48	22.78	23.10	23.43	19.93	21.87	15.17	25.14
<i>Telugu</i>	17.51	25.12	25.26	25.15	27.37	27.53	23.27	24.93	19.83	30.78
<i>Malayalam</i>	1.32	27.07	27.05	27.68	27.79	28.45	21.20	25.95	23.55	30.31
<i>Swahili</i>	25.01	27.55	27.18	27.70	28.40	28.38	14.81	31.22	19.37	31.91
<i>Hausa</i>	3.36	18.45	15.90	18.34	18.04	20.05	1.01*	6.07	1.07	16.29
<i>Yorùbá</i>	2.62	11.14	10.66	11.04	10.62	11.18	12.64	15.36	2.31	7.35
<i>Igbo</i>	1.80*	11.46	9.86	11.60	13.23	13.93	0.19	11.65	1.63	2.19
<i>Luganda</i>	4.07*	11.36	11.34	11.56	13.14	13.35	5.95	18.92	4.95	11.93
Average	11.69	21.26	20.72	21.34	21.82	22.24	15.23	21.28	13.63	22.09

* Starred (*) BLEUs indicate that the target languages were unseen by the model. **Bolded BLEUs** indicate the best score across different finetuning strategies and baseline.

Table 4: Overview of **BLEU** scores (\uparrow) achieved by SOTA models with different finetuning strategies. please refer to **Section 3.3** for definitions of finetuning strategies, and **Section 4.1** for detailed analysis.

before, French is an exception: the Whisper-Large-v3 baseline attains the highest BLEU of 38.30, surpassing GPT-4o Audio (37.49) and Gemini 2.0 Flash (36.16). This underscores the robustness of Whisper’s original capacity on high-resource languages – further finetuning may introduce degradation in such well-represented language settings.

4.3 Generalization vs. Specialization

A typical challenge for finetuned multilingual models is balancing **specialization** and **generalization**. While finetuning solely on a target language might yield the lowest ASR WER and the highest BLEU score for that language, severe performance degradation in other languages must be avoided. This consideration is also critical for practical applications. When serving a speech translation model for Hindi to English, users in the same region might not always speak Hindi but may use other local languages such as Punjabi. Even predominantly Hindi speakers might code-switch between Hindi and other local languages – this is a signif-

icant concern in the engineering and application of speech translation models. Therefore, we measured the ASR and MT performances not only on target languages but also on their average performance across other languages within the same geographical region (dubbed “Average Other”). As shown in Table 3, for monolingual finetuned ASR models, even if their WER for a single target language is slightly lower than that of multilingual + monolingual finetuned models (e.g. 23.85% WER *vs.* 24.06% WER on Hindi, obtained by the two finetuned models, respectively), the monolingual model clearly shifts too heavily toward Hindi. This specialization causes finetuned model to fail to perform well on other Indic languages, as indicated by the 56.07% average WER on other languages. In contrast, the first stage of multilingual finetuning allows the final finetuned models to maintain their performance on the other Indic languages, with a 22.76% average WER, which is a **59%** relative improvement over their monolingual finetuned counterparts. We found similar patterns in terms

of BLEU scores among the MT models. The necessity of a two-stage finetuning approach is thus highlighted by two significant benefits: it maintains ASR and MT performance on related languages and offers potential gains from sharing common cross-lingual features.

4.4 Effect of finetuning Data Volume

Acquiring finetuning speech data for extremely LRLs is highly challenging. Therefore, we conducted an ablation study to investigate the minimum hours of speech required to develop a speech translation model with acceptable performance. We use all five African languages as examples, and present ablation studies in terms of both WER and BLEU, across different finetuning data amount: 0, 1, 2.5, 5, 10, and 20 hours per language, in Figure 1 and 2 for ASR and MT component of cascaded system respectively.

Zero-shot evaluation is a better choice when finetuning data is too limited. While the initial one hour of fine-tuning on Common Voice or Naija Voice indeed yields a marked degradation in ASR quality and downstream translation – evidenced by WER jumps (Hausa 42.5 % \rightarrow 54.4%, Yorùbá 68.6% \rightarrow 70.5%) and BLEU drops (Hausa 18.45 \rightarrow 16.87, Yorùbá 11.14 \rightarrow 10.26) – subsequent training yields recovery and improvement: at 2.5 h, WER for all five languages recedes toward or below baseline (Igbo 59.2% \rightarrow 55.7%) and BLEU surpasses the baseline model (Igbo 11.46 \rightarrow 12.38).

Gains are most pronounced between 2.5 – 5 h, as BLEU increases by up to +1.30 points (Yorùbá 11.14 \rightarrow 12.44), while WER reduces by up to -8.4% (Hausa 54.4% \rightarrow 46.0%). Between 5–10 h, improvements continue but at a reduced rate (e.g. Swahili BLEU plateaus at 28.20, Luganda WER only marginally improves from 59.5% to 59.0%), indicating that the model rapidly ingests new acoustic-textual patterns within the first 10 h. Beyond 10 h, additional data yields diminishing, or even slightly negative returns (Hausa BLEU 19.13 \rightarrow 19.01; Luganda BLEU 12.42 \rightarrow 12.13), suggesting an inflection point where the domain shift of the supplemental corpus begins to outweigh its benefit. Nonetheless, we observe that on average, the addition of new unseen data to the monolingual model matches best scores shown in Tables 2 and 4.

Especially for the ablation on MT, results showed a “U-shaped” curve, suggesting initial overfitting to new data followed by swift adaptation. We

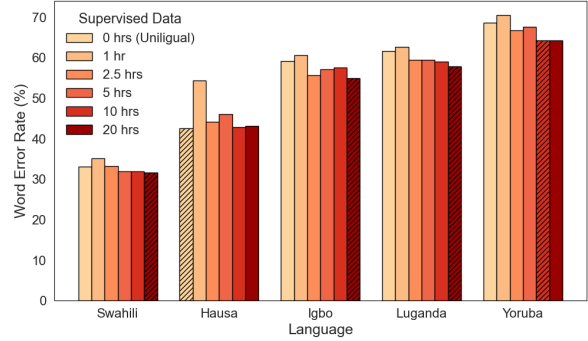


Figure 1: Sample efficiency measured by ASR WER (%) scores (\downarrow) with varying amounts of finetuning hours; dashed bars indicate the best system for each language. Please refer to Section 4.4 for details.

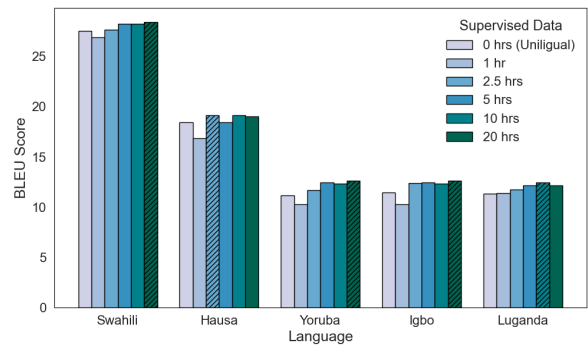


Figure 2: Sample efficiency measured by MT BLEU scores (\uparrow) with varying amounts of finetuning hours; dashed bars indicate the best system for each language. Please refer to Section 4.4 for details.

identified an optimal fine-tuning window of 2.5–10 h for maximizing ASR robustness and translation fidelity in African low-resource languages.

4.5 Beyond BLEU: Part-of-speech Tag Steering Analysis

To gain insights beyond a single BLEU score, we analyzed part-of-speech (POS)–specific translation errors for our baseline cascaded model (T1) and the cascaded architecture with ASR correction (T6), across five African languages. POS tagging was performed using spaCy⁵’s large English statistical model, which produced Universal Dependencies tags for each token.

Following the methodology of (Popović and Ney, 2007), we computed POS-specific WER, which reflects sequence-level accuracy and highlights error patterns across linguistic categories. Our analysis (Tables 5–6) shows that T1 exhibits high WER for NOUN, PUNCT, and DET categories, especially

⁵spaCy is a library for NLP in Python and Cython.

POS Tag	Swahili	Hausa	Igbo	Luganda	Yorùbá	Avg
ADJ	5.31%	10.29%	10.39%	7.79%	9.68%	8.69%
ADP	6.55%	16.32%	13.65%	11.56%	16.41%	12.89%
ADV	2.49%	8.21%	6.99%	5.55%	5.30%	5.71%
AUX	3.34%	9.22%	9.13%	6.30%	14.23%	8.44%
CCONJ	1.70%	5.92%	5.91%	3.15%	5.44%	4.42%
DET	5.91%	17.57%	24.76%	14.91%	16.72%	15.97%
NOUN	13.04%	31.54%	34.15%	25.97%	31.96%	27.33%
NUM	1.20%	1.86%	2.10%	1.56%	1.55%	1.65%
PART	1.50%	3.12%	3.01%	2.87%	7.97%	3.69%
PRON	2.68%	10.05%	10.71%	5.23%	19.50%	9.63%
PROPN	3.91%	14.01%	9.04%	8.57%	10.02%	9.11%
PUNCT	4.72%	23.92%	28.41%	15.90%	21.68%	18.93%
SCONJ	0.77%	1.88%	1.68%	1.68%	2.95%	1.79%
VERB	6.78%	13.36%	12.44%	10.27%	20.84%	12.74%
Macro Avg	5.04%	12.60%	12.80%	9.17%	13.47%	10.62%
Weighted Avg	5.99%	16.86%	17.27%	12.14%	18.44%	14.14%

Table 5: **WER** (\downarrow) over English POS tags of translation by Whisper Baseline (T1) for all five African languages.

POS Tag	Swahili	Hausa	Igbo	Luganda	Yorùbá	Avg
ADJ	4.64%	5.84%	6.97%	6.39%	6.54%	6.08%
ADP	5.64%	7.48%	8.76%	7.45%	7.79%	7.42%
ADV	2.36%	2.77%	3.42%	3.26%	3.11%	2.98%
AUX	2.77%	3.93%	4.25%	3.64%	4.03%	3.72%
CCONJ	1.72%	2.65%	2.61%	2.23%	2.37%	2.32%
DET	4.97%	8.58%	8.48%	7.37%	7.61%	7.40%
NOUN	12.38%	16.51%	18.53%	16.74%	16.91%	16.21%
NUM	0.86%	1.35%	1.45%	1.21%	1.08%	1.19%
PART	1.40%	1.50%	1.97%	1.75%	1.66%	1.66%
PRON	2.47%	3.30%	3.57%	3.40%	3.39%	3.23%
PROPN	3.75%	5.41%	6.53%	5.54%	5.26%	5.30%
PUNCT	5.38%	7.54%	8.21%	8.69%	7.09%	7.38%
SCONJ	0.69%	0.81%	1.17%	1.02%	1.03%	0.94%
VERB	5.90%	7.86%	8.78%	8.06%	8.69%	7.86%
Macro Avg	4.18%	5.79%	6.47%	5.81%	6.05%	5.66%
Weighted Avg	5.49%	7.56%	8.48%	7.68%	7.66%	7.37%

Table 6: **WER** (\downarrow) over English POS tags of translation by our best recipe (T6) for all five African languages.

for Yorùbá, the lowest-BLEU language. This indicates frequent issues with content words, determiners, and punctuation, limiting translation quality.

Setting a threshold of 15% for POS-wise WER, then as highlighted in Table 5, the most common errors were made over NOUN, PUNCT, and DET classes, indicating the deficiencies of Whisper model, on the African language group. For Yorùbá, the language with the lowest BLEU score, high WERs are observed across multiple POS classes. This unveils underlying error patterns and suggests that these specific word types require focused attention to improve translation performance.

Comparing Table 6 to Table 5, we observed a large reduction in errors for PUNCT and DET, along with a smaller, yet significant, reduction for NOUN. These substantial improvements across all five languages—particularly in Yorùbá, Hausa, Igbo, and Luganda—further demonstrate the effectiveness of the best T6 recipe. We also conducted more detailed analysis of position-independent error, inflectional error and missing words, details

are in Appendix B.

4.6 Summary of Trends

Across our experiments, three consistent patterns were observed. First, in the cascaded method, finetuning from SOTA ASR model Whisper on even modest amounts of in-domain data produces substantial WER reductions for low-resource languages (Table 2). The Multi. + Mono. + ASR Corrected variant yielded the best WER for 9 of 10 languages, as it leverages extended exposure and cross-lingual transfer. Only French deviates from this trend, underscoring the risk of overfitting when pretraining already provides ample coverage. Second, in multimodal machine translation quality (Table 4), a complementary pattern appears: audio-LLMs like Gemini 2.0 Flash can translate well in Indic languages \rightarrow English and Swahili \rightarrow English, achieving BLEU gains of 4–7 points over cascaded baselines, whereas finetuned translation expert models (either built multimodally or ASR+MT cascadedly) excel on low-resource African languages, often exceeding Gemini’s scores by 2–10 BLEU points. Third, our ablation on finetuning volume (Figs. 1–2) reveals a pronounced “U-shaped” curve: an initial performance dip at 1 h, rapid recovery and peak gains between 2.5–10 h, and plateau or slight regression beyond 10 h. This identifies an optimal finetuning window for balancing adaptation speed against domain shift.

Together, these trends suggest a best recipe for speech-translation in low-resource contexts: (1) apply multilingual finetuning followed by targeted monolingual finetuning, with Corrector to minimize WER and maximize the final translation performances on related languages; (2) reserve audio-LLMs for languages with ample training data, while relying on cascaded or multimodal MT systems for under-represented tongues; (3) allocate finetuning budgets within the identified “sweet spot” of 2.5–10 h to maximize returns without incurring diminishing gains.

5 Conclusions

Our systematic comparison of cascaded ASR+MT, multimodal speech translation, and audio-centric LLMs across 11 diverse languages yields several important insights: (1) Our 2-stage FT strategy can improve translation performances on target language, and offer the additional performance benefit on regional related languages for both ASR and

MT, with a up to 5.8x boost in BLEU on them than monolingual FT. This approach is particularly effective for meeting the demands of practical, real-world scenarios. (2) Our 2-stage FT + ASR Corrector recipe can further improve WER across 9 of 10 languages, and carry on the additional gains to ultimate MT task. (3) While SOTA audio-LLMs excel on higher-resource languages, our evaluations unveil that they may struggle on truly low-resource languages such as African ones. Finetuned Whisper variants and SeamlessM4T can match or exceed audio-LLM performance by up to 10 BLEU, suggesting the most reliable choices for AST of under-represented spoken languages. (4) Our ablation study reveals that not always “the more finetuning data, the better” in low-resource ASR. Future work should focus on expanding high-quality parallel speech–text resources and developing regularized, domain-aware adaptation techniques to ensure robust translation across the full spectrum of the world’s languages.

6 Acknowledgment

This research was supported by the Google grant via Mila. David Adelani acknowledges the funding of the Natural Sciences and Engineering Research Council of Canada (NSERC)—Discovery Grants Program, IVADO and the Canada First Research Excellence Fund. We would also like to thank Google Cloud for the GCP credits Award through the Gemma 2 Academic Program for providing API credits.

7 Limitations

This study provides valuable insights into speech-to-text translation for low-resource languages, but its scope is bounded by several factors. There is bias introduced the selection of low-resource languages, *e.g.* we experimented with clean speech rather than noisy speech to initialize the comparative studies. Future work with diverse, in-the-wild data is crucial for robust systems. Secondly, while we selected 10 typologically diverse African and Indic languages to evaluate low-resource performance, our findings may not extend to all such languages, especially those with different linguistic features or data availability. Thirdly, we focused on selected architectures (Whisper+NLLB, SeamlessM4T, GPT-4o Audio, Gemini 2.0 Flash). While proprietary APIs offered state-of-the-art insights, their closed nature and cost limited extensive test-

ing. Open models were finetuned within practical compute budgets, constraining exploration of larger variants and complex adaptation. These choices, driven by resource constraints, introduce selection bias in model coverage and task prioritization.

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A ASR Corrector Training Details

Goal. We train a text-to-text ASR corrector to reduce recognition errors made by the ASR model. The corrector is a language-specific mT5-Base model that maps noisy ASR hypotheses to corrected transcripts.

Data and pairing. For each language, we take predictions from the finetuned WHISPER LARGE V3 (S3, see §3.3.1) on the FLEURS *training* split and pair them with their gold references to form (hypothesis, reference) examples. The FLEURS *dev* split is used only for early stopping and hyperparameter selection. This ensures no data leakage: the corrector never sees dev/test references during training.

Model and objective. We finetune mT5-Base for up to **20 epochs** with early stopping on the dev set. The model is trained as a standard seq2seq text editor: input is the ASR hypothesis; target is the reference transcript.

Compute. All runs use **2× A100L GPUs**, **6 CPUs**, and **32 GB RAM**.

Setting	Value
Base model	mT5-base (Text-to-Text)
Task framing	ASR post-correction (seq2seq)
Max src / tgt length	200
Epochs	20 (early stopping on dev loss)
Batch size (per device)	8
Decoding	Beam search, num_beams=10
Model selection	metric_for_best_model=loss
Eval / Save strategy	epoch
Optimizer / LR / Scheduler	HF defaults (not overridden)

Table 7: Hyperparameters for the mT5-base ASR corrector (Hausa).

Outputs. At inference, the corrector takes WHISPER LARGE V3 outputs and returns corrected text. Training and decoding hyperparameters are summarized in Table 7.

B More Detailed POS-specific Metrics

In addition to WER, we compute the F-Based Position-independent Error Rate (FPER) (Popović and Ney, 2007), which disregards word order and instead captures errors in the distribution of POS classes. FPER is defined as:

$$\text{FPER}(p) = \frac{1}{N_{\text{ref}}^* + N_{\text{hyp}}} \cdot \sum_{k=1}^K (n(p, \text{rerr}_k) + n(p, \text{herr}_k)) \quad (1)$$

where p is a POS class, N_{ref}^* and N_{hyp} are the reference and hypothesis token counts (excluding punctuation), and $n(\cdot)$ counts errors of class p in reference (rerr) or hypothesis (herr) for each sentence k . The metric gives the proportion of position-independent errors for p over the corpus. WER and FPER together capture complementary aspects of translation quality: WER is sensitive to word order and thus reflects overall sequence-level accuracy, while FPER disregards position and focuses on the distribution of POS-specific errors. Using both allows us to assess not only how closely a translation matches the reference in form, but also which linguistic categories contribute most to the errors, providing a more targeted diagnostic of system performance.

The POS-specific FPER results (Tables 8–9) complement WER by highlighting position-independent mismatches. T6 cuts errors sharply for PUNCT and DET, indicating fewer spurious or missing tokens regardless of order. Reductions for AUX and PROP further suggest stronger preservation of grammatical auxiliaries and named enti-

POS Tag	Swahili	Hausa	Igbo	Luganda	Yorùbá	Avg
ADJ	4.11%	4.97%	5.09%	4.94%	4.41%	4.70%
ADP	4.79%	7.62%	6.27%	6.47%	7.23%	6.48%
ADV	1.66%	3.67%	2.96%	2.94%	2.24%	2.69%
AUX	2.48%	4.97%	4.85%	4.31%	6.51%	4.62%
CCONJ	1.22%	2.62%	2.82%	1.88%	2.41%	2.19%
DET	4.07%	8.03%	11.16%	8.84%	7.22%	7.86%
NOUN	10.62%	15.38%	16.49%	15.89%	14.35%	14.55%
NUM	0.92%	0.84%	1.01%	0.99%	0.69%	0.89%
PART	1.11%	1.73%	1.53%	1.95%	3.32%	1.93%
PRON	2.18%	5.24%	5.03%	3.58%	8.65%	4.94%
PROPN	2.75%	7.44%	4.37%	4.48%	4.73%	4.75%
PUNCT	4.20%	11.45%	13.11%	9.53%	10.04%	9.67%
SCONJ	0.64%	0.91%	0.78%	1.00%	1.39%	0.94%
VERB	5.23%	6.59%	5.97%	6.31%	9.20%	6.66%
Macro Avg	3.87%	5.87%	5.74%	5.45%	6.23%	5.43%
Weighted Avg	4.60%	8.21%	8.16%	7.32%	8.25%	7.31%

Table 8: **FPER** (\downarrow) over English POS tags of translation by Whisper Baseline (T1) for all five African languages.

POS Tag	Swahili	Hausa	Igbo	Luganda	Yorùbá	Avg
ADJ	3.80%	4.59%	5.41%	5.16%	5.25%	4.84%
ADP	4.23%	5.06%	6.23%	5.76%	5.90%	5.44%
ADV	1.71%	1.98%	2.28%	2.33%	2.22%	2.10%
AUX	2.27%	2.87%	3.19%	3.01%	3.37%	2.94%
CCONJ	1.22%	1.71%	1.77%	1.64%	1.70%	1.61%
DET	3.49%	5.46%	5.85%	5.30%	5.54%	5.13%
NOUN	10.17%	13.31%	15.33%	14.36%	14.37%	13.51%
NUM	0.61%	1.01%	1.10%	1.00%	0.89%	0.92%
PART	1.04%	1.06%	1.42%	1.44%	1.41%	1.27%
PRON	1.90%	2.39%	2.70%	2.59%	2.91%	2.50%
PROPN	2.53%	3.48%	3.83%	3.68%	3.59%	3.42%
PUNCT	4.11%	4.44%	4.62%	5.53%	4.98%	4.74%
SCONJ	0.56%	0.64%	0.90%	0.83%	0.85%	0.76%
VERB	4.89%	6.03%	6.74%	7.09%	7.08%	6.37%
Macro Avg	2.99%	3.98%	4.54%	4.40%	4.55%	4.09%
Weighted Avg	4.26%	5.41%	6.14%	5.98%	6.01%	5.56%

Table 9: **FPER** (\downarrow) over English POS tags of translation by our best recipe (T6) for all five African languages.

ties. Even NOUN exhibits modest improvements, consistent with its WER gains. Together, WER and FPER reveal that T6 improves both ordering accuracy and lexical coverage.

Beyond WER and FPER, Popović and Ney (2007) introduced two additional complementary diagnostics: Inflectional POS Error Rates (IFPER) and Missing Words Distribution.

IFPER evaluates morphological competence by identifying cases where a system produces the correct lemma but with the wrong inflection. As shown in Tables 10 and 11, this analysis highlights the POS categories most prone to inflectional errors, thus uncovering weaknesses not visible in WER/FPER alone.

Missing words analysis distinguishes between truly omitted words and those simply reordered. Results in Tables 12 and 13 indicate which grammatical categories are systematically under-produced. These findings can directly inform targeted improvements in model design, such as handling of phrase coverage and language modeling.

POS Tag	Swahili	Hausa	Igbo	Luganda	Yoruba	Average
ADJ	0.47%	0.14%	0.13%	0.21%	0.13%	0.22%
ADP	0.10%	0.07%	0.05%	0.10%	0.11%	0.09%
ADV	0.15%	0.40%	0.03%	0.04%	0.05%	0.13%
AUX	0.72%	2.21%	2.92%	2.04%	2.10%	2.01%
CCONJ	0.06%	0.02%	0.02%	0.03%	0.04%	0.03%
DET	0.13%	0.08%	0.05%	0.08%	0.12%	0.09%
NOUN	2.67%	1.02%	0.84%	2.25%	1.70%	1.70%
NUM	0.10%	0.03%	0.14%	0.06%	0.14%	0.09%
PART	0.17%	0.06%	0.07%	0.08%	0.12%	0.10%
PRON	0.28%	0.17%	0.08%	0.17%	0.30%	0.20%
PROPN	0.73%	0.94%	0.51%	0.67%	0.57%	0.68%
SCONJ	0.00%	0.01%	0.01%	0.00%	0.01%	0.01%
VERB	0.93%	0.44%	0.31%	0.54%	0.42%	0.53%

Table 10: IFPER (\downarrow) over English POS tags of translation by T1 for all five African languages.

POS Tag	Swahili	Hausa	Igbo	Luganda	Yorùbá	Average
ADJ	0.50%	0.45%	0.46%	0.43%	0.42%	0.45%
ADP	0.12%	0.14%	0.12%	0.14%	0.15%	0.13%
ADV	0.25%	0.24%	0.16%	0.12%	0.12%	0.18%
AUX	0.74%	1.00%	1.25%	1.01%	1.32%	1.06%
CCONJ	0.08%	0.08%	0.06%	0.07%	0.06%	0.07%
DET	0.13%	0.19%	0.12%	0.13%	0.08%	0.13%
NOUN	3.57%	3.20%	3.08%	2.84%	2.65%	3.07%
NUM	0.24%	0.29%	0.24%	0.19%	0.23%	0.24%
PART	0.19%	0.09%	0.12%	0.11%	0.15%	0.13%
PRON	0.29%	0.23%	0.27%	0.13%	0.26%	0.24%
PROPN	0.82%	0.85%	0.83%	0.80%	0.63%	0.79%
SCONJ	0.01%	0.01%	0.02%	0.01%	0.02%	0.01%
VERB	1.01%	1.10%	1.00%	1.10%	1.04%	1.05%

Table 11: IFPER (\downarrow) over English POS tags of translation by T6 for all five African languages.

POS Tag	Swahili	Hausa	Igbo	Luganda	Yorùbá	Total
ADJ	122	204	283	198	210	1017
ADP	163	233	357	264	226	1243
ADV	70	87	132	128	108	525
AUX	91	133	207	124	140	695
CCONJ	59	65	80	58	82	344
DET	146	241	283	234	272	1176
NOUN	302	449	642	483	503	2379
NUM	22	33	56	29	54	194
PART	39	48	93	59	56	295
PRON	93	119	207	111	123	653
PROPN	63	172	266	166	182	849
PUNCT	101	169	215	143	169	797
SCONJ	22	40	74	36	47	219
VERB	166	218	332	250	238	1204

Table 12: Missing word counts by POS tag for English POS tagging across the five African languages for T1 translations.

POS Tag	Swahili	Hausa	Igbo	Luganda	Yorùbá	Total
ADJ	118	184	237	295	308	1142
ADP	178	239	336	437	358	1548
ADV	66	91	137	186	159	639
AUX	74	93	145	173	203	688
CCONJ	77	85	121	131	137	551
DET	161	224	327	417	344	1473
NOUN	320	443	677	795	701	2936
NUM	20	47	62	47	52	228
PART	43	44	63	94	79	323
PRON	73	115	164	183	165	700
PROPN	69	173	172	185	209	808
PUNCT	109	170	231	253	266	1029
SCONJ	20	20	37	45	26	148
VERB	149	216	327	337	356	1385

Table 13: Missing word counts by POS tag for English POS tagging across the five African languages for T6 translations.

Quality-Aware Translation Tagging in Multilingual RAG system

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Abstract

Multilingual Retrieval-Augmented Generation (mRAG) often retrieves English documents and translates them into the query language for low-resource settings. However, poor translation quality degrades response generation performance. Existing approaches either assume sufficient translation quality or utilize the rewriting method, which introduces factual distortion and hallucinations. To mitigate these problems, we propose Quality-Aware Translation Tagging in mRAG (QTT-RAG), which explicitly evaluates translation quality along three dimensions—semantic equivalence, grammatical accuracy, and naturalness & fluency—and attaches these scores as metadata without altering the original content. We evaluate QTT-RAG against CrossRAG and DKM-RAG as baselines in two open-domain QA benchmarks (XORQA, MKQA) using six instruction-tuned LLMs ranging from 2.4B to 14B parameters, covering two low-resource languages (Korean and Finnish) and one high-resource language (Chinese). QTT-RAG outperforms the baselines by preserving factual integrity while enabling generator models to make informed decisions based on translation reliability. This approach allows for effective usage of cross-lingual documents in low-resource settings with limited native language documents, offering a practical and robust solution across multilingual domains. Code available at <https://github.com/HoyeonM/QTT-RAG>.

1 Introduction

Retrieval-augmented generation (RAG) has become a standard approach for large language models (LLMs) for open-domain question answering tasks by accessing external sources of knowledge (Lewis et al., 2020). One core challenge in multilingual RAG (mRAG) is retrieving relevant documents in a different language that would not de-

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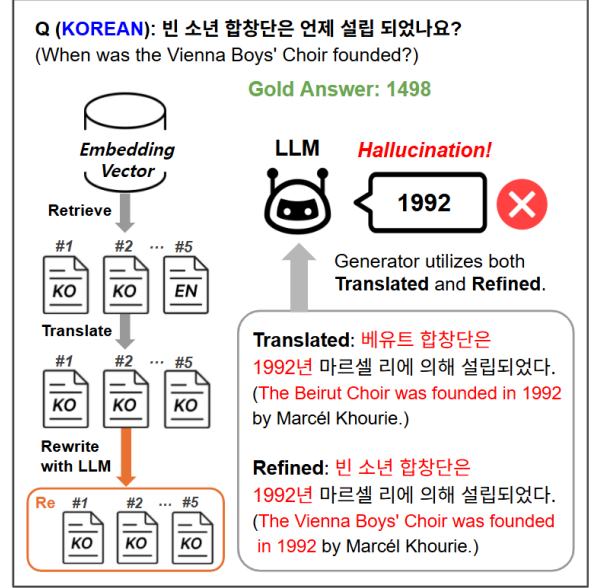


Figure 1: This figure illustrates a failure case of the previous approach (DKM-RAG). Hallucination arises when the LLM rewrites the translated documents, causing the generator to eventually produce an incorrect answer.

grade the quality of the generation. This difficulty is exacerbated by a data imbalance: high-resource languages such as English dominate web-scale corpora, while medium- and low-resource languages (e.g., Korean, Finnish) remain underrepresented. This imbalance leads to inconsistent performance quality across languages in LLMs, even in safety and reliability issues (Shen et al., 2024a).

When queries and retrieved documents are in different languages, retrievers fail to identify relevant passages, and generators tend to produce code-switched or inaccurate responses (Park and Lee, 2025). The same study also shows that performance improves substantially when the retrieved passages match the query language, highlighting a strong preference for the query language. This mismatch problem leads to a strong language preference bias, whereby generation performance im-

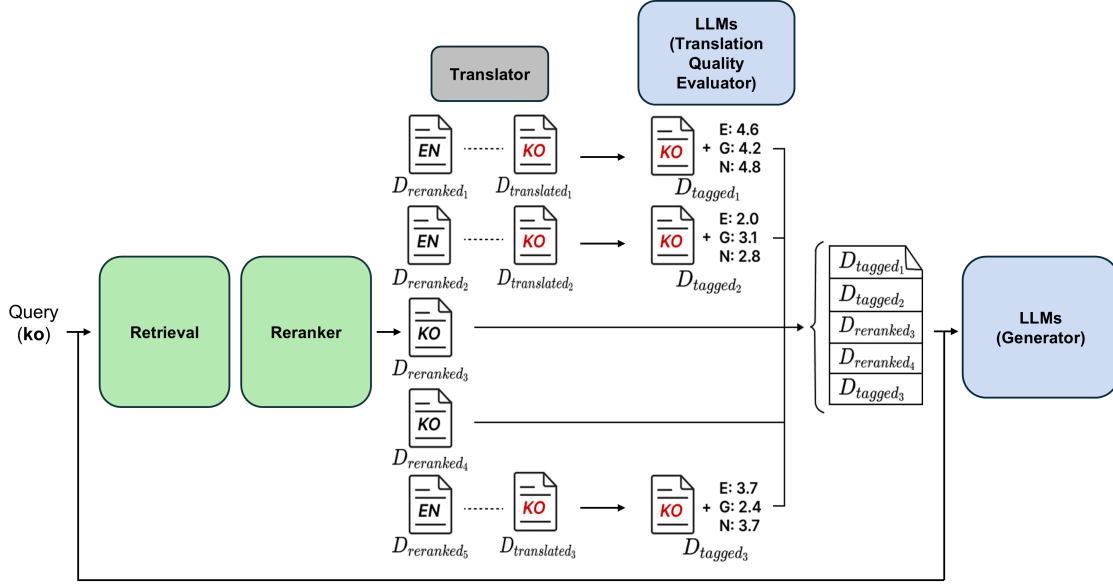


Figure 2: Overview of QTT-RAG System. After retrieving and reranking the top-5 most relevant documents, documents originally written in the query language (KO) are passed directly to the generator, whereas documents in foreign languages (EN) are translated and automatically scored along three dimensions: semantic equivalence (E), grammatical accuracy (G), and naturalness & fluency (N). These passages are then re-inserted with the corresponding quality tags. The generator receives this quality-aware, tagged input, enabling it to produce factually grounded and translation-sensitive responses.

proves when retrieved passages match the query language. Wang et al. (2024) shows that LLM performance drops when input and output languages are mismatched, often leading to repetition and incoherence in multilingual generation and translation.

To address the language mismatch problem, two primary approaches have been explored: 1) Translating queries into English to match the dominant language of document collections, 2) Translating documents into the query language. Research in Cross-Lingual Information Retrieval (CLIR) has shown that document translation outperforms query translation (McCarley, 1999; Saleh and Pecina, 2020; Valentini et al., 2025; Yang et al., 2024). Recent work in mRAG has reinforced these findings, which shows that translating documents into the query language maintains cultural knowledge and word sense boundaries more accurately (Park and Lee, 2025).

DKM-RAG (Park and Lee, 2025) introduces a document-centric approach that translates retrieved English passages into the query language and refines them using an LLM-based rewriting module. Its refining method removes redundant sentences,

ensures natural connections with the original text, and produces smooth query language writing. However, DKM-RAG has a key limitation: its refinement process can invoke hallucinations by inadvertently altering factual content, making irrelevant passages appear artificially relevant to the query, as shown in Figure 1. It even refines the retrieved documents that are already in query language, unnecessarily modifying their contents and potentially distorting the original information. Beyond these content-level issues, recent studies have revealed deeper limitations of LLMs in multilingual contexts, such as cultural commonsense understanding (Shen et al., 2024b), as well as barriers in transferring knowledge across languages (Chua et al., 2025).

To address such problems, we propose Quality-Aware Translation Tagging in Multilingual RAG (QTT-RAG). Our approach employs explicit quality assessment instead of implicit quality control mechanisms. Specifically, we translate only those documents that are not already in the query language into the target language, and then employ an LLM to assess the translation quality based on three criteria: semantic equivalence, grammatical accu-

racy, and naturalness & fluency. Unlike implicit quality control approaches such as CrossRAG and DKM-RAG, which either assume adequate translation quality (CrossRAG) or rely on rewriting passages to improve fluency (DKM-RAG), our quality assessment method preserves factual integrity by providing detailed quality scores as metadata. This allows the generation model to make informed decisions without altering the original semantic content.

Our key contributions are as follows:

- **LLM-based Translation Quality Assessment:** We propose an LLM-driven evaluation module that scores translation quality based on semantic equivalence, grammatical correctness, and linguistic naturalness.
- **QTT-RAG Architecture:** We introduce QTT-RAG, a multilingual RAG pipeline that attaches translation quality scores as metadata, enabling the generator to weigh information sources more reliably and thereby reducing factual distortion.
- **Empirical Validation:** Experiments across multilingual benchmarks show that QTT-RAG consistently improves 3-gram recall and robustness to translation errors compared to existing baselines such as CrossRAG and DKM-RAG.

2 Background

2.1 Multilingual RAG

Traditional Retrieval-Augmented Generation (RAG) systems primarily rely on English documents, retrieving and generating responses using dense passage encoders. Recent works have extended RAG to multilingual settings by integrating multilingual retrievers such as LaBSE (Feng et al., 2022) and BGE-M3, often in combination with cross-lingual LLMs. However, Chirkova et al. (2024) demonstrate persistent language preference bias in multilingual RAG systems: generators achieve better performance when retrieved passages are in the same language as the query language but degrade when the context contains mixed or mismatched languages.

Two main strategies have been proposed to address the language mismatch: (i) query translation (tRAG), which translates the user query into English before retrieval, and (ii) document transla-

tion (CrossRAG), which translates all retrieved passages into a single language (Ranaldi et al., 2025). Query translation approaches suffer from information loss when relevant documents exist only in the original language, while document translation approaches may introduce translation noise that affects the generation stage. To improve document translation quality, DKM-RAG (Park and Lee, 2025) applies an LLM-based rewriting step to translated passages, enhancing fluency but at the risk of factual distortion.

Despite these advances and their notable contributions to mRAG, existing methods still cannot reliably prevent translation-induced hallucinations. In contrast, our proposed QTT-RAG introduces an explicit quality evaluation framework that preserves the benefits of document translation while mitigating the risk of factual distortion. Rather than modifying content, QTT-RAG leverages quality assessments as metadata to better guide the generation process.

3 Methodology

We address a cross-lingual retrieval scenario where user queries q are posed in medium or low-resource languages L_q (e.g., Korean, Finnish), while the target document collection \mathcal{D} predominantly contains documents in high-resource languages L_h (e.g., English).

Our proposed pipeline, shown in Figure 2 consists of five sequential modules designed to handle cross-lingual retrieval and generation: (1) retrieval, (2) reranking, (3) language detection & translation, (4) quality tagging, and (5) generation.

3.1 Document Retrieval and Reranking

Given a user query q in language L_q , we first retrieve the top- k candidate documents D_k from the document collection \mathcal{D} .

For this initial retrieval step, we use BGE-M3, a state-of-the-art multilingual dense retrieval model that maps both queries and documents into a shared cross-lingual embedding space through a dual-encoder architecture.

The retrieved candidate list D_k is then reranked using BGE-M3 as the reranking model, producing a reordered set of documents $D_{reranked}$. This reranking step computes more precise relevance scores for each query-document pair, enabling improved ranking of the initially retrieved candidates based on deeper semantic understanding.

3.2 Cross-lingual Document Translation

For each document $d \in D_{reranked}$, we first perform automatic language detection to identify its source language L_d .

Documents already in the query language ($L_d = L_q$) bypass the translation process and are preserved in its original form, thereby avoiding unnecessary translation artifacts. For documents in other languages ($L_d \neq L_q$), we employ neural machine translation using NLLB-200-600M, a multilingual translation model supporting over 200 languages. The model translates each document d from its source language L_d into the query language L_q , producing the translated document $D_{translated}$.

3.3 Quality-Aware Translation Tagging

We use an LLM-based agent to evaluate the translation quality of documents in $D_{translated}$ with the structured prompt shown in Table 8 of Appendix A. The agent assesses each translated document across three criteria:

- **Semantic Equivalence:** Verifies that the translation faithfully preserves the original meaning and factual content.
- **Grammatical Accuracy:** Evaluates syntactic, morphological, and structural correctness in the target language.
- **Naturalness and Fluency:** Assesses whether the translation reads smoothly and idiomatically to native speakers.

Each criterion is scored based on the ELO rating system from 0.0 to 5.0. We attach these quality scores as tags to each translated document, creating the quality-tagged document D_{tagged} . Examples of the tagged documents can be found in Table 12 and Table 13 in Appendix B, where Table 12 represents low-quality translation cases and Table 13 shows high-quality translation cases for Korean, Finnish, and Chinese. If a document is originally written in the query language, no quality score is added. This tagging approach preserves and fully utilizes all translated documents while providing the quality information to guide the generation model.

3.4 Response Generation

The generator LLM receives the user query q concatenated with the quality-tagged document set through a structured prompt template detailed in

Table 9 of Appendix A. Rather than employing additional fine-tuning, we leverage in-context learning by explicitly exposing the quality scores within the input prompt.

The template instructs the LLM to prioritize passages with higher quality scores, enabling responses to rely more heavily on high-quality translations while down-weighting or cautiously handling lower-quality passages.

4 Experiments and Results

In this section, we describe the datasets used in our experiments, the experimental setup, evaluation metrics, and results, followed by ablation studies to analyze the contribution of each component.

As baselines, we compare our method against three approaches: (i) Base, a retrieval-only system without translation, which relies solely on reranked retrieved documents; (ii) CrossRAG, which translates all retrieved passages into the query language; and (iii) DKM-RAG, which refines translated passages using an LLM-based rewriting step.

4.1 Dataset

We conduct experiments on two multilingual open-domain QA benchmarks: MKQA: Multilingual Knowledge Questions & Answers (Longpre et al., 2021) and XOR-TyDi: Cross-lingual Open-Retrieval Question Answering (Asai et al., 2021) datasets for multilingual open-domain question answering tasks. MKQA consists of 10,000 examples from the Natural Questions (NQ) benchmark (Kwiatkowski et al., 2019), translated into 26 languages, creating parallel multilingual QA pairs grounded in English Wikipedia. However, MKQA does not provide document-level annotations. For consistency with prior benchmarks that include gold document labels, we therefore adopt a subset of 2,827 MKQA samples that overlap with KILT-NQ (Knowledge Intensive Language Tasks Natural Questions).

XOR-TyDi QA extends the TyDi QA (Clark et al., 2020) benchmark by introducing cross-lingual open retrieval challenges, where questions are written in typologically diverse languages and paired with English Wikipedia articles.

In our experiments, we use the Korean, Finnish, and Chinese splits of MKQA. For XOR-TyDi QA, we evaluate on the Korean and Finnish splits, comprising 371 and 615 questions respectively.

4.2 Experimental Setup

We implement our QTT-RAG framework using Bergen (Rau et al., 2024) as the experimental framework and conduct baseline comparisons on Korean, Finnish, and Chinese language settings.

Knowledge Base We construct our document index from Wikipedia, comprising 25M English, 1.6M Korean, 1.5M Finnish, and 11M Chinese examples. Wikipedia is selected for two main reasons: (i) both XOR-TyDi QA and MKQA are curated against Wikipedia pages, ensuring high answer coverage; (ii) it offers broad multilingual coverage with consistent article quality and structured formatting across languages.

Retrieval & Reranking We adopt a two-stage retrieval pipeline: (i) an initial dense retriever to maximize recall over a large index, (ii) followed by a reranker that re-scores the top- K candidates through query–passage interactions to improve precision at early ranks. This is crucial because only a limited number of passages can be provided to the LLM. Reranking ensures that answer-bearing passages are prioritized while topical but non-answer passages and near duplicates are suppressed.

We choose BGE-M3 (Xiao et al., 2024) as both retriever and reranker for three practical reasons: (i) it provides a single multilingual checkpoint with strong cross-lingual retrieval across 100+ languages; (ii) it has been adopted in prior work such as DKM-RAG and CrossRAG, enabling direct comparability; and (iii) it offers publicly available weights and a built-in reranker, facilitating reproducibility.

Translation Documents that are retrieved in languages other than the query language are translated by NLLB-200-distilled-600M (NLLB) (Costa-jussà et al., 2022), a multilingual neural machine translation model supporting more than 200 languages. NLLB achieves BLEU scores in the 30–40 range for many low-resource language pairs, making it a strong baseline for translation quality. While NLLB offers credible and scalable translation capabilities, relying solely on translated content can still introduce errors or stylistic inconsistencies. This limitation motivates our design choice to incorporate translation quality assessment, allowing the generator to dynamically weigh the reliability of translated passages rather than treating all translations equally.

Translation Quality Assessment We adapt Llama-3.1-8B-Instruct (Dubey et al., 2024) as our quality assessment agent to evaluate translation quality across three criteria (semantic equivalence, grammatical accuracy, and naturalness & fluency) as described in Section 3.3. For each query language, we design the assessment prompt in the same language. The exact prompts are provided in Table 9 of Appendix A.

Response Generation We evaluate our framework with six pretrained, instruction-tuned language models of varying scales: Exaone-3.5-2.4B-Instruct, Exaone-3.5-7.8B-Instruct (Yoo et al., 2024), Qwen2.5-7B-Instruct (Hui et al., 2024), Llama-3.1-8B-Instruct (Dubey et al., 2024), Aya-Expanse-8B (Dac et al., 2024), and Phi-4 (14b) (Abdin et al., 2024). This diverse set of models enables us to assess the generalization ability of our approach across different model architectures and capabilities.

Evaluation Metric We use character 3-gram recall as the evaluation metric (Chirkova et al., 2024). Given a gold answer, character 3-gram recall first extracts all overlapping three-character sequences (trigrams) from the entire gold string. The score is then calculated as the proportion of these gold trigrams that appear anywhere in the model’s prediction. Character 3-gram recall is well-suited for multilingual QA as it tolerates orthographic variations while still penalizing hallucinations and missing content. Unlike word-level metrics, this character-level approach is language-agnostic and requires no language-specific processing, making it well-suited for cross-lingual evaluation.

4.3 Failure Cases of DKM-RAG and CrossRAG

DKM-RAG improves translation quality by rewriting retrieved passages conditioned on the query. Although this process can mitigate noisy translations, it often results in knowledge drift, where the rewritten passages introduce query terms or assert relations unsupported by the original documents. To validate this, we manually analyze 1,855 retrieved documents for 371 questions from XOR-TyDi-ko. In 214 cases (11.5%), entities in the query (e.g. names, places, and dates) that were absent from the original documents are added during rewriting. This rate of entity hallucination indicates a notable limitation of rewriting-based approaches.

Table 1 illustrates how rewriting can change the factual content. In Case 1, the retrieved passage describes an unrelated person named “Rumer Godden”. However the rewritten output asserts a death date for “Gwisil Boksil,” bridging the query to irrelevant evidence and fabricating a fact that the source does not contain. The downstream generator then treats the rewritten passage as authoritative and produces the fabricated answer.

Table 2 presents a failure case of translation in the CrossRAG method. In this case, the original retrieved passage is incorrectly translated, omitting an important part of the original content.

Case 1	
Query	귀실복신 사망일은 언제 인가요? (When did Gwisil Boksil die?)
Retrieved	Rumer Godden died on 8 November 1998, aged 90, following a stroke...
Refined	귀실복신의 사망일은 1998년 11월 8일입니다. (Gwisil Boksil’s date of death is November 8, 1998.)
LLM Output	주어진 정보만으로는 1998년 11월 8일이 가장 유력한 답변입니다. (Based on the given information, November 8, 1998 is the most likely answer.)

Table 1: Case study of factual distortion in DKM-RAG for a Korean query.

Case 2	
Query	북유럽의 노르딕 국가는 몇 개인가요? (How many Nordic countries are there in Northern Europe?)
Retrieved	"Scandinavia" is sometimes used as a synonym for the Nordic countries, although within the Nordic countries the terms are considered distinct.
Translated	북유럽 국가들 내에서는 스칸디나비아라는 용어가 구별되는 것으로 간주된다. (Within the Nordic countries, the term Scandinavia is regarded as distinct.)

Table 2: Case study of incorrect translation in CrossRAG for a Korean query.

4.4 Quality-Aware Translation Tagging

Our QTT-RAG explicitly tags translation quality as metadata using an LLM without rewriting retrieved content. Unlike refinement-based methods, which risk distorting original information into inaccurate content, our approach preserves the original translations and supplements them with quality scores as metadata. This non-destructive design enables the generation model to prioritize higher-quality sources while maintaining access to potentially

Model	Character 3-gram Recall (%)			
	Base	Cross	DKM	QTT
XOR-TyDi-ko				
Exaone-3.5-2.4B-Instruct	37.0	37.3	35.1	41.3
Qwen2.5-7B-Instruct	34.3	36.5	34.2	36.9
Exaone-3.5-7.8B-Instruct	40.7	42.0	39.7	43.8
Aya-Expanse-8B	38.2	39.7	37.0	42.8
Llama-3.1-8B-Instruct	33.7	34.2	33.7	37.2
Phi-4 (14B)	40.6	41.0	35.7	42.5
MKQA-ko				
Exaone-3.5-2.4B-Instruct	29.2	30.1	32.0	36.0
Qwen2.5-7B-Instruct	28.6	28.5	30.6	33.3
Exaone-3.5-7.8B-Instruct	33.4	33.4	36.4	40.0
Aya-Expanse-8B	32.6	33.8	35.5	39.0
Llama-3.1-8B-Instruct	28.5	27.5	28.3	33.4
Phi-4 (14B)	33.8	33.4	35.8	37.7

Table 3: Character 3-gram recall (%) on the XOR-TyDi and MKQA benchmarks (Korean subset). Six LLMs are evaluated under four retrieval pipelines: **Base**, **Cross** = CrossRAG, **DKM** = DKM-RAG, and **QTT** = QTT-RAG.

useful information from lower-quality translations. We validate this advantage through experiments across three languages—Korean, Finnish, and Chinese—where QTT-RAG consistently outperforms baseline methods.

Korean Korean is considered a low-resource language (Jang et al., 2024). As shown in Table 3, QTT-RAG consistently outperforms all baselines on XOR-TyDi-ko and MKQA-ko across six LLMs. In Korean, performance gains range from 0.4% to 6.8% over the baselines. Among the evaluated models, Exaone-3.5-7.8B-Instruct achieves the highest score, which is expected given its training on a collection of instruction-tuned bilingual (English–Korean) generative models.

Finnish Finnish is also considered a low-resource language like Korean (Ouzerrout, 2025). Our method achieves comparable performance on the XOR-TyDi Finnish dataset except for one LLM. The results are shown in Table 4.

Chinese Chinese is a high-resource language (Jang et al., 2024), which most of the top-ranked passages are already in Chinese. As a result, opportunities for cross-lingual translation are limited, leaving less headroom for further gains. In the MKQA-zh experiment results (Table 5), CrossRAG achieves better performance with Exaone-3.5-2.4B-Instruct, Exaone-3.5-7.8B-Instruct, and Llama-3.1-8B-Instruct.

Model	Character 3-gram Recall (%)			
	Base	Cross	DKM	QTT
XOR-TyDi-fi				
Exaone-3.5-2.4B-Instruct	45.0	45.6	50.4	50.4
Qwen2.5-7B-Instruct	55.9	56.7	55.7	58.6
Exaone-3.5-7.8B-Instruct	56.0	55.6	56.1	59.3
Aya-Expanse-8B	57.6	60.1	58.3	55.4
Llama-3.1-8B-Instruct	54.9	54.9	52.7	60.0
Phi-4 (14B)	64.0	63.5	60.1	66.8

Table 4: Character 3-gram recall (%) on the XOR-TyDi benchmarks (Finnish subset). Six LLMs are evaluated under four retrieval pipelines: **Base**, **Cross** = CrossRAG, **DKM** = DKM-RAG, and **QTT** = QTT-RAG.

Model	Character 3-gram Recall (%)			
	Base	Cross	DKM	QTT
MKQA-zh				
Exaone-3.5-2.4B-Instruct	19.0	25.2	23.9	24.4
Qwen2.5-7B-Instruct	27.7	30.0	28.7	31.9
Exaone-3.5-7.8B-Instruct	22.2	26.2	26.1	25.8
Aya-Expanse-8B	26.3	32.8	33.2	33.9
Llama-3.1-8B-Instruct	25.2	30.1	28.8	29.3
Phi-4 (14B)	30.9	33.8	33.0	34.5

Table 5: Character 3-gram recall (%) on the MKQA benchmark (Chinese subset). Six LLMs are evaluated under four retrieval pipelines: **Base**, **Cross** = CrossRAG, **DKM** = DKM-RAG, and **QTT** = QTT-RAG.

However, when a non-Chinese document appears, QTT-RAG’s explicit, non-rewriting quality cues benefit models that reliably follow metadata, resulting clear improvements with Aya-Expanse-8B, Qwen2.5-7B-Instruct, and Phi-4 (14B).

4.5 Leveraging Translation Quality

To examine our design choice of quality tagging, we conduct an ablation study comparing two strategies: (1) **Hard filtering**, which excludes documents that are below all specified quality thresholds; and (2) **QTT-RAG**, which is our proposed method utilizing quality scores as metadata.

For Hard filtering, we use the same prompt employed for translation quality evaluation (Table 8) to obtain scores along three criteria: Semantic Equivalence, Grammatical Accuracy, and Naturalness & Fluency. Based on these scores, we exclude documents if they fall below a threshold of 3.5 on all criteria.

Table 6 and Table 7 show the comparison between Hard filtering and QTT-RAG. In Korean (Table 6), QTT-RAG consistently outperforms Hard filtering on all models, with average relative gains of

Model	XOR-TyDi-ko		MKQA-ko	
	Hard	QTT	Hard	QTT
Exaone-3.5-2.4B-Instruct	40.3	41.3	32.1	36.0
Qwen2.5-7B-Instruct	36.6	36.9	30.6	33.3
Exaone-3.5-7.8B-Instruct	43.2	43.8	34.2	40.0
Aya-Expanse-8B	40.4	42.8	35.7	39.0
Llama-3.1-8B-Instruct	35.0	37.2	28.7	33.4
Phi-4 (14B)	40.2	42.5	33.7	37.7

Table 6: Ablation on filtering strategy. **Hard** = Hard filtering; **QTT** = QTT-RAG. Values are Character 3-gram Recall (%).

Model	XOR-TyDi-fi		MKQA-zh	
	Hard	QTT	Hard	QTT
Exaone-3.5-2.4B-Instruct	51.3	50.4	25.4	24.4
Qwen2.5-7B-Instruct	58.7	58.6	30.1	31.9
Exaone-3.5-7.8B-Instruct	58.7	59.3	26.8	25.8
Aya-Expanse-8B	61.0	55.4	33.0	33.9
Llama-3.1-8B-Instruct	60.0	60.0	29.9	29.3
Phi-4 (14B)	66.8	66.8	33.7	34.5

Table 7: Ablation on filtering strategy. **Hard** = Hard filtering; **QTT** = QTT-RAG. Values are Character 3-gram Recall (%).

3.8% on XOR-TyDi-ko and 12.6% on MKQA-ko. In XOR-TyDi-fi (Table 7, left), the results are generally comparable across methods. Notably, Hard filtering achieves the best score on Aya-8B, outperforming QTT-RAG as well as all other baselines (Base, CrossRAG, and DKM-RAG). In MKQA-zh (Table 7, right), Hard filtering surpasses both QTT-RAG and CrossRAG on Exaone-3.5-2.4B-Instruct and Exaone-3.5-7.8B-Instruct. QTT-RAG remains the best on Aya-Expanse-8B, Phi-4 (14B), and Qwen2.5-7B-Instruct, while CrossRAG leads with Llama-3.1-8B-Instruct by a small performance difference.

With these additional experiments, we observe that effectiveness varies across languages and setups—such as resource level, the proportion of cross-lingual passages, retriever and MT quality, filtering thresholds, retained ratio, and the generator backbone—so no single strategy dominates universally.

Hard filtering simplifies the generator input and can be effective in certain regimes, particularly when in-language evidence is already abundant, and removing a small set of low-scored translated passages leaves most relevant evidence intact. However, it risks discarding rare but critical information and is sensitive to choice of threshold and language. In contrast, QTT-RAG avoids brittle

thresholds and preserves coverage, which is crucial when high-quality translations are sparse or unevenly distributed.

Together, these findings suggest that while Hard filtering may offer gains under favorable conditions, quality tagging delivers more consistent improvements across languages and models.

5 Discussion

We analyze cases where QTT-RAG delivers smaller gains in Chinese compared to Korean and Finnish. To formalize this observation, we denote the cross-lingual share by

$$r_{\text{lang}} = \frac{N_{\text{translated}}}{N_{\text{input}}}$$

where $N_{\text{translated}}$ denotes the number of translated documents and N_{input} denotes the total number of retrieved documents.

In our experiments, the MKQA-zh split has a relatively low cross-lingual share ($r_{\text{lang}} = 5.0\%$), whereas the MKQA-ko split shows a much higher cross-lingual share ($r_{\text{lang}} = 22.7\%$). This disparity helps explain why QTT-RAG’s improvements tend to be smaller in Chinese than in Korean: there are simply fewer instances where translated evidence is involved. More broadly, overall effectiveness also depends on retriever and MT quality, generator backbone, the distribution of retrieved languages, and the evaluation setting.

For future work, we aim to expand our evaluation to a wider set of languages to further test the scalability of our approach. We also plan to explore hybrid retrieval strategies, such as deliberately inducing cross-lingual usage via English-only retrieval for non-English queries.

6 Conclusion

We propose QTT-RAG, a novel multilingual RAG framework that introduces translation quality tagging as an explicit mechanism to mitigate factual distortions and translation-induced errors. Unlike prior approaches such as CrossRAG, which assumes adequate translation quality, or DKM-RAG, which relies on rewriting and risk semantic drift, our method preserves the original translated content and supplements it with fine-grained quality scores as metadata. Through extensive experiments on two multilingual QA benchmarks (XOR-TyDi QA and MKQA) across three typologically diverse languages—Korean, Finnish, and Chinese—and

six instruction-tuned LLMs ranging from 2.4B to 14B parameters, we demonstrate that QTT-RAG consistently improves character 3-gram recall over strong baselines particularly in low-resource settings (Korean and Finnish). Ablation studies further reveal that quality tagging offers a more reliable default than Hard filtering, while still leaving room for filtering-based strategies in specific regimes with abundant in-language evidence.

Limitations

QTT-RAG is most effective when a substantial portion of retrieved documents is in a different language from the query and translation quality is heterogeneous. In other words, when the majority of retrieved passages already match the query language, opportunities for translation and tagging diminish, and gains naturally become smaller.

One other limitation is that the generator must reliably interpret and utilize the structured metadata; models with weaker instruction-following capabilities or shorter effective context windows may fail to fully exploit these quality cues.

We also acknowledge that the experiments are limited to only few languages—Korean, Finnish and Chinese—which may be insufficient to generalize the effectiveness of our method. Further experiments on a more diverse set of languages are required to validate its broader applicability.

Acknowledgments

We would like to thank Manasa Bharadwaj and Kevin Ferreira for their contributions and support throughout this project. This work was made possible by the support from LG Toronto AI Lab and CARTE, and we sincerely appreciate the opportunity to collaborate with them. This work was supported by the Institute of Information & Communications Technology Planning & Evaluation (IITP) grant funded by the Korea government (MSIT) (RS-2022-00143911, AI Excellence Global Innovative Leader Education Program). Byeolhee Kim was supported by a grant of the Korea Health Technology R&D Project through the Korea Health Industry Development Institute (KHIDI), funded by the Ministry of Health & Welfare, Republic of Korea (grant number: HR21C0198).

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A Prompt Templates

Table 8 presents the template used for the LLM to assign translation quality scores for each translated document. It evaluates scores across three dimensions: Semantic Equivalence, Grammatical Accuracy, and Naturalness & Fluency.

Table 9 shows the generation prompt template, which contains both System and User messages in three languages. This template instructs the LLM to prioritize passages with higher quality scores across all three dimensions, enabling generator to output quality-aware answer leveraging the most reliable translated contents first.

B Translation Quality Assessment Cases

Tables 12 and 13 present case studies of our translation quality assessment process, demonstrating low- and high-quality translations.

The cases in Table 12 show a translation with relatively low scores in all criteria. In Case 1: Korean, it shows semantic distortions (e.g., "would not trigger a localized ice age" incorrectly translated as "would not occur"), grammatical errors including awkward sentence structures, and unnatural expressions that compromise fluency. In case 2: Finnish, it shows a translation with relatively low scores across all criteria (e.g., a quantity shift "to 10,000 Nazi war criminals" rendered as "over 10,000" and omissions of the El-Kurru and Nuri subsections) producing semantic distortions, grammatical issues, and reduced fluency. In Case 3: Chinese, it likewise shows low scores across all criteria (e.g., the title "Who Framed Roger Rabbit?" mis-translated as "Who fell into Roger's trap", "sense of humor" shifted to "original intention" and the proper name Dolores dropped to just "girlfriend" with duplicated tokens) leading to semantic drift, grammatical errors, and poor fluency.

The cases in Table 13 demonstrate high-quality translations across all three languages. In Case 1 (Korean), the output uses natural expressions and appropriate terminology (e.g., "주권" for "states' rights"), accurately conveying complex political notions while maintaining readability. In Case 2 (Finnish), the translation preserves chronology and factual detail (e.g., correct date inflection "25. huhtikuuta 1945" and idiomatic phrasing such as "Kolmen valtakunnan rajapyykillä"), yielding strong grammatical accuracy and fluency. In Case 3 (Chinese), named entities and quantitative details are rendered precisely (e.g., "多用途体育

场”、“可容纳8,000人”、“于2017年4月更名，以纪念格林纳达首位奥运奖牌得主基拉尼·詹姆斯”), resulting in consistently high scores for semantic equivalence, grammatical accuracy, and fluency.

These cases illustrate how our quality assessment framework effectively captures the nuances of translation quality and provides meaningful meta-data for the generation process.

C More cases of DKM-RAG and CrossRAG

In Table 10 and 11, they show more failure cases in Finnish and Chinese queries. In DKM-RAG, during the refinement process, LLM tends to alter the content of the retrieved passage into query-related content, which distorts the actual meaning of the original retrieved passages. In CrossRAG, certain words are incorrectly translated by NLLB, which eventually leads the generator to rely on wrong passages. In both cases, these limitations result in failure to generate the correct answer.

Translation Quality Assessment Prompt (Korean / Finnish / Chinese)
<p>Korean: 영어 원문: {original english passage} 한국어 번역문: {translated korean passage} 다음 영어 원문과 한국어 번역문의 품질을 세 가지 기준(의미론적 일치성, 문법적 정확성, 자연스러움과 유창성)에 대해 각각 0.0점에서 5.0점 사이의 소수점 첫째 자리까지의 점수로 평가해주세요. 다른 설명 없이 JSON 형식으로만 응답해주세요. 예시: "의미론적 일치성": 5.0, "문법적 정확성": 2.5, "자연스러움과 유창성": 4.3</p> <p>Finnish: Alkuperäinen teksti (englanti): {original english passage} Käännös (suomi): {translated finnish passage} Arvioi käännöksen laatu englanninkielisen alkuperäistekstin ja suomenkielisen käännöksen välillä kolmen kriteerin perusteella: semanttinen johdonmukaisuus, kieliopillinen tarkkuus ja luontevuus ja sujuvuus. Anna pisteet jokaiselle kriteerille välillä 0.0–5.0 yhdellä desimaalilla. Vastaa vain JSON-muodossa ilman mitään lisäselityksiä tai kommentteja. Esimerkki: "Semanttinen johdonmukaisuus": 5.0, "Kieliopillinen tarkkuus": 2.5, "Luontevuus ja sujuvuus": 4.3</p> <p>Chinese: 原文(英文): {original english passage} 翻译(中文): {translated chinese passage} 请根据以下三个标准评估英文原文与其中文翻译之间的翻译质量: 语义一致性、语法准确性、以及语言的自然流畅度。请为每个标准打分, 分数范围为0.0到5.0, 保留一位小数。只需以JSON格式作答, 不要添加任何额外说明或评论。 示例: "语义一致性": 5.0, "语法准确性": 2.5, "语言流畅度": 4.3</p> <p>English Version: Original Passage: {original english passage} Translated Passage: {translated {query language} passage} Please evaluate the quality of the following English-to-{query language} translation using the three criteria: Semantic Equivalence, Grammatical Accuracy and Naturalness & Fluency from 0.0 to 5.0. Respond strictly in JSON format, without additional explanations. Example: "Semantic Equivalence": 5.0, "Grammatical Accuracy": 2.5, "Naturalness & Fluency": 4.3</p>

Table 8: The prompt used for evaluating translated passages based on three dimensions of translation quality. An example (few-shot) output format is also provided for better generation. Quality scores are then attached as metadata to each translated document.

Generation Prompt (Korean / Finnish / Chinese)
<p>System (Korean): 이제부터 너는 내 유능한 비서야. 내가 제공하는 문서들은 일부는 원래 한국어로 작성된 문서이고, 일부는 영어 원문을 한국어로 번역한 후 품질 평가 점수가 부여된 문서야. 번역된 문서에는 의미론적 일치성, 문법적 정확성, 자연스러움과 유창성에 대한 점수가 포함되어 있으며, 각각 0.0에서 5.0 사이의 값이야. 원래 한국어로 작성된 문서를 가장 신뢰하고 우선적으로 참고해 줘. 번역된 문서는 점수가 높은 순서대로 활용해 줘. 확신이 들지 않는 정보는 신중하게 판단해. 모든 질문에는 가능한 한 짧고 정확하게, 반드시 한국어로 대답해 줘.</p> <p>System (Finnish): let nyt minun osaava assistenttini. Antamani asiakirjat ovat joko alun perin suomeksi kirjoitettuja tai englanninkielisestä alkuperästä suomeksi käännettyjä, ja niihin on liitetty laadun arviointipisteet. Käännettyillä asiakirjoilla on pistemäärät semanttisesta yhteneväisyydestä, kieliopillisesta oikeellisuudesta sekä luonnollisuudesta ja sujuvuudesta, asteikolla 0.0–5.0. Luota eniten alun perin suomeksi kirjoitettuihin asiakirjoihin ja käytä niitä ensisijaisesti. Käännösasiakirjoja voit käyttää apuna korkeimman pistemäärän mukaisessa järjestyksessä. Ole varovainen, jos tieto ei vaikuta varmalta. Vastaa kaikkiin kysymyksiin mahdollisimman lyhyesti ja tarkasti, aina suomeksi.mj</p> <p>System (Chinese): 你现在是我聪明能干的助手。我提供的文档有些是原始中文写成的，有些是从英文翻译成中文并附有质量评分的翻译文档。翻译文档包含三个评分指标：语义一致性、语法准确性和语言流畅度，评分范围为0.0到5.0。请优先参考原始中文文档，因为它们最可靠。翻译文档可以作为补充信息，按评分高低依次参考。对于不确定的信息，请谨慎判断。所有问题请用简体中简洁准确地回答。</p> <p>English Version:</p> <p>System: You are a helpful assistant. The documents I provide include documents that were originally written in {query language} and others that are translations from English into {query language} with quality evaluation scores. The translated documents are scored on semantic consistency, grammatical accuracy, and fluency, each ranging from 0.0 to 5.0. You should prioritize and rely on the original {query language} documents first. Use the translated ones as sources in order of highest score. Be cautious with any uncertain information. Always answer as briefly and accurately as possible, and respond only in {query language}.</p> <p>User Message</p> <p>Background: {documents with quality scores}</p> <p>Question: {question}</p>

Table 9: The prompt used for response generation. Documents with quality scores are provided to generator for better guidance. The system prompt explicitly instructs the model to prioritize higher-quality translations and respond only in query language.

Finnish	
Query	<i>Mikä on Ilmestyskirja. Nyt -elokuvan genre?</i> (What is the genre of the movie Apocalypse Now?)
Retrieved	A war film directed by Francis Ford Coppola from 1979...
Refined	Francis Ford Coppolan ohjaama romanttinen komediaelokuva vuodelta 1979... (A romantic comedy film directed by Francis Ford Coppola from 1979...)
LLM Output	Romanttinen komediaelokuva. (Romantic comedy film.)
Chinese	
Query	在我睡前要走几英里是谁写的 (Who wrote "I walk a few miles before I go to sleep")
Retrieved	在我睡前要走几英里(I have to walk a few miles before I sleep.)
Refined	我睡前写了几封信，还有几英里要走(Before I sleep, I wrote a few letters and still had a few miles to go.)
LLM Output	这段话表示作者在睡眠前会同时完成两件(This passage indicates that the author will complete two things at the same time before going to sleep.)

Table 10: Case study of factual distortion in DKM-RAG for a Finnish and Chinese query.

Finnish	
Query	kuka laulaa sugar pie honey bunch (Who sings Sugar Pie Honey Bunch?)
Retrieved	I Can't Help Myself (Sugar Pie Honey Bunch). chart in 1989. The "Motorcity All-Stars" released a rerecorded version of song in 1989 on Ian Levine's Motown revival label Motorcity.
Translated	I Can't Help Myself (Sugar Pie Honey Bunch). sarja vuonna 1989. "Motorcity All-Stars" julkaisi uuden kappaleen vuonna 1989 Ian Levine'n Motown-elokuvalla Motorcity. (I Can't Help Myself (Sugar Pie Honey Bunch). series in 1989. "Motorcity All-Stars" released a new song in 1989 on Ian Levine's Motown movie Motorcity.)
Chinese	
Query	'The world is like a great big onion' 是谁演唱的 (Who sang "The world is like a great big onion"?)
Retrieved	The Onion Song — a 1969 hit by soul singers Marvin Gaye and Tammi Terrell. It entered the UK singles chart on 15 November 1969, peaking at No.9 on 9 December. Terrell died, aged 24, just prior to the U.S. single release.
Translated	洋歌曲。 — “洋歌曲”是灵魂歌手马文·盖伊和塔米·特雷尔1969年的热门歌曲。这首歌在美国表现不佳。但它却成为盖伊和特雷尔在英国最热门的歌曲，于1969年11月15日进入单曲榜，并于12月9日最高排名第九。 ("Western Song" was a 1969 hit by soul singers Marvin Gaye and Tammy Terrell. The song performed poorly in the United States. It became Gaye and Terrell's biggest hit in the United Kingdom, entering the singles chart on November 15, 1969, and peaking at No.9 on December 9.)

Table 11: Case study of incorrect translation in CrossRAG for a Finnish and Chinese query.

Case 1: Korean	
Original	Retrieved English documents: The film implies that a geomagnetic pole-shift would trigger a localized ice age in Miami, although regions at lower latitudes receive more direct sunlight. A temperature drop to absolute zero (−273 °C) is scientifically impossible; before reaching −196 °C the two dominant atmospheric gases would liquefy and precipitate.
Tagged	영화는 암시하는 바와 같이 마이애미에 현지화된 빙하기가 발생하지 않을 것입니다. 지구 온도 감소 (최후 -273 °C) 를 경험하는 지구 지역의 묘사는 과학적으로 정확하지 않습니다. −196 °C (−320 °F) 아래는 지구 대기 중 두 가지 지배적인 가스가 액화되어 표면에 떨어질 것입니다. [점수] 의 미론적 일치성: 2.5, 문법적 정확성: 2.0, 자연스러움과 유창성: 2.3
Case 2: Finnish	
Original	Egyptian pyramids. Egypt. Its builders reduced the amount of work necessary to construct it by ingeniously using as its foundation and core a 12-meter-high natural limestone hill. Section: Number and location of pyramids.: El-Kurru. Piye, the king of Kush who became the first ruler of the Twenty-fifth Dynasty of Egypt, built a pyramid at El-Kurru. He was the first Egyptian pharaoh to be buried in a pyramid in centuries. Section: Number and location of pyramids.: Nuri. Taharqa, a Kushite ruler of the Twenty-fifth Dynasty, built his pyramid at Nuri. It was the largest in the area (North Sudan)
Tagged	Egyptiläiset pyramidit. Egypti. Sen rakentajat vähensivät sen rakentamiseen tarvittavan työn määrää käyttämällä älykkäästi pohjana ja ytimenä 12 metrin korkean luonnollisen kalkkikivikukkulan. [pisteet] Semanttinen johdonmukaisuus: 2.5, Kielipillinen tarkkuus: 2.0, Luontevuus ja sujuvuus: 2.0
Case 3: Chinese	
Original	Who Framed Roger Rabbit? Eddie Valiant, having fully regained his sense of humor, begins moving forward with his girlfriend, Dolores. The residents of Toontown gather to celebrate the victory. Bob Hoskins portrays Eddie Valiant, a private investigator with a soft spot for toons and a weakness for drink.
Tagged	谁陷入子罗杰的陷.自完全全重拾初心,与女友友友迈步前行,动画 城众人也开 始庆祝他人的胜利.演员 勃勃· 霍斯金斯饰 艾迪·瓦利安特,一位对动画角色心有喜欢的空隙而又 酒的私家侦探. [分数] 语义一致性: 2.5, 语法准确性: 1.0, 语言流畅度: 1.0

Table 12: Case studies of low-quality translation assessment in Korean, Finnish and Chinese. Quality scores are provided for semantic equivalence, grammatical accuracy, and fluency

Case 1: Korean	
Original	John Tyler (March 29, 1790 – January 18, 1862) was the tenth president of the United States, serving from 1841 to 1845, after briefly holding office as the tenth vice president in 1841. He was elected vice president on the 1840 Whig ticket with President William Henry Harrison, succeeding to the presidency following Harrison's death 31 days after assuming office. Tyler was a stalwart supporter and advocate of states' rights, and he adopted nationalistic policies as president only when they did not infringe on the states' powers.
Tagged	존 타일러 (1790년 3월 29일 – 1862년 1월 18일)는 1841년부터 1845년까지 10대 부통령을 지낸 후 10대 대통령이다. 그는 1840년 윌리엄 헨리 해리슨 대통령과 함께 위기당 당선되었다. 타일러는 1841년 4월 해리슨의 사망 후 대통령직에 올랐다. 새로운 행정부 출범 후 불과 한 달 만에 대통령직에 올랐다. 그는 주권 지지자이자 주권 옹호자였으며, 대통령으로서 국가주의 정책을 채택했을 때만 주권권을 침해하지 않았다. [점수] 의미론적 일치성: 4.5, 문법적 정확성: 4.8, 자연스러움과 유창성: 4.5
Case 2: Finnish	
Original	End of World War II in Europe. to 10,000 Nazi war criminals eventually fled Europe using ratlines such as ODESSA. German forces leave Finland: On 25 April 1945, the last German troops withdrew from Finnish Lapland and made their way into occupied Norway. On 27 April 1945, the Raising the Flag on the Three-Country Cairn photograph was taken. Mussolini's death: On 25 April 1945, Italian partisans liberated Milan and Turin. On 27 April 1945, as Allied forces closed in on Milan, Italian dictator Benito Mussolini was captured by Italian partisans. It is disputed whether he was trying to flee from Italy to Switzerland (through the Splügen Pass).
Tagged	Toisen maailmansodan lopussa Euroopassa yli 10 000 natsisotarikollista pakeni mantereelta ODESSA:n kaltaisten ratline-reittien kautta. Saksalaiset joukot poistuivat Suomesta: 25. huhtikuuta 1945 viimeiset saksalaiset vetäytyivät Lapista miehitettyyn Norjaan. 27. huhtikuuta otettiin valokuva, jossa nostettiin lippu Kolmen valtakunnan rajapyykillä. Mussolinin kuolema: 25. huhtikuuta italialaiset partisaanit vapauttivat Milanon ja Turinin. 27. huhtikuuta, kun liittoutuneet lähestyivät Milanoa, Benito Mussolini vangittiin partisaanien toimesta. [pisteet] Semanttinen johdonmukaisuus: 4.5, Kieliopillinen tarkkuus: 4.5, Luontevuus ja sujuvuus: 4.5
Case 3: Chinese	
Original	Kirani James Athletic Stadium is a multi-purpose stadium in St. George's, Grenada. Formerly known as the Grenada National Stadium, it is used mostly for football matches and has a capacity of 8,000. In April 2017 the venue was renamed Kirani James Athletic Stadium in honour of Kirani James, Grenada's first Olympic medallist.
Tagged	基拉尼詹姆斯竞技场体育场警察场是格莱纳达圣乔治的多用途体育场。目前主要用于足球比赛。该体育场容纳8000人。于2017年4月改名为基拉尼詹姆斯竞技场体育场,以纪念格莱纳达第一个奥运奖得主基拉尼詹姆斯。 [分数] 语义一致性: 4.8, 语法准确性: 4.5, 语言流畅度: 4.2

Table 13: Case studies of high-quality translation assessment in Korean, Finnish, and Chinese. Quality scores are provided for semantic equivalence, grammatical accuracy, and fluency.

Improving Language Transfer Capability of Decoder-only Architecture in Multilingual Neural Machine Translation

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Abstract

Existing multilingual neural machine translation (MNMT) approaches mainly focus on improving models with the encoder-decoder architecture to translate multiple languages. However, decoder-only architecture has been explored less in MNMT due to its underperformance when trained on parallel data solely. In this work, we attribute the issue of the decoder-only architecture to its lack of language transfer capability. Specifically, the decoder-only architecture is insufficient in encoding source tokens with the target language features. We propose dividing the decoding process into two stages so that target tokens are explicitly excluded in the first stage to implicitly boost the transfer capability across languages. Additionally, we impose contrastive learning on translation instructions, resulting in improved performance in zero-shot translation. We conduct experiments on TED-19 and OPUS-100 datasets, considering both training from scratch and fine-tuning scenarios. Experimental results show that, compared to the encoder-decoder architecture, our methods not only perform competitively in supervised translations but also achieve improvements of up to 3.39 BLEU, 6.99 chrF++, 3.22 BERTScore, and 4.81 COMET in zero-shot translations. We release our codes at <https://github.com/zhiqu22/PhasedDecoder>.

1 Introduction

Multilingual neural machine translation (MNMT) (Firat et al., 2016) aims to integrate multiple language translation directions into a single model. Although multilingual translation systems based on large language models have demonstrated strong performance (Zhang et al., 2023; Yang et al., 2023; Xu et al., 2024), current MNMT models with the encoder-decoder architecture (Fan et al., 2020; Goyal et al., 2022; Team et al., 2022) remain a focus of research due to the competitive performance, fewer parameters, and reduced training costs (Zhu

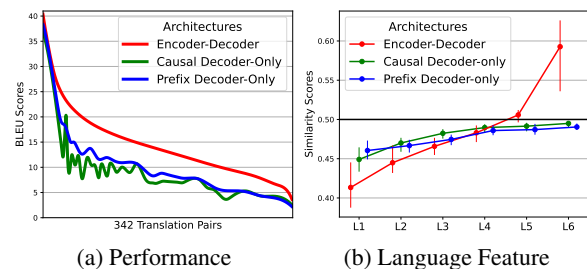


Figure 1: Comparison between different architectures in preliminary experiments on TED-19. Figure 1a shows the BLEU score. Figure 1b shows the layer-wise language feature representations of a sentence where the x-axis indicates the layer number and the vertical line indicates the value range. Specifically, we follow Qu et al. (2024) to compute a similarity score, where values higher than 0.5 mean the representation exhibits the target language features more and lower than 0.5 indicates showing more source language features. Appendix A provides the details of implementation.

et al., 2023). However, in MNMT, models with the decoder-only architecture¹ have shown underperformance by the empirical research of Gao et al. (2022); Zhang et al. (2022), as further evidenced by Figure 1a. Therefore, addressing the underdevelopment of decoder-only architectures in MNMT is crucial due to the advantage of zero-shot generalization (Wang et al., 2022), which potentially benefits zero-shot translation, i.e., translating language pairs unseen during training.

We attribute the issue to the lack of language transferability, causing generations to rely solely on representations that always manifest the source language features. Specifically, MNMT encoder-decoder models typically add a language tag indicating the target language at the beginning of the source tokens as a translation instruction (Johnson et al., 2017; Wu et al., 2021), then, Kudugunta et al. (2019); Qu et al. (2024) show that the encoder of MNMT models transfers source tokens to represent

¹The term "decoder-only architecture" encompasses both causal decoder-only architectures (Radford et al., 2018) and prefix decoder-only architectures (Dong et al., 2019).

target language features more than source language features. As shown in Figure 1b, the representation of source tokens extracted from the model with the encoder-decoder architecture mainly exhibits the target language features at the output of the encoder (red line), however, this characteristic is absent in decoder-only architectures (green and blue lines). We hypothesize that the decoder-only architectures merely capture the surface information of source tokens instead of transferring source tokens into a state with more target language features.

We propose dividing the decoder-only architecture into two stages, namely, Two-stage Decoder-only (TDO). Specifically, the representations of target tokens are excluded in the first stage to enforce language transfer using the translation instruction, and the target tokens are fused in the second stage, which follows the normal decoder-only manner. Moreover, unlike the encoder-decoder architecture, where source and target tokens are processed separately, in the decoder-only architecture, source tokens pass through all layers. However, the training objective of MNMT only focuses on the target tokens, leading to the degradation of the target language features on the source token representation. Thus, we introduce Instruction-level Contrastive Learning (InstruCL) as a training objective to supervise source tokens in the second stage.

We evaluate the proposed methodologies on two datasets, TED-19 (Ye et al., 2018), and OPUS-100 (Zhang et al., 2020a; Yang et al., 2021), using four automatic evaluation metrics: BLEU (Papineni et al., 2002; Post, 2018), chrF++ (Popović, 2015, 2017), BERTScore (Zhang et al., 2020b) and COMET (Rei et al., 2020). Experimental results show that, compared to encoder-decoder models, our models perform competitively in supervised translations and achieve improvements of up to 3.39 BLEU, 6.99 chrF++, 3.22 BERTScore, and 4.81 COMET in zero-shot translations. We also analyze the variation of layer-wise representations at the sentence level to demonstrate the effects of our proposed methods. Results prove that the gains of proposed methods in the decoder-only architecture derived from improving language transfer.

2 Related Work

Although the large language model based on the decoder-only architecture performs satisfactorily in the multilingual translation (Zhu et al., 2023; Xu et al., 2024), the SOTA models specialized on

MNMT are still based on the encoder-decoder architecture (Fan et al., 2020; Team et al., 2022) due to the balance between costs and performances. Gao et al. (2022); Zhang et al. (2022) empirically show that the decoder-only architecture does not have a distinct advantage in MNMT, and Dabre et al. (2020); Raffel et al. (2023) demonstrate that the reason could be the onefold style of training data comprising only translations, degrading the zero-shot ability of the decoder-only architecture (Brown et al., 2020; Wang et al., 2022).

Recent investigations of the encoder-decoder architecture in MNMT reveal the deficiency of the decoder-only architecture at the representation level. Kudugunta et al. (2019); Stap et al. (2023) point out that the sentence representations translating to two different target languages are gradually separated with the increase of layers. Qu et al. (2024) demonstrate that the encoder of MNMT model transfers the source sentence representation to the target side, leading to the representation of source tokens used in the generation with more target language features. This finding aligns with the prior empirical studies (Wu et al., 2021; Qu and Watanabe, 2022; Pires et al., 2023), which shows that increasing target language information can lead to performance improvements. Moreover, this also supports our hypothesis that the weakness of the decoder-only architecture can be attributed to the lack of language transfer.

3 Backgrounds

3.1 Multilingual Neural Machine Translation

A parallel multilingual corpus, denoted by \mathbb{C} , consists of translation pairs in the form of (\mathbf{x}, \mathbf{y}) . Here, $\mathbf{x} = x_1, \dots, x_I$ is the source sentence comprising I tokens, and $\mathbf{y} = y_1, \dots, y_J$ is the target sentence with J tokens. We also denote language tags by $\mathbf{l} = l_1, \dots, l_K$, where each tag is an artificial token uniquely corresponding to one of the K languages in \mathbb{C} . To serve as a translation instruction, we add the language tag specifying the target language at the beginning of the source tokens (Johnson et al., 2017; Wu et al., 2021), denoted by l_y .² Thus, the training data comprises instances in the form of $(l_y, \mathbf{x}, \mathbf{y})$. The model is trained over all instances in \mathbb{C} by the standard cross-entropy objective:

$$\mathcal{L}_{ce} = - \sum_{l_y, \mathbf{x}, \mathbf{y} \in \mathbb{C}} \sum_{j=1} \log p(y_j | l_y, \mathbf{x}, \mathbf{y}_{<j}), \quad (1)$$

²Appendix B shows the comparison between different strategies of translation instructions in MNMT.

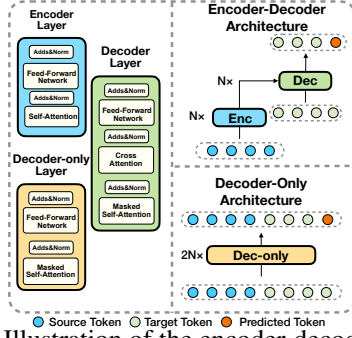


Figure 2: Illustration of the encoder-decoder architecture and the decoder-only architecture.

where $p(y_j | l_y, \mathbf{x}, \mathbf{y}_{<j})$ is a probability distribution for each token generated by MNMT model.

3.2 Architectures

All architectures discussed in this work follow the Transformer architecture (Vaswani et al., 2017), and almost all MNMT models are based on the encoder-decoder architecture (Johnson et al., 2017; Fan et al., 2020; Team et al., 2022; Raffel et al., 2023), as illustrated in Figure 2. It comprises an encoder and a decoder in which both are composed of N layers with each encoder layer comprising a self-attention mechanism and a feed-forward network (FFN), and with each decoder layer comprising a masked self-attention mechanism, a cross-attention mechanism, and an FFN. The encoder receives $I+1$ tokens combining by $(l_y, \mathbf{x})^3$, and output the representations $\mathbf{H} = \{h_1, \dots, h_{I+1}\}$, $h \in \mathbb{R}^d$, d is the model dimension. Then, the decoder relies on \mathbf{H} and $\mathbf{y}_{<j}$ to generate the next token:

$$\mathbf{H}^N = \text{encoder}(l_y, \mathbf{x}), \quad (2)$$

$$y_j = \text{decoder}(\mathbf{H}^N, \mathbf{y}_{<j}), \quad (3)$$

where \mathbf{H}^N is an intermediate state used in the cross-attention mechanism in each decoder layer without further transformation. Thus, Equation 1 implicitly aligns the output of the encoder in the representational subspace of the target language, i.e., the language transfer as shown in the red line of Figure 1b, because the ideal decoder should translate two sentences \mathbf{x}^a and \mathbf{x}^b , which have the same target language, parallel semantics, and different source languages, to the same target sentence \mathbf{y} . Formally, an ideal encoder meets the following:

$$\text{encoder}(l_y, \mathbf{x}^a) = \text{encoder}(l_y, \mathbf{x}^b). \quad (4)$$

A decoder-only architecture refers to a model that consists solely of a decoder (Figure 2). Each

decoder-only layer consists of a masked self-attention mechanism and an FFN (Radford et al., 2018), and each model has $2N$ layers to approximately match the parameter size of an encoder-decoder architecture. We define the decoder-only process as follows:

$$y_j = \text{decoder-only}(l_y, \mathbf{x}, \mathbf{y}_{<j}). \quad (5)$$

Notably, the difference between $\text{decoder-only}(\cdot)$ and $\text{decoder}(\cdot)$ is that $\text{decoder-only}(\cdot)$ fuses the source and target information by a concatenated input, namely, l_y , \mathbf{x} , and \mathbf{y} are equally treated⁴, instead of using a cross-attention mechanism. Thus, there exists no intermediate state to align different source languages as Equation 4, resulting in the blue and green lines of Figure 1b. Moreover, we follow Gao et al. (2022); Raffel et al. (2023) to distinguish the decoder-only by the manner of masked self-attention mechanism as causal decoder-only and prefix decoder-only (Appendix D). Finally, compared to the encoder-decoder architecture, the decoder-only architecture requires around 10% fewer parameters (Appendix E).

4 Methodologies

4.1 Two-stage Decoder-only Architecture

The limitations of the decoder-only architecture in MNMT likely arise from inadequate language transfer capabilities, i.e., the absence of Equation 4. To address this issue, we propose the Two-stage Decoder-only (TDO) architecture, which divides the decoder-only process into two stages to implicitly align representations of different source languages in the subspace of the target language. Specifically, as illustrated in Figure 3, the target tokens are explicitly excluded in the first stage, i.e., the first M layers, and these target tokens are fused in the second stage, i.e., the subsequent $2N - M$ layers. The process of TDO is formally expressed:

$$\mathbf{H}^M = \text{decoder-only}_1(l_y, \mathbf{x}), \quad (6)$$

$$y_j = \text{decoder-only}_2(\mathbf{H}^M, \mathbf{y}_{<j}), \quad (7)$$

where $\text{decoder-only}_1(\cdot)$ enables the implicit alignment as done in Equation 4. Notably, the first stage logically acts as an encoder when prefixed masking is applied to the self-attention mechanism. However, the first and second stages remain unified structures, and the fusing of source and target information follows the manner of $\text{decoder-only}(\cdot)$

³The operation of combining means adding l_y at the beginning of \mathbf{x} . Appendix C shows the specific forms in detail.

⁴Appendix C compares the difference of the input and output forms between encoder-decoder and decoder-only models.

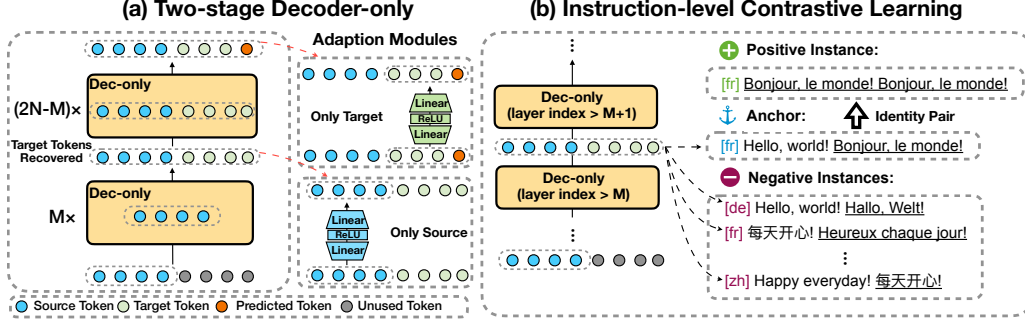


Figure 3: Illustration of proposed methods. Notably, the term, Token, not only means the real token before and after the processing of model, but also refers to the representation in the corresponding position. (a) shows the Two-stage Decoder-only and shows the Adaption, i.e., using an additional FFN to narrow the gap between source and target representations by non-linear transformation. (b) shows the Instruction-level Contrastive Learning. Underline marks target tokens, and [*] means the instruction of this instance. For the anchor, negative instances in this figure meet at least one of two features: 1) different target language and 2) unparallel semantics.

rather than $\text{decoder}(\cdot)$. Therefore, TDO architecture preserves the decoder-only architecture.

Notably, a representational gap arises at the $M + 1$ layer due to our imbalance design where the source tokens have passed through the preceding M layers, while the target tokens are not. To bridge this gap, as shown in Figure 3, we employ an additional FFN as an adaption module⁵ at the output of the M layer to nonlinearly transform the representation of source tokens. Similarly, since the source and target tokens share the same representational space in the second stage, we employ another adapter at the output of the $2N$ layer to ensure that the output representation of target tokens remains unaffected by the source language.

4.2 Instruction-level Contrastive Learning

Although Equation 6 transfers \mathbf{H} , i.e., the representation of source tokens, to \mathbf{H}^M , which aligns with the target language, \mathbf{H} potentially tends to degrade towards the source language in Equation 7 because Equation 1 does not supervise \mathbf{H} directly.⁶

Contrastive learning, which is a technique to encourage representations towards the target states (Jaiswal et al., 2021), is helpful to mitigate this degradation. However, two challenges remain in this process. The first is the lack of optimization objectives for aligning \mathbf{H} with the target language. For instance, the \mathbf{H} derived by a translation from German to English cannot be considered an anchor to optimize another \mathbf{H} derived by a translation from French to English because neither adequately rep-

resents the optimal state of English. The second challenge is that the optimization at the sentence representation level potentially leads to suboptimal results. For instance, Pan et al. (2021) suggest averaging representations of all tokens to get a sentence representation for contrastive learning, which loses the syntactic information.

We propose Instruction-level Contrastive Learning (InstruCL), which only aligns l_y , i.e., the translation instruction, of each instance, given that MNMT remains sensitive to l_y (Wu et al., 2021). As shown in Figure 3, given an anchor (l_y, x, y) , we establish an identity pair in the form of (l_y, y, y) , namely a pseudo pair translating the target sentence to itself, as the positive instance because the identity pair can serve as a proxy for the target language (Qu et al., 2024). Specifically, in a training batch, we have a set of representations $\mathbb{B} = \{h_1^1, h_1^2, \dots\}$ where h_1 is the representation of l_y collected from \mathbf{H} . Then, we designate one instance of \mathbb{B} as the anchor, denoted by h^{anc} . Other instances are treated as negative instances, which meet one or both of the following features compared to the anchor: different target languages or unparallel semantics. Subsequently, the identity pair established by the anchor would be fed into the model and we collect the representation of l_y at the same layer, and denote it by h^{pos} . The objective of InstruCL is formulated as:

$$\begin{aligned} \mathcal{L}_{\text{ctr}} &= - \sum_{h \in \mathbb{B}} \log \frac{\exp(s^+)}{\exp(s^+) + \sum_{i=1}^{|\mathbb{B}|-1} \exp(s_i^-)}, \\ s^+ &= \text{sim}(h^{\text{anc}}, h^{\text{pos}}), \\ s_i^- &= \text{sim}(h^{\text{anc}}, h_1^i), h_1^i \neq h^{\text{anc}}, \end{aligned} \quad (8)$$

where $\text{sim}(\cdot)$ calculates the similarity of representa-

⁵Adaptation module is shared for all languages instead of a language-specific component (Bapna and Firat, 2019).

⁶Although the language modeling loss (Radford et al., 2018) can provide supervision for the representation of source tokens, Gao et al. (2022) show that supervising the representation of source tokens does not benefit MNMT.

tions using the cosine similarity. The final training objective is simply jointed as:

$$\mathcal{L} = \mathcal{L}_{\text{ce}} + \mathcal{L}_{\text{ctr}}. \quad (9)$$

5 Experiments

5.1 Datasets and Evaluations

Following prior works (Wu et al., 2021; Zhang et al., 2022; Tan and Monz, 2023; Stap et al., 2023; Qu et al., 2024), we use English-centric datasets in our experiments, where the training and validation data consist of translation pairs both from English and to English. It is an ideal setup for the evaluation of zero-shot translation capabilities, because non-central languages have never seen each other. We utilize two datasets in our experiments: 1) TED-19 (Qu et al., 2024), a sub-collection of TED Talks (Ye et al., 2018), comprising 6.5 million instances across 19 languages from various language families; and 2) OPUS-100 (Zhang et al., 2020a; Yang et al., 2021), which includes 95 languages and a total of 92 million instances. Detailed information about these datasets is provided in Appendix F.

We set the beam size to 4 during inference and evaluate the output quality using four automatic evaluation metrics for a comprehensive assessment: SacreBLEU (Papineni et al., 2002; Post, 2018), chrF++ (Popović, 2015, 2017), BERTScore (Zhang et al., 2020b), and COMET (Rei et al., 2020). Moreover, we measure the target-off ratio on zero-shot pairs, i.e., the ratio of cases where the source sentence is not translated into the correct target language, as a secondary metric. Finally, we conduct statistical significance testing for zero-shot pairs by using paired bootstrap resampling (Koehn, 2004). The settings of these evaluation metrics are described in Appendix G.

5.2 Experimental Setups

We conduct experiments from two perspectives: training from scratch and fine-tuning. Based on the findings by Gao et al. (2022); Zhang et al. (2022), which empirically demonstrate that the decoder-only architecture underperforms compared to the encoder-decoder architecture in MNMT, and our motivation, which aims to improve the decoder-only architecture, our baselines are vanilla models with the encoder-decoder and decoder-only architectures. Specifically, we train models with the encoder-decoder architecture from scratch using TED-19 and OPUS-100 as baselines. Additionally, we fine-tune three pre-trained models with the

encoder-decoder architecture: M2M-418M (Fan et al., 2020), NLLB-600M (Team et al., 2022), and M2M-1.2B (Fan et al., 2020), in TED-19. Moreover, although the proposed methods are not restricted to a specific architecture, the adaptation modules are not implemented for the models with the encoder-decoder architecture, because, when the hyper-parameters are consistent, the decoder-only architecture with adaptation modules still contains fewer learnable parameters⁷ to ensure fairness, i.e., models have the same magnitude of parameters. In addition to discussing the parameters, we further discuss the impact of computational complexity in Appendix J. Finally, we conduct experiments that apply InstruCL to models with different architectures, and we provide the experimental results and discussions in Appendix I as assisted evidence to support the motivation in Section 4.2, namely, InstruCL supplements the inadequate supervision of Equation 1 in the second stage.

Our models in this work conform to the manner of the Transformer (Vaswani et al., 2017). For training from scratch, we configure the models with $N = 6$, $d = 512$, and an FFN inner size of $4d$ for models trained on TED-19. The FFN in the adaptation module is dimensionally matched to the FFN in the main network. For OPUS-100, we explore both a deeper model with $N = 12$ and a wider model with $N = 6$ and $d = 1024$. Fine-tuning experiments are conducted solely on TED-19. Given that pre-trained models for MNMT typically employ an encoder-decoder architecture, we initialize our model’s parameters from the decoder, freezing the embedding layer during training. For M2M-418M and NLLB-600M, we set $N = 6$, and for M2M-1.2B, we set $N = 12$, maintaining the original settings for d and the FFN inner size. To ensure comparability across different architectures, we consistently set $M = N$ and the layer index of InstruCL to $1.5N$ in the main experiments. Detailed settings for training and the count of learnable parameters can be found in Appendix H.

5.3 Results: Training from scratch

Table 1 shows the experimental results. The comparison between the basic architectures shows that, first, the prefix decoder-only consistently outperforms the causal decoder-only, which aligns with Raffel et al. (2023). Second, the decoder-only architecture consistently underperforms the encoder-

⁷Appendix H lists the count of modeling parameters for different cases in detail.

				BLEU \uparrow			chrF++ \uparrow			BERTScore \uparrow			COMET \uparrow			off \downarrow	
		Pref.	Adap.	CL	en \rightarrow	\rightarrow en	zero	en \rightarrow	\rightarrow en	zero	en \rightarrow	\rightarrow en	zero	en \rightarrow	\rightarrow en	zero	zero
TED N=6 $d=512$	Enc-Dec				25.46	28.31	12.32	45.96	50.86	32.13	84.10	93.37	78.03	80.49	78.15	67.26	3.82
	Dec-only				22.54	24.14	7.33	42.84	45.08	23.36	82.96	92.31	74.38	76.60	72.99	57.50	6.01
		✓				24.00	26.97	8.18	44.49	48.93	25.35	83.54	92.97	74.52	78.46	76.10	56.74
					25.47	28.88	13.56	45.98	51.33	34.04	84.11	93.45	78.90	80.41	78.42	69.74	3.54
			✓			25.55	28.98	13.61	46.03	51.49	34.11	84.15	93.50	78.94	80.56	78.65	70.09
	TDO			✓	25.37	28.46	13.95 \dagger	45.99	51.13	34.41 \dagger	84.09	93.40	79.15	80.35	78.26	70.43 \dagger	3.45
		✓	✓		25.60	28.82	14.16 \dagger	46.11	51.35	34.76 \dagger	84.13	93.45	79.29 \dagger	80.52	78.47	70.98 \dagger	3.43
					25.53	28.76	14.26 \dagger	46.01	51.09	34.72 \dagger	84.13	93.41	79.27 \dagger	80.43	78.18	70.82 \dagger	3.43
		✓	✓		25.61	28.52	14.51 \dagger	46.04	50.89	35.01 \dagger	84.16	93.40	79.41 \dagger	80.60	78.16	71.48 \dagger	3.49
				✓	25.62	28.94	14.70 \dagger	46.15	51.46	35.34 \dagger	84.15	93.47	79.57 \dagger	80.55	78.55	71.94 \dagger	3.39
		✓	✓	✓	25.61	28.66	14.81\dagger	46.05	51.01	35.35\dagger	84.16	93.41	79.60\dagger	80.61	78.22	72.07\dagger	3.42
OPUS N=12 $d=512$	Enc-Dec				25.18	29.79	5.13	44.75	48.40	12.95	82.98	92.33	72.44	76.59	76.21	58.51	64.21
	Dec-only				23.09	26.80	5.42	42.18	45.05	13.55	82.19	91.72	72.48	74.66	73.65	58.17	60.22
		✓			23.96	28.41	6.62	42.98	47.22	15.36	82.47	92.06	73.57	75.48	75.34	59.56	58.91
					24.88	29.97	5.32	44.72	49.39	13.29	82.91	92.41	72.50	76.26	76.73	58.30	51.56
		✓	✓		24.79	29.22	5.97	44.69	48.35	14.30	82.87	92.34	72.97	76.04	76.25	58.33	53.80
	TDO			✓	24.35	29.52	7.93 \dagger	44.44	48.74	18.65 \dagger	82.84	92.37	73.97	75.93	76.23	58.71	48.37
		✓	✓	✓	24.73	29.70	8.52\dagger	44.60	48.72	19.94\dagger	82.90	92.38	74.32\dagger	76.16	76.59	58.82	43.38
OPUS N=6 $d=1024$	Enc-Dec				27.71	31.60	6.95	46.84	50.31	15.89	83.55	92.62	74.12	78.10	77.58	59.99	57.15
	Dec-only				26.09	29.09	7.55	44.51	47.44	16.98	82.93	92.12	73.94	76.77	75.80	61.21	63.80
		✓			26.79	30.42	8.15	45.48	48.92	17.65	83.21	92.37	74.17	77.53	76.69	62.32	55.67
					27.22	31.58	7.06	46.54	50.59	15.96	83.44	92.64	73.78	77.68	77.89	60.60	52.43
		✓	✓		27.51	31.64	7.70	46.87	50.39	17.32	83.58	92.58	74.32	78.05	77.58	61.24	49.87
	TDO			✓	27.12	31.49	9.28 \dagger	46.55	50.23	21.33\dagger	83.50	92.65	75.04\dagger	77.63	77.64	60.84	39.71
		✓	✓	✓	27.45	31.36	9.36\dagger	46.79	50.06	21.05 \dagger	83.52	92.64	74.88 \dagger	77.97	77.75	61.78 \dagger	43.36

Table 1: Averaged scores of results in the experiments of training from scratch. Enc-Dec and Dec-only are abbreviations of encoder-decoder and decoder-only, respectively. Pref., Adap., and CL abbreviates Prefix, Adaption and InstruCL, respectively. ✓ in the Prefix column means the masked self-attention mechanism follows Prefix manner, conversely, follows Causal manner. en \rightarrow and \rightarrow en means the supervised pairs translating from English to non-central languages and translating from non-central languages to English, respectively. zero abbreviates zero-shot pairs, off abbreviates the target-off ratio. The best score in each column and block is in bold and the numbers with \dagger are significantly better than Enc-Dec according to the significance test with $p < 0.1$.

decoder architecture in supervised pairs of all three settings, with maximum deficits of -4.17, -5.78, -1.14, and -5.16 on the BLEU, chrF++, BERTScore, and COMET respectively. On the other hand, while the decoder-only architecture shows weaker performance on TED-19 for zero-shot translation, it achieves higher scores in two settings on OPUS-100. This suggests that the zero-shot capability of the decoder-only architecture in MNMT relates to the amount of data and parameters.

In comparison with the encoder-decoder architecture, TDO first achieves competitively supervised capabilities using fewer parameters. Second, our method exhibits stronger zero-shot translation scores, achieving scores improvements of +2.49, +3.22, +1.57, and +4.81; +3.39, +6.99, +1.88, and +0.31; +2.41, +5.16, +0.76, +1.79 across three settings respectively. Meanwhile, the results of significance testing endorse that our proposed methods can resolve inadequate language transfer capabilities in the decoder-only architecture (Section 4.1). We also find that the Adaptation module enhances both supervised and zero-shot translation performance.⁸ On the other hand, InstruCL signifi-

cantly boosts zero-shot capability, though there is a degradation in supervised translation performance. Additionally, with the Adaptation module implemented, the degree of degradation in supervised performance is reduced.

Moreover, the prefix decoder-only architecture achieves the highest COMET score on OPUS-100, though, it remains weaker on BERTScore compared to TDO, where both two metrics are based on semantics. This phenomenon can be explained by the target-off ratio, in which models with decoder-only architecture still have a high target-off ratio with biasing towards English primarily (Chen et al., 2023) to hamper the evaluation of COMET by considering the source sentence at the same time.

5.4 Results: Fine-tuning

Table 2 shows the experimental results by fine-tuning the pre-trained models, which shows a similar tendency to Table 1 in general. First, since we initialize the model using parameters from the decoder, the training processes for the encoder-decoder, decoder-only, and TDO architectures are relatively fair. Thus, we can conclude

⁸Appendix K shows the improvement is not because of

increased parameters.

		BLEU \uparrow			chrF++ \uparrow			BERTScore \uparrow			COMET \uparrow			off \downarrow
		en \rightarrow	\rightarrow en	zero	en \rightarrow	\rightarrow en	zero	en \rightarrow	\rightarrow en	zero	en \rightarrow	\rightarrow en	zero	zero
M2M	Enc-Dec	26.59	31.62	15.73	46.79	54.07	36.25	84.48	94.02	80.12	82.39	81.30	75.11	3.24
	Dec-only	25.72	30.06	14.67	45.88	52.52	34.51	84.12	93.70	79.45	81.61	79.89	73.33	3.51
	TDO	26.63	32.44	15.96	46.90	54.80	36.56	84.49	94.15	80.28	82.31	81.80	75.45	3.24
	+Adap.	26.87	31.93	16.12	47.08	54.21	36.73	84.58	94.08	80.35	82.62	81.54	75.80	3.31
	+CL	26.61	32.34	16.01	47.03	55.07	36.87	84.51	94.16	80.37	82.29	81.82	75.70	3.31
	+Adap.,+CL	26.75	31.83	16.20	46.98	54.09	36.82	84.56	94.07	80.41	82.56	81.52	75.95	3.30
NLLB	Enc-Dec	26.39	32.04	15.44	46.90	54.51	36.09	84.46	94.07	79.96	81.98	81.16	74.05	3.42
	Dec-only	26.35	30.20	14.69	46.36	51.96	34.16	84.35	93.72	79.45	82.20	79.94	73.62	3.63
	TDO	25.82	32.15	15.48	46.42	54.76	36.35	84.30	94.10	80.09	81.34	81.28	74.17	3.28
	+Adap.	26.60	32.47	15.82	47.04	54.83	36.62	84.54	94.15	80.23	82.08	81.48	74.89	3.41
	+CL	25.87	32.29	15.48	46.44	54.71	36.21	84.31	94.11	80.09	81.43	81.27	74.18	3.47
	+Adap.,+CL	26.58	32.37	15.85	46.94	54.69	36.52	84.52	94.14	80.24	82.12	81.44	74.93	3.36
1.2B	Enc-Dec	27.02	31.75	16.21	47.05	53.82	36.51	84.60	94.03	80.29	82.93	81.38	76.13	3.20
	Dec-only	26.47	29.99	15.40	46.47	52.01	35.10	84.36	93.72	79.83	82.51	80.21	75.33	3.46
	TDO	27.17	31.95	16.45	47.37	54.66	37.24	84.64	94.11	80.48	82.96	81.71	76.47	3.29
	+Adap.	27.32	31.05	16.57	47.53	53.76	37.47	84.68	93.99	80.56	83.11	81.29	76.72	3.31
	+CL	27.27	31.83	16.57	47.32	54.42	37.08	84.67	94.11	80.54	83.04	81.75	76.72	3.32
	+Adap.,+CL	27.41	30.72	16.60	47.49	53.38	37.23	84.70	93.96	80.55	83.24	81.21	76.88	3.28

Table 2: Averaged scores of results in the experiments of fine-tuning. Abbreviations align with Table 2. Notably, the decoder-only and TDO architectures use Prefix masked self-attention only. The best score is in bold.

that, when compared with the decoder-only architecture, the proposed TDO architecture supports an efficient transformation from pre-trained encoder-decoder models. Secondly, when compared with the encoder-decoder models, TDO models achieve the highest scores across four metrics, reaching up to +0.39, +0.48, +0.10, and +0.31 for pairs translating to en, up to +0.82, +1.00, +0.14, and +0.52 for pairs translating from en, and up to +0.47, +0.96, +0.29, and +0.88 for zero-shot pairs. TDO models also show an improvement in the off-target ratio compared to the decoder-only models. Moreover, we observe that InstruCL does not show significant improvements in the case of NLLB-600M, whereas it remains effective in the two M2M cases. This may be attributed to that NLLB supports 205 languages, compared to 100 languages of M2M, implying a denser representational space that affects the effectiveness of InstruCL in aligning representations across languages.

6 Discussion

6.1 Representation Analysis

The limitation of the decoder-only architecture in MNMT is due to the lack of language transfer, which is shown in Figure 1b. To verify whether our proposed methods can address this issue, we analyze the layer-wise sentence representations of five models trained on TED-19: (i) a prefix decoder-only model with $N = 6$; (ii) a TDO model with $M = 6$; (iii) a TDO model with Adaption modules; (iv) a TDO model with InstruCL; (v) a TDO model with Adaption modules and InstruCL.

As illustrated in Figure 4, the representation of

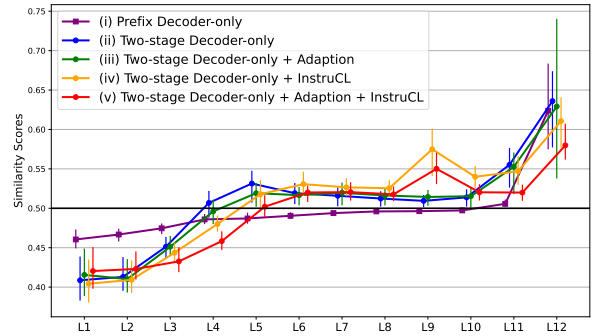


Figure 4: Illustration of linguistic preference, which follows Figure 1b. All cases in this figure use the Prefix manner for the masked self-attention mechanism. The marker of prefix decoder-only is square, and our proposed methods are round. The x-axis is the index of layers, and the vertical line indicates the value range.

(i) only exhibits a preference for the target language in the last two layers. However, (ii) shows a preference for the target language from the fourth layer, and this trend continues into the second stage. Although (iii) exhibits a more stable layer-wise trend compared to (ii), it shows significant differences in the final output across languages. Meanwhile, (iv) exhibits smaller differences across languages. Finally, (v) incorporates all the advantages of (iii) and (iv). Therefore, we can conclude that the TDO enables better language transfer by aligning different languages in the representational subspace of the target language. Meanwhile, the Adaption module and InstruCL improve the transferability of multilingual representations.

6.2 How to balance two stages?

In Section 5, we always set M equals N to ensure a fair comparison between the TDO and the

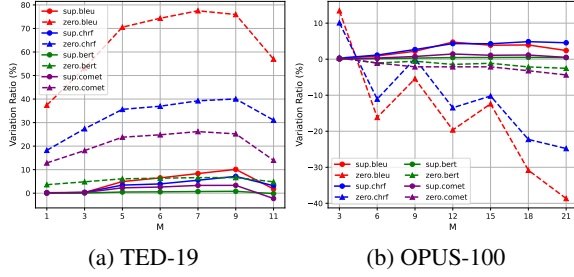


Figure 5: Variation in different values of M . The y-axis is the variation ratio compared to the performance of the model with prefix decoder-only architecture, and the x-axis is the value of M . The values of N are 6 and 12 in TED-19 and OPUS-100 respectively. Additionally, the line and the dotted line indicate supervised and zero-shot translations respectively.

encoder-decoder architectures. However, the balanced design is not optimal (Kasai et al., 2021; Pires et al., 2023). Thus, we test different M on TED-19 and OPUS-100 to investigate balancing two stages. As shown in Figure 5a, the performance is always improved with the increase of M on TED-19. On OPUS-100, as depicted in Figure 5b, the case with $M = 3$ achieves the best zero-shot translation scores, but there is a noticeable decline in zero-shot translation performance with the increase of M , although supervised translation scores continue to rise.

Those results align with our expectations. As shown in Table 1: 1) models with the decoder-only architecture consistently underperform compared to those with the encoder-decoder architecture in supervised translation; 2) models with the decoder-only architecture underperform in zero-shot translation on TED-19 but outperform on OPUS-100. Moreover, based on the trends in Figure 5b, we can state that the first stage enhances language transfer but at the cost of learning linguistic diversity, and the second stage benefits linguistic diversity. This statement aligns with Zhang et al. (2022) and is further proven by Table 1 where incorporating InstruCL can significantly improve the performance of zero-shot translation on OPUS-100. Thus, we conclude that the first stage is crucial in small-scale datasets, whereas the second stage becomes more significant in large-scale datasets.

6.3 How to set layer index for InstruCL?

In Section 5, we set the layer index for InstruCL to $1.5N$ to prevent the degradation of language transfer in the second stage. Given that Section 6.2 shows the different roles of the first and second stages, we test the performance of models with

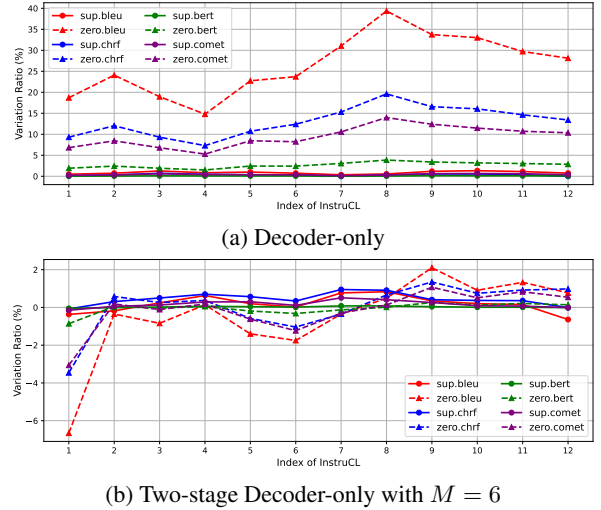


Figure 6: Variation in different layer index of InstruCL. The y-axis is the variation ratio compared to the performance of the model without InstruCL, and the x-axis is the index of the layer where InstruCL is employed.

different layer indexes of InstruCL for the decoder-only and the TDO models. Figure 6a demonstrates that InstruCL consistently yields positive gains for the decoder-only architecture. On the other hand, Figure 6b shows a decline in the first stage but benefits in the second stage. These results indicate that InstruCL primarily affects layers that follow the decoder-only manner, namely, the second stage of TDO, which is further supported by Appendix I⁹. Moreover, another observation aligning our motivation is that an excessively high index leads to reduced gains. Therefore, we can conclude that the optimal position for implementing InstruCL is the middle layer of the second stage.

7 Conclusions

In this work, we analyzed the reasons behind the underperformance of the decoder-only architecture in MNMT, identifying the lack of language transfer capability as the primary challenge. To address this, we introduced the Two-stage Decoder-only architecture. We also proposed Instruction-level Contrastive Learning to overcome the issue from the perspective of representation optimization. We conducted experiments on two settings, i.e., training from scratch and fine-tuning, using the TED-19 and OPUS-100 datasets, and the results validate the effectiveness of our approach. Through further experiments and representation analysis, we confirm that the improvements in our methods are derived from enhanced language transfer capabilities.

⁹Appendix I shows experiments on implementing InstruCL in different architectures and datasets as a supplement.

8 Limitations

As mentioned in Section 1, this work primarily focused on addressing the challenges faced by models with a decoder-only architecture in multilingual neural machine translation (MNMT), rather than exploring how to apply large language models (LLMs), which also have the decoder-only architecture. This focus is because small models in MNMT still offer the advantages of low training and deployment costs while remaining competitive with LLMs (Zhu et al., 2023). With the increasing interest in improving multilingual translation with LLMs (Xu et al., 2024), further exploration is needed to determine whether the representation-level methods proposed in this work can be extended to LLMs. However, this is beyond the scope of the current study, as the data used to train MNMT models significantly differs from that used to train LLMs. Therefore, we leave this question for future research.

9 Ethical Considerations

All datasets and toolkits used in this work are public, common, and general in the research on multilingual neural machine translation, meanwhile, the usage of those datasets and toolkits follows the license. Moreover, this work is foundational research and is not a report of specific applications. Therefore, this work is harmless and has no ethical risks.

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A Introduction of Illustrating Linguistic Preference

Overview In this work, we only quantify the language features of the sentence representation by the similarity scores, although the analysis of Qu et al. (2024) further quantified the semantic features of representations. Specifically, the score presents whether the sentence representations at a certain state exhibit more features related to the target language or more features related to the source language.

Setup First, quantifying the language features of the sentence representation requires a semantically parallel dataset. Therefore, we conduct analysis experiments on TED-19, which provides six fully parallel languages, including ar, he, zh, hr, vi, and ja. We connect these languages to generate 30 zero-shot translation pairs, each pair consisting of 967 sentences. The model setup is consistent with our main experiments (Section 5).

Computing the similarity score First, we follow the process of Qu et al. (2024) to measure representation similarity in MNMT, employing singular value canonical correlation analysis (Raghu et al., 2017). As the definition in Section 3, we obtain the token-wise hidden representations of the source sentence, i.e. \mathbf{H} , from a translation pair. Notably, for a decoder-only model, we cut out the source part, namely, $|\mathbf{H}|$ is always $I + 1$. Then, we derive the sentence-level representation $\bar{\mathbf{h}}$ using average pooling $\bar{\mathbf{h}} = \frac{\sum_{i=1}^q \mathbf{h}_i}{q}$. Given \mathbf{H}^a and \mathbf{H}^b derived from two sentences, we first perform singular value decomposition on $\bar{\mathbf{h}}^a$ and $\bar{\mathbf{h}}^b$ to obtain subspace representations $\bar{\mathbf{h}}^a \in \mathbb{R}^{d^a}$ and $\bar{\mathbf{h}}^b \in \mathbb{R}^{d^b}$. Then we perform canonical correlation analysis to determine $\mathbf{W}^a \in \mathbb{R}^{d' \times d^a}$ and $\mathbf{W}^b \in \mathbb{R}^{d' \times d^b}$. Formally, we compute correlation ρ between $\bar{\mathbf{h}}^a$ and $\bar{\mathbf{h}}^b$ as

$$\rho = \frac{\langle \mathbf{W}^a \bar{\mathbf{h}}^a, \mathbf{W}^b \bar{\mathbf{h}}^b \rangle}{\|\mathbf{W}^a \bar{\mathbf{h}}^a\| \|\mathbf{W}^b \bar{\mathbf{h}}^b\|}, \quad (10)$$

where $\langle \cdot, \cdot \rangle$ indicates the inner product. We use ρ to represent the similarity of two sentences.

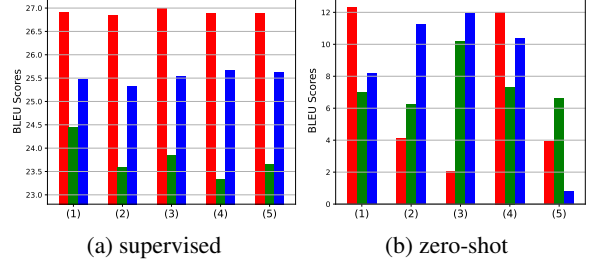


Figure 7: Averaged BLEU scores in different architectures. The palette follows Figure 1, i.e., red is encoder-decoder, green is causal decoder-only, and blue is prefix decoder-only.

Subsequently, we get the similarity ρ_x between (l_y, x, y) and (l_x, x, x) and the similarity ρ_y between (l_y, x, y) and (l_y, y, y) , respectively. Therefore, a similarity score of linguistic preference is computed as follows:

$$s(l_y, x, y) = \frac{\rho_y}{\rho_y + \rho_x}, \quad (11)$$

where $s(l_y, x, y)$ is the similarity score for the given translation pair. Finally, we compute the set-level score by taking the average scores of all sentences over the test set.

Meaning of the similarity score Equation 11 simply compares the importance of source information and target information in the representation. Therefore, a value higher than 0.5 means the representation prefers the target language, otherwise the representation prefers the source language. Moreover, the value reflects the degree of linguistic preference, for example, compared to 0.6, 0.7 means the representation presents much more features of the target language or fewer features of the source language. In addition, we also denote the highest and lowest values by the vertical lines on each point in Figures 1b and 4 to show the value range, which can present stability. Finally, we can find that models with decoder-only architecture cannot align the representation of the source tokens in the representational subspace of the target language, and they try to align source and target languages to be a language-agnostic state.

B Comparison between Different Instruction Strategies in MNMT

MNMT is sensitive to the strategy of translation instruction (Wu et al., 2021). We summarize the possible strategies as follows: (1) Adding a language tag specified to the target language at the beginning

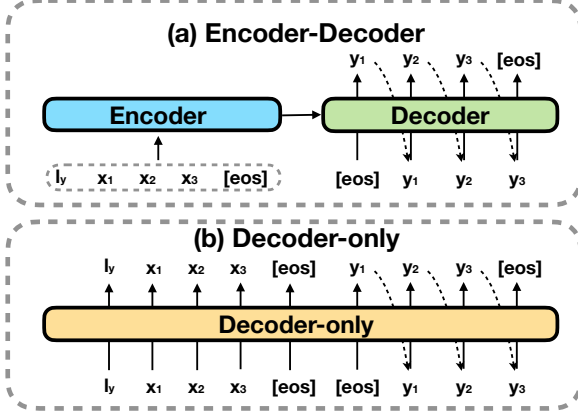


Figure 8: Illustration of input and output forms in MNMT. Subfigures are for the encoder-decoder architecture and the decoder-only architecture, respectively. [eos] is a special token, which means the end of a sentence and is regarded as a token of x and y .

of source tokens; (2) Adding a language tag specified to the target language at the beginning of target tokens; (3) Based on the (2), using the language tag to replace the [eos] token, which is used to be the trigger of inference; (4) Adding two language tag specified to the target language at the beginning of source tokens and the beginning of target tokens, simultaneously; (5) Adding a language tag specified to the source language and a language tag specified to the target language at the beginning of source tokens and target tokens, respectively. Then, we conduct preliminary experiments on three architectures: encoder-decoder, causal decoder-only, and prefix decoder-only, to support the validity of using approach (1). As shown in Figure 7, the performance of encoder-decoder architecture meets the analysis of Wu et al. (2021). However, a language tag at the beginning of target tokens, i.e., (2), (3), and (4), is more beneficial for the zero-shot capability in Decoder-only architecture. Considering that (1) also benefits decoder-only architectures in the supervised translation, using (1) in this work is reasonable.

C Different Input and Output Forms

Figure 8 illustrates input and output forms for two architectures involved in this work. Initially, within the encoder-decoder architecture, the encoder receives parallel input from source tokens, including l_y , x , and a special token [eos]. As a supplement of Section 3.2, for the $I + 1$ tokens feeding to the encoder, l_y is the first token and corresponds to the h_1 , then, each index of x is shifted, namely, x corresponds to $\{h_2, \dots, h_{I+1}\}$. Furthermore, the input

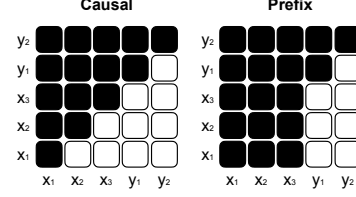


Figure 9: Different manners of the masked self-attention mechanism in the decoder-only architectures. Black blocks mean visible and white blocks mean masked. Thus, source tokens are masked in the causal decoder-only while are visible in the prefix decoder-only.

of the decoder is shifted. Specifically, in training, [eos] is placed at the beginning of the target tokens, and the output at each position always points to the token in the next position; in inference, [eos] serves as the trigger, and the model would generate the next token step by step until the predicted token is [eos]. Finally, the output of the encoder-decoder architecture only includes target tokens, i.e., y . On the other hand, the decoder-only architecture combines source tokens and target tokens as the input. In this work, we follow Zhang et al. (2022); Gao et al. (2022) to employ MNMT loss instead of language modeling loss, namely, cutting off the source tokens and saving the target tokens only in the output,

D Attention Mechanisms of Decoder-Only Architectures

As illustrated in Figure 9, the causal attention mechanism in the decoder-only architecture treats source and target tokens equally, meaning that each token is influenced solely by preceding tokens and itself. In contrast, the prefix attention mechanism maintains bi-directional attention for source tokens where source tokens are influenced by each other, while target tokens use mono-directional attention, meaning they are influenced only by prior tokens and themselves.

E Estimation of Parameters

We follow the notation in Section 5.2, that is, d is the dimension of the model and the inner size of FFN is $4d$. Therefore, each attention mechanism has $4d^2$ parameters because there are 4 matrices with dimensions of $d \times d$, and each FFN has $8d^2$ parameters (Vaswani et al., 2017). Then, all layers have the structure illustrated in Figure 2. Given $N = 1$, the model with encoder-decoder architecture has $28d^2$ parameters and the model

with Decoder-only architecture has $24d^2$ parameters. Thus, considering the fixed parameters of normalization modules and embedding layer, Decoder-only architecture is implemented with around 10% fewer parameters than encoder-decoder architecture.

F Detailed Information of Datasets

First, the language codes used in our descriptions adhere to ISO 639-1¹⁰. As described in Section 5.1, the first dataset is TED-19 (Qu et al., 2024), a subset of TED Talks (Ye et al., 2018) containing 6.5 million instances across 19 languages from various language families. This dataset includes 32 supervised translation pairs and 306 zero-shot translation pairs. Detailed information about TED-19 is provided in Table 7. The second dataset is the revised version of OPUS-100 (Zhang et al., 2020a; Yang et al., 2021), which includes 95 languages and a total of 92 million instances. Notably, the zero-shot translation in OPUS-100 involves only six languages (ar, nl, de, zh, ru, and fr), resulting in 30 translation pairs. Additionally, we further cleaned the dataset by removing noisy instances containing unreadable characters, even though Yang et al. (2021) had already removed repetitions from the original OPUS-100 dataset (Zhang et al., 2020a). Detailed information about OPUS-100 can be found in Table 8. Generally, each pair of validation and test sets in these two datasets contains 2,000 instances, though several pairs in OPUS-100 have fewer instances. Finally, we used SentencePiece (Kudo and Richardson, 2018) to generate the vocabulary for training, with the vocabulary size set to 50,000 for TED-19 and 64,000 for OPUS-100.

G Evaluation Metrics

First, SacreBLEU (Post, 2018), an implementation of BLEU (Papineni et al., 2002), measures the lexical overlap between generated translations and reference translations. chrF++ evaluates overlap at the character level and accounts for a balance between precision and recall. These two metrics can corroborate each other’s results. On the other hand, BERTScore¹¹ (Zhang et al., 2020b)

measures the similarity between generated translations and references at the representation level. COMET¹² (Rei et al., 2020) also evaluates representational similarity, with an additional emphasis on the source text for enhanced semantic relevance. Intuitively, BERTScore may penalize instances that do not translate into the expected target language, while COMET is more sensitive to semantic relevance. To validate this intuition, we employ *fasttext-langdetect*¹³ to measure the target-off ratio on zero-shot pairs, i.e., the ratio of cases where the source sentence is not translated into the correct target language, as a secondary metric. Notably, it is considered secondary because the testing tools are not entirely accurate, particularly when recognizing low-resource languages, as they rely on language-specific tokens. Finally, to show whether the improvements of zero-shot translations brought by proposed methods are significant, we also conduct the statistical significance testing (Koehn, 2004) using paired bootstrap resampling with 1,000 iterations and 0.5 resampling ratios, consequently, the case of $p < 0.1$ means that the difference is significant.

H Detailed Model Settings

We implement models by Fairseq (Ott et al., 2019), an open-source toolkit. First of all, in this work, we apply independent sinusoidal positional embeddings for source tokens and target tokens (Vaswani et al., 2017) for the input of the decoder-only architecture. Notably, the estimation of parameters in modeling is introduced in Appendix E.

Model settings of training from scratch In the case of training from scratch on TED-19, we set N to 6, d to 512, inner size of FFN to $4d$. Thus, the model with an encoder-decoder architecture has 70 million parameters, while the model with a decoder-only architecture has 63 million parameters. Moreover, the FFN in the adaptation module matches the dimensions of the FFN in the main part, so in this case, the model has 67 million parameters. In the training, we set the learning rate to 0.0005 and the model is trained for 30 epochs on eight NVIDIA V100 GPUs with a batch size of 4,000 per GPU to ensure full convergence. Moreover, we set the head number of the attention mechanism to 8, the dropout rate to 0.1, label smoothing to

¹⁰https://www.loc.gov/standards/iso639-2/php/code_list.php

¹¹For BERTScore, en is computed using *xlmr.large* (Conneau et al., 2019; Goyal et al., 2021), while other languages are computed using *bert-base-multilingual-cased* (Devlin et al., 2018).

¹²All COMET scores are computed using *Unbabel/wmt22-comet-da* (Rei et al., 2022).

¹³<https://pypi.org/project/fasttext-langdetect>

				BLEU \uparrow			chrF++ \uparrow			BERTScore \uparrow			COMET \uparrow			
				#enc	#dec	idx.	en \rightarrow	\rightarrow en	zero	en \rightarrow	\rightarrow en	zero	en \rightarrow	\rightarrow en	zero	
TED $d=512$	Enc-Dec	6	6	-	25.46	28.31	12.32	45.96	50.86	32.13	84.10	93.37	78.03	80.49	78.15	67.26
		6	6	6	24.92	28.39	12.96	45.56	50.97	33.42	83.94	93.68	79.10	79.99	78.21	70.37
		0	12	-	24.00	26.97	8.18	44.49	48.93	25.35	83.54	92.97	74.52	78.46	76.10	56.74
	Dec-only	0	12	6	24.16	27.18	10.12	44.61	49.11	28.49	83.63	93.01	76.32	78.80	76.30	61.41
		0	12	9	24.26	27.31	10.94	44.69	49.24	29.55	83.69	93.05	77.05	79.08	76.45	63.77
		0	12	-	25.53	28.76	14.26	46.01	51.09	34.72	84.13	93.41	79.27	80.43	78.18	70.82
	TDO	0	12	6	25.46	29.02	14.06	45.98	51.44	34.38	84.10	93.48	79.15	80.47	78.54	70.51
		0	12	9	25.62	28.94	14.70	46.15	51.46	35.34	84.15	93.47	79.57	80.55	78.55	71.94
OPUS $d=512$		Enc-Dec	12	12	-	25.18	29.79	5.13	44.75	48.40	12.95	82.98	92.33	72.44	76.59	76.21
	12		12	12	24.98	29.61	6.56	44.65	48.30	15.49	82.97	92.34	73.45	76.46	76.23	59.61
	0		24	-	23.96	28.41	6.62	42.98	47.22	15.36	82.47	92.06	73.57	75.48	75.34	59.56
	Dec-only	0	24	12	24.22	28.26	6.99	43.23	46.83	15.98	82.49	92.04	73.66	75.55	74.94	59.42
		0	24	18	23.98	28.22	6.73	43.18	46.80	16.17	82.52	92.07	73.67	75.60	75.12	59.37
		0	24	-	24.88	29.97	5.32	44.72	49.39	13.29	82.91	92.41	72.50	76.26	76.73	58.30
	TDO	0	24	12	24.61	29.37	6.46	44.68	48.72	15.14	82.87	92.37	73.30	76.16	76.21	59.41
		0	24	18	24.35	29.52	7.93	44.44	48.74	18.65	82.84	92.37	73.97	75.93	76.23	58.71
OPUS $d=1024$		Enc-Dec	6	6	-	27.71	31.60	6.95	46.84	50.31	15.89	83.55	92.62	74.12	78.10	77.58
	6		6	6	27.74	31.52	7.75	46.92	49.91	18.06	83.56	92.66	74.44	78.07	77.69	60.43
	0		12	-	26.79	30.42	8.15	45.48	48.92	17.65	83.21	92.37	74.17	77.53	76.69	62.32
	Dec-only	0	12	6	26.87	30.72	8.47	45.58	49.18	17.78	83.53	92.51	74.38	77.74	77.82	61.61
		0	12	9	26.72	30.09	8.42	45.34	48.52	17.33	83.16	91.83	74.23	77.31	76.61	61.55
		0	12	-	27.22	31.58	7.06	46.54	50.59	15.96	83.44	92.64	73.78	77.68	77.89	60.60
	TDO	0	12	6	26.72	31.05	7.43	45.49	49.54	16.25	83.19	92.40	74.00	77.45	77.49	61.89
		0	12	9	27.12	31.49	9.28	46.55	50.23	21.33	83.50	92.65	75.04	77.63	77.64	60.84

Table 3: Averaged scores of results in experiments of training from scratch and verifying InstruCL across different architectures. Both the decoder-only and TDO architectures adopt the prefix attention mechanism. All terms, settings, and abbreviations follow the Table 1. Moreover, #enc, #dec, and idx. indicate the number of encoder layers, the number of decoder layers, and the layer index where to implement InstruCL, respectively. In addition, the placeholder (-) in the column of idx. means that InstruCL is not implemented in this row. The best score in each column and block is in bold.

0.1, and weight decay to 0.0001. We also employ Adam (Kingma and Ba, 2017) as our optimizer and set *share-all-embeddings* of Fairseq. We evaluate by averaging the top-5 best checkpoints selected based on validation loss. In the case of training from scratch on OPUS-100, we first increase N to 12, resulting in parameter counts of 121 million, 108 million, and 113 million, respectively. In the training, we set the number of gradient accumulation steps to 16 to increase the batch size and train for 50,000 steps with a learning rate of 0.0007. We also consider a wider model where N is 6, d is 1024, and the head number of the attention mechanism is 16, resulting in parameter counts of 242 million, 217 million, and 234 million, respectively. When, we additionally set an attention dropout to 0.05 and reduce the learning rate to 0.0005 for a stable gradient. Moreover, we reduce the batch size per GPU to 2,000, set the number of gradient accumulation steps to 32, and train for 100,000 steps due to GPU memory constraints. For two cases of OPUS-100, we test the checkpoint with the best validation loss. Additionally, in training on OPUS-100, we set *encoder-normalize-before*

and *decoder-normalize-before* in Fairseq and reduce the weight decay to 0, which lead to a quick convergence in a complex data condition (Liu et al., 2020; Fan et al., 2020; Team et al., 2022).

Model settings of fine-tuning In the model settings of fine-tuning, M2M-418M has 12 layers for encoder and decoder, respectively, where d of M2M-418M is 1024, and the inner size of FFN is 4096, based on the description in Section 5.2, we set N to 6, resulting in parameter counts of 307 million, 282 million, and 299 million, respectively. In the training, the label smoothing is 0.2, the dropout is 0.3, the attention dropout is 0.05, and the batch size and the learning rate keep the settings of training from scratch. Then, given that NLLB-600M has the same configuration as M2M-418M but with a larger vocabulary size, the same setting of hyper-parameters leads to the count of parameters increased to 439 million, 413 million, and 430 million, respectively, and, we reduce the batch size to 2000 and set gradient accumulation to 2 for NLLB-600M because of the GPU memory constraints. In M2M-1.2B, which has 24 decoder

layers and a larger inner size of FFN compared to M2M-418M, we set N to 12, leading to parameter counts of 685 million, 635 million, and 668 million, respectively, and our experiments are conducted on four NVIDIA A6000 GPUs, and we set gradient accumulation to 2. We also reduce the learning rate to 0.0002 and the number of training epochs to 10 because of more parameters.

I The Effectiveness of InstruCL on Encoder-Decoder Architecture

As a supplementary trail for Sections 5.3 and 6.3, we conduct experiments on applying InstruCL to the encoder-decoder, the prefix decoder-only, and TDO architectures, and then compare their performances on three cases of training from scratch described in Section 5.2. The layer index where InstruCL is implemented at the TDO is $1.5N$. We also implement InstruCL for the decoder-only architecture at the same layer as a comparison. However, given that the number of encoder layers in an encoder-decoder architecture is N , InstruCL is implemented at the output of the encoder, namely, the layer index is N . Therefore, as comparison groups, we also implement InstruCL for the decoder-only and TDO architectures at the N layer.

Table 3 shows the experimental results. The first observation is that the encoder-decoder architecture can be gained from InstruCL due to the improved performance in all cases. Notably, the first observation is not violated from the statement in Section 6.3 that InstruCL mainly affects the layer following the decoder-only manner, because of the performance of TDO in TED-19 and OPUS-100. Specifically, considering the decoder-only architecture, first, in the TED-19, when the index is set to N , Dec-only shows a significant improvement in zero-shot translations with BLEU scores increasing by 1.94, while TDO degraded by 0.64. Second, in two cases from the OPUS-100, when the index is set to $1.5N$, TDO achieves significant improvements of 2.61 and 2.22, respectively. Third, in three cases, compared to setting the index to N , the decoder-only model showed smaller gains or even degradations when the index is set to $1.5N$, with scores increasing by 0.82, -0.26, and -0.05.

These results are consistent with our statement in Section 4.2. Specifically, the first stage of TDO overlaps with InstruCL in terms of facilitating the learning of target language representations, which explains the suboptimal performance when both

Scenario	Model	Seconds
TED N=6 $d=512$	Enc-dec	22854
	Dec-only	24277
	TDO	22359
OPUS N=12 $d=512$	Enc-dec	102509
	Dec-only	114514
	TDO	101826
OPUS N=6 $d=1024$	Enc-dec	258845
	Dec-only	298344
	TDO	247964

Table 4: Training times of different models in three experimental settings. The smallest value is in bold.

are used together. Additionally, InstruCL is most effective when applied in the middle layers, which align with the decoder-only manner. On the other hand, considering the performance of the vanilla models, i.e., Enc-Dec and Dec-only, we can assert that InstruCL, which does not require additional data costs, generally benefits all architectures.

J The Impact of Computational Complexity

Intuitively, when comparing the decoder-only architectures, TDO model exhibits lower computational complexity than the vanilla decoder-only model. This is due to the removal of the first M layers from the vanilla decoder-only model when generating target token sequences. Despite the reduced computational complexity, TDO achieves superior performance compared to the vanilla decoder-only architecture. Second, we present an empirical comparison of training times across different models. Table 4 summarizes the results, showing that TDO has the shortest training time, comparable to the encoder-decoder model.

Next, we formally estimate the computational complexity for each architecture. For simplicity, we omit the layer normalization and output projection components from the analysis. Let the model dimension be denoted by d , the inner size of the feed-forward network by $4d$, and the total number of tokens be $2n$, where n represents both the source and target tokens. The number of layers is assumed to be one encoder layer, one decoder layer, and two decoder-only layers. As shown in Table 5, the estimated FLOPs for TDO fall between those of the encoder-decoder (enc-dec) model and the vanilla decoder-only model. Specifically, the computational cost of TDO is lower than the vanilla decoder-only model but higher than the

enc-dec model. Despite this, TDO achieves significantly better performance than the decoder-only model and competitive performance with the enc-dec model.

Component or Architecture	Estimated FLOPs
multi-head self-attention	$4 \cdot n \cdot d^2 + 2 \cdot n^2 \cdot d$
feed-forward network	$8 \cdot n \cdot d^2$
encoder layer	$12 \cdot n \cdot d^2 + 2 \cdot n^2 \cdot d$
decoder layer	$12 \cdot n \cdot d^2 + 4 \cdot n^2 \cdot d$
decoder-only layer	$24 \cdot n \cdot d^2 + 8 \cdot n^2 \cdot d$
Enc-dec	$24 \cdot n \cdot d^2 + 6 \cdot n^2 \cdot d$
Dec-only	$48 \cdot n \cdot d^2 + 16 \cdot n^2 \cdot d$
TDO	$36 \cdot n \cdot d^2 + 10 \cdot n^2 \cdot d$

Table 5: Estimated FLOPs for various components and architectures.

Furthermore, the discrepancy between training time and theoretical FLOP counts can be attributed to the fact that TDO contains approximately 10% fewer parameters compared to the encoder-decoder architecture. This reduction in parameters contributes to faster training times, as discussed in Appendix K and cited in Section 4.1 of our manuscript. In conclusion, the observed improvements in model performance are not the result of increased computational complexity but rather due to the architectural design choices in the TDO model. The combination of empirical results and theoretical analysis demonstrates that TDO offers a more computationally efficient alternative to the decoder-only model, with competitive performance comparable to the encoder-decoder model.

K Adaption Modules Do Not Equal Simply Increasing Parameters

Adding adaptation modules increases the number of parameters, so it is crucial to determine whether the gains from these modules are primarily due to the increased parameters. As shown in Table 6, we directly increased the parameters of the TDO model using various strategies, ensuring that the number of parameters is comparable to or even greater than that of the TDO model with adaptation modules. The results demonstrate that the TDO model with adaptation modules outperforms in zero-shot translation and in translating supervised pairs from English to non-central languages. Notably, considering the previous point, the reason why adaptation modules do not achieve the best performance when translating from non-central languages to English can be attributed to their effec-

	d	d_{ffn}^1	d_{ffn}^2	en→	→en	zero
TDO+adapt.	512	2048	2048	25.61	28.52	14.51
	544	2048	2048	25.55	28.28	14.22
TDO	512	2432	2432	25.51	28.51	14.31
	512	2048	2816	25.32	27.98	13.89
	512	2816	2048	25.56	28.95	14.01

Table 6: Averaged BLEU scores of models with TDO architecture trained on TED-19. Abbreviations in this table follow Table 1. In addition, d_{ffn}^1 is the inner size of FFN in the first stage, and d_{ffn}^2 is in the second stage. The best score is in bold.

tiveness in preventing overfitting of English, which dominates the multilingual representations due to most of the training data being in English (Gu et al., 2019; Qu and Watanabe, 2022). Therefore, the results in this table support our assertion that the gains from adaptation modules cannot be simply attributed to increasing parameters.

Code	Language	Family	Sub-Family	#Train	Code	Language	Family	Sub-Family	#Train
es	Spanish	Indo-European	Romance	196026	ar	Arabic	Afro-Asiatic	Semitic	214111
fr	French	Indo-European	Romance	192304	he	Hebrew	Afro-Asiatic	Semitic	211819
ro	Romanian	Indo-European	Romance	180484	ru	Russian	Indo-European	Slavic	208458
nl	Dutch	Indo-European	Germanic	183767	ko	Korean	Koreanic		205640
de	German	Indo-European	Germanic	167888	it	Italian	Indo-European	Romance	204503
pl	Polish	Indo-European	Slavic	176169	ja	Japanese	Japonic		204090
hr	Croatian	Indo-European	Slavic	122091	zh	Chinese	Sino-Tibetan	Sinitic	199855
cs	Czech	Indo-European	Slavic	103093	tr	Turkish	Turkic		182470
fa	Persian	Indo-European	Iranian	150965	vi	Vietnamese	Austroasiatic	Vietic	171995

Table 7: Detailed information of TED-19 datasets. #Train indicates the number of training instances.

Code	Language	Family	Sub-Family	#Train	Code	Language	Family	Sub-Family	#Train
fa	Persian	Indo-European	Iranian	934413	yi	Yiddish	Indo-European	Romance	1865
bn	Bengali	Indo-European	Iranian	724719	ga	Irish	Indo-European	Celtic	187967
ur	Urdu	Indo-European	Iranian	724226	br	Breton	Indo-European	Celtic	96951
si	Sinhala	Indo-European	Iranian	613702	cy	Welsh	Indo-European	Celtic	92615
hi	Hindi	Indo-European	Iranian	374472	gd	Scottish Gaelic	Indo-European	Celtic	11104
tg	Tajik	Indo-European	Iranian	183216	lt	Lithuanian	Indo-European	Baltic	797693
ne	Nepali	Indo-European	Iranian	144520	lv	Latvian	Indo-European	Baltic	779972
gu	Gujarati	Indo-European	Iranian	108564	tr	Turkish	Turkic		918838
ku	Kurdish	Indo-European	Iranian	107110	az	Azerbaijani	Turkic		237533
pa	Punjabi	Indo-European	Iranian	72160	uz	Uzbek	Turkic		148319
as	Assamese	Indo-European	Iranian	58009	tt	Tatar	Turkic		97746
mr	Marathi	Indo-European	Iranian	26117	ug	Uyghur	Turkic		71241
ps	Pashto	Indo-European	Iranian	14254	kk	Kazakh	Turkic		62227
or	Oriya	Indo-European	Iranian	13410	ky	Kyrgyz	Turkic		12724
de	German	Indo-European	Germanic	968252	tk	Turkmen	Turkic		98
nl	Dutch	Indo-European	Germanic	936611	ar	Arabic	Afro-Asiatic	Semitic	959868
sv	Swedish	Indo-European	Germanic	916259	he	Hebrew	Afro-Asiatic	Semitic	913493
no	Norwegian	Indo-European	Germanic	914187	mt	Maltese	Afro-Asiatic	Semitic	672134
da	Danish	Indo-European	Germanic	911156	ha	Hausa	Afro-Asiatic	Chadic	91869
is	Icelandic	Indo-European	Germanic	813820	am	Amharic	Afro-Asiatic	Semitic	64369
nn	Norwegian Nynorsk	Indo-European	Germanic	172187	el	Greek	Indo-European	Hellenic	932811
af	Afrikaans	Indo-European	Germanic	146600	sq	Albanian	Indo-European	Albanian	855095
nb	Norwegian Bokmål	Indo-European	Germanic	128374	ml	Malayalam	Dravidian		633920
fy	Frisian	Indo-European	Germanic	42372	ta	Tamil	Dravidian		184699
li	Limburgish	Indo-European	Germanic	3331	te	Telugu	Dravidian		37792
ru	Russian	Indo-European	Slavic	951611	kn	Kannada	Dravidian		13777
sr	Serbian	Indo-European	Slavic	935342	xh	Xhosa	Niger-Congo	Bantu	231708
hr	Croatian	Indo-European	Slavic	927541	rw	Kinyarwanda	Niger-Congo	Bantu	62159
pl	Polish	Indo-European	Slavic	926940	zu	Zulu	Niger-Congo	Bantu	6834
bg	Bulgarian	Indo-European	Slavic	925647	ig	Igbo	Niger-Congo	Volta-Niger	691
cs	Czech	Indo-European	Slavic	924282	fi	Finnish	Uralic	Finnic	938601
bs	Bosnian	Indo-European	Slavic	921232	et	Estonian	Uralic	Finnic	893074
sl	Slovenian	Indo-European	Slavic	912248	hu	Hungarian	Uralic	Finno-Ugric	920592
mk	Macedonian	Indo-European	Slavic	881176	se	Northern Sami	Uralic	Sami	32289
sk	Slovak	Indo-European	Slavic	878540	vi	Vietnamese	Austroasiatic	Vietic	883581
uk	Ukrainian	Indo-European	Slavic	759826	id	Indonesian	Austronesian	Malayo-Polynesian	881198
sh	Serbo-Croatian	Indo-European	Slavic	209379	ms	Malay	Austronesian	Malayo-Polynesian	819431
be	Belarusian	Indo-European	Slavic	61862	mg	Malagasy	Austronesian	Malayo-Polynesian	292520
fr	French	Indo-European	Romance	963140	km	Khmer	Austroasiatic	Khmeric	101294
es	Spanish	Indo-European	Romance	929677	zh	Chinese	Sino-Tibetan	Sinitic	954358
it	Italian	Indo-European	Romance	928427	my	Burmese	Sino-Tibetan	Lolo-Burmese	5326
pt	Portuguese	Indo-European	Romance	919755	th	Thai	Kra-Dai	Tai	892433
ro	Romanian	Indo-European	Romance	913451	ko	Korean	Koreanic		892064
ca	Catalan	Indo-European	Romance	633826	ja	Japanese	Japonic		886850
gl	Galician	Indo-European	Romance	353596	eu	Basque	Language isolate		786645
wa	Walloon	Indo-European	Romance	48894	eo	Esperanto	Constructed		257560
oc	Occitan	Indo-European	Romance	27773	ka	Georgian	Kartvelian		240335

Table 8: Detailed information of OPUS-100 datasets. #Train indicates the number of training instances.

How Can We Relate Language Modeling to Morphology?

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Abstract

The extent to which individual language characteristics influence tokenization and language modeling is an open question. Differences in morphological systems have been suggested as both unimportant and crucial to consider (e.g., Cotterell et al., 2018; Park et al., 2021; Arnett and Bergen, 2025). We argue this conflicting evidence is due to confounding factors in experimental setups, making it hard to compare results and draw conclusions. We identify confounding factors in analyses trying to answer the question of *whether, and how, morphology relates to language modeling*. Next, we introduce token bigram metrics as an intrinsic way to predict the difficulty of causal language modeling, and find that they are *gradient proxies* for morphological complexity that do not require expert annotation. Ultimately, we outline necessities to reliably answer whether, and how, morphology relates to language modeling.¹

1 Introduction

Are certain languages *inherently* easier or harder to model (Cotterell et al., 2018; Mielke et al., 2019)? The interplay between language modeling and individual differences among languages is an open problem. One angle it can be approached from is morphological complexity (Gerz et al., 2018a; Park et al., 2021): if in one language the internal structure of words is more unpredictable according to some standard than another, then perhaps language models (LMs) have a harder time learning to predict text in that language.

Morphological systems are widely recognized as being gradient, but coarse groupings are often used, especially in NLP (Oncevay et al., 2022). *Agglutinative* languages (ALs) tend to add one grammatical feature to a word with each added morpheme, resulting in long words with many mor-

phemes. *Fusional* languages (FLs) tend to express information through inflection, where a single morpheme can express multiple features, resulting in shorter words with fewer morphemes. Results contrasting ALs and FLs have been mixed, with some evidence pointing to ALs being harder to model than FLs (e.g., Gerz et al., 2018b) whereas others have shown that there is no difference between the two groupings (e.g., Arnett and Bergen, 2025).

We outline what experimental conditions and metrics are necessary to reliably answer whether, and how, morphology relates to language modeling. Our contributions: (1) We list confounding factors that have to be taken into account when attempting to answer the central question above. They can be seen as criteria for an "ideal" experiment. (2) We propose predicting CLM difficulty with the variety and entropic efficiency of neighboring tokens, and find they are proxies for morphological complexity.

2 Confounding Factors

It is not obvious how morphology impacts language modeling. What is clear is that research that seeks to draw reliable conclusions relating the two must control for the following confounding factors:

1. **Languages:** What set of languages is under consideration? If multiple hypotheses are tested, that set should ideally stay constant.
2. **Grouping:** If results/languages are grouped, is there enough in-group agreement?
3. **Tokenization algorithm:** What subword tokenization algorithm is used? What are its hyperparameters?
4. **Vocabulary size vs. data size:** How does the amount of subword types relate to the amount of training data?
5. **Corpus domain:** Are tokenizers and models trained on the same data? Are datasets comparable across languages (ideally, multi-parallel), or made to be so?

* Equal contribution.

¹This is an extended abstract of Poelman et al. (2025) which is accepted at the EMNLP 2025 main conference.

Language	Grouping*	Token Bigrams				Token Unigrams			Words	
		AV	η (\downarrow)	AU	LR	MATTR	MTL	RE	\mathcal{S}	MWL
English	Fusional	2.12	15.92	61.08	59.29	31.78	4.89	36.68	9.27	5.54
French	Fusional	2.39	19.11	57.77	51.55	34.27	5.08	40.30	2.30	5.91
Dutch	Fusional	3.33	20.75	60.61	43.60	33.85	5.17	37.83	8.36	6.01
Portuguese	Fusional	3.06	21.31	52.64	51.49	35.38	4.91	36.38	10.64	5.79
Spanish	Fusional	2.95	22.70	56.97	52.62	33.85	5.05	36.16	9.05	5.72
Danish	Fusional	3.84	24.12	57.44	38.71	33.32	4.78	35.53	11.91	5.82
Bulgarian	Fusional	3.37	24.12	52.91	40.74	36.37	4.86	34.88	12.21	5.97
Swedish	Fusional	3.84	24.18	57.29	35.71	35.90	5.11	39.79	8.73	6.10
Greek	Fusional	4.20	24.48	51.62	46.81	38.71	5.11	37.44	10.35	6.15
Romanian	Fusional	3.12	25.09	51.81	51.01	37.80	5.04	36.98	10.52	5.95
German	Fusional	4.04	26.33	57.29	33.66	35.83	5.28	35.14	12.12	6.52
Italian	Fusional	3.65	27.10	61.54	59.88	37.56	5.22	38.85	9.39	6.21
Latvian	Fusional	4.45	28.07	50.99	43.81	41.75	5.00	32.29	15.76	6.41
Czech	Fusional	4.58	30.07	50.71	41.32	43.06	4.70	35.15	13.67	6.01
Polish	Fusional	4.74	30.85	50.61	43.80	44.51	5.25	35.76	12.75	6.68
Slovak	Fusional	4.70	31.12	51.43	44.68	43.04	4.82	34.91	13.39	6.13
Slovenian	Fusional	4.09	32.04	52.85	48.35	40.42	4.77	33.74	13.66	5.88
Lithuanian	Fusional	6.26	33.62	52.82	44.35	44.11	5.00	32.26	16.58	6.61
Finnish	Agglutinative	7.14	36.83	55.05	28.95	45.72	5.37	34.60	16.23	7.78
Hungarian	Agglutinative	6.69	39.11	56.24	31.37	41.73	5.05	34.10	14.63	6.78
Estonian	Agglutinative	6.27	40.31	55.89	34.39	43.66	5.22	34.58	14.87	6.96

Table 1 – We propose to use gradient proxies of morphology that operate on token *bigrams*: the variety of a type’s accessors (AV), their uniqueness (AU), and the Shannon efficiency of their distribution (η). We report averages over types in the tokenizer’s vocabulary that appear at least once and were not filtered; the fraction of types excluded from each average is its lexicalization ratio (LR). We also give existing metrics operating on token *unigrams*: micro-average characters per token (MTL), moving-average type-token-ratio (MATTR), and Rényi efficiency (RE). Last are word-based metrics: tokens per character averaged per word (\mathcal{S}) and mean word length (MWL). All metrics are calculated on EuroParl (Koehn, 2005) using monolingual tokenizers from the Goldfish suite of models (Chang et al., 2024). *Groupings taken from Arnett and Bergen (2025). The gradient in the columns ranges from its minimum to maximum and are intended to highlight how well a metric corresponds with the "Grouping" column. For AU and LR, the top three are highlighted yellow, the bottom orange.

6. Performance indicator: What metric is used to evaluate and compare tokenizers and models across languages? Is the setup monolingual or multilingual? Is the metric comparable between any two languages?

These factors show a way *towards* an ideal experimental setup. Practically, one must work *backwards* from this to a feasible setup.

3 Accessor Variety

We need a reliable proxy for morphological complexity. Harris (1955) first suggested to count the variety of predecessor and successor units of a given string, where unusual spikes would imply the string’s edges delineated something meaningful like a morpheme. Feng et al. (2004) coined *accessor variety* (AV) as the minimum of predecessor and successor variety. Wu and Zhao (2018) applied this to learn BPE merges. We use ULM tokens.

In Table 1, we calculate our metrics on a multi-parallel aligned subset of EuroParl (Koehn, 2005). AV recovers the coarse groupings, with ALs having the highest AV. Additionally, within FLs, a more fine-grained view of morphological complexity is revealed. For instance, higher AV values point to

languages using compounding (e.g., German vs English). The shape of the accessor distribution (η) follows the same trend, being higher (more uniform) for ALs. These results for AV and η suggest that the difficulty of causal language modeling, and hence higher PPLs regardless of models, is having *more and more equally likely follow-up options* at each token. This is what AV and η measure.

The word-based metrics recover the groupings somewhat, but are less reliable for CLMs, unless those models also use words instead of subword tokens. The token unigram metrics MTL, RE, and MATTR look rather even across the languages in EuroParl. Since these estimators become more accurate with more data, their low variance calls into question higher-variance results computed for much smaller corpora like FLORES-200.

Lastly, AV operates on *tokens*, which means it’s applicable to other units. For character- or byte-level tokenizers, AV can still provide an estimate of the degree of choice of accessors for a given type.

In the full paper, we discuss hypotheses of other papers, present results for a larger set of languages, and suggest general methodological improvements for future investigations.

Acknowledgments

WP and TB are funded by a KU Leuven Bijzonder Onderzoeksfonds C1 project with reference C14/23/096. The computational resources and services used were provided by the VSC (Flemish Supercomputer Center), funded by the Research Foundation - Flanders (FWO) and the Flemish Government - department EWI.

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On the Consistency of Multilingual Context Utilization in Retrieval-Augmented Generation

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Abstract

Retrieval-augmented generation (RAG) with large language models (LLMs) has demonstrated strong performance in multilingual question-answering (QA) tasks by leveraging relevant passages retrieved from corpora. In multilingual RAG (mRAG), the retrieved passages can be written in languages other than that of the query entered by the user, making it challenging for LLMs to effectively utilize the provided information. Recent research suggests that retrieving passages from multilingual corpora can improve RAG performance, particularly for low-resource languages. However, the extent to which LLMs can leverage different kinds of multilingual contexts to generate accurate answers, *independently from retrieval quality*, remains understudied. In this paper, we conduct an extensive assessment of LLMs’ ability to (i) make consistent use of a relevant passage regardless of its language, (ii) respond in the expected language, and (iii) focus on the relevant passage even when multiple ‘distracting’ passages in different languages are provided in the context. Our experiments with four LLMs across three QA datasets covering 48 languages reveal a surprising ability of LLMs to extract relevant information from passages in a different language than the query, but a much weaker ability to produce a full answer in the correct language. Our analysis, based on both accuracy and feature attribution techniques, further shows that distracting passages negatively impact answer quality regardless of their language. However, distractors in the query language exert a slightly stronger influence. Taken together, our findings deepen the understanding of how LLMs utilize context in mRAG systems, providing directions for future improvements.¹

1 Introduction

Retrieval-augmented generation has shown strong results in multilingual question-answering (QA)

tasks (Chirkova et al., 2024; Thakur et al., 2024). Given a query in the user language, informative passages are retrieved from a reference corpus and provided jointly with the query, promoting the large language model (LLM) to generate more precise responses (Lewis et al., 2020; Asai et al., 2021). In multilingual RAG (mRAG), retrieval can be performed either monolingually or cross-lingually. In the former, retrieval is performed only over passages in the same language as the query (Asai et al., 2023; Gao et al., 2023; Fan et al., 2024), which can be successful for high-resource languages. However, this approach is marginally useful, or even harmful, when the question is posed in a low-resource language, since relevant information is likely to be available only in different languages (Muller et al., 2023). In addition, for questions regarding a specific geographical region or culture, essential information may be present only in corpora of the languages spoken in that region. To address this issue, cross-lingual retrieval attempts to extract useful information simultaneously from multiple languages (Asai et al., 2021; Li et al., 2024), leading to visible gains in low-resource languages (Chirkova et al., 2024).

Evaluating RAG pipelines is notoriously difficult due to the open-endedness of the retrieval task, and to the complex interactions of retrieval quality with model understanding and generation abilities. On top of this, multilinguality adds another layer of complexity. Ideally, retrieved passages should be equally useful when the same question is posed in different languages. Besides, LLM-generated answers should be consistently correct across languages so that users with different language backgrounds enjoy a similar experience. However, despite the reported accuracy improvements, the abilities of LLMs to exploit cross-lingually retrieved contexts in mRAG remain poorly understood.

In this paper, we conduct an in-depth assessment of these abilities, using standard accuracy

¹All codes and data released at <https://github.com/BetSwish/mRAG-Context-Consistency>.

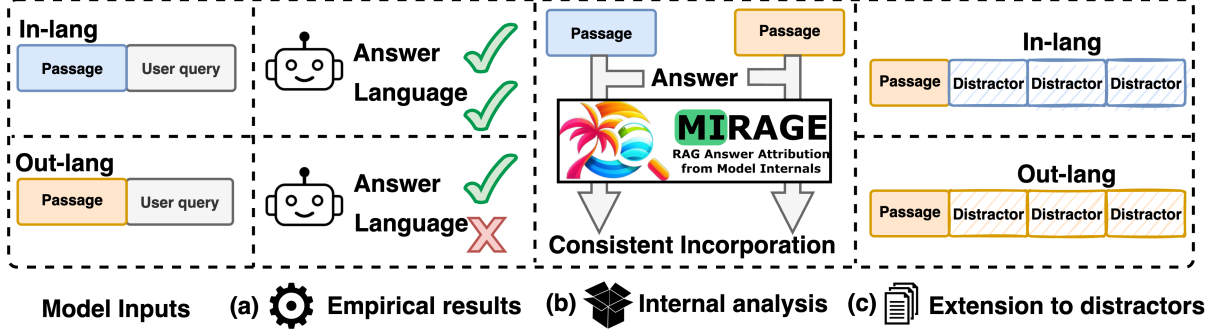


Figure 1: Illustration of the contributions and proposed assessment frameworks of this paper.

evaluation as well as feature attribution analysis. Unlike recent mRAG evaluations (Chirkova et al., 2024; Park and Lee, 2025), which test the LLM performance for each language in the entire RAG pipeline (i.e., retrieval + generation), we disentangle these two factors and focus on the LLM’s ability to exploit context independently from retrieval quality. As shown in Figure 1, our key contributions include: (a) We evaluate how LLMs leverage retrieved passages in different languages in various multilingual QA tasks, revealing remarkably robust input understanding but much more brittle generation abilities. (b) Besides the standard accuracy evaluation, we apply a recently proposed RAG answer attribution method based on model internals (Qi et al., 2024) to confirm that LLMs consistently incorporate retrieved content from various languages, providing insights from an interpretability perspective. (c) We consider both single-passage and multi-passage mRAG setups and examine how distracting passages in different languages affect model performance, shedding light on the complex interplay between relevance and content of the retrieved passages. Taken together, our results deepen our understanding of how LLMs utilize context in mRAG systems and reveal important areas for future improvements.

2 Related Work

2.1 Retrieval Strategies for mRAG

Retrieval is a key component of mRAG, which can be performed in at least two ways: monolingually (in-language) or cross-lingually. Chirkova et al. 2024 investigated mRAG systems across 13 languages, highlighting the limited gains of in-language retrieval in their setup. Nie et al. 2023 proposed the Prompts Augmented by Retrieval Crosslingually (PARC) pipeline, which

augments contexts with semantically similar sentences retrieved from high-resource languages to enhance zero-shot performance in low-resource languages. Gao et al. 2022 introduced a retrieval-augmented method for multilingual keyphrase generation, leveraging keyphrase annotations in English to aid keyphrase generation in low-resource languages through cross-lingual dense passage retrieval.

2.2 Consistency in Multilingual LLMs

Ensuring model consistency across languages is a key objective for multilingual LLMs. A series of recent works has focused on the consistency of factual knowledge encoded in the weights of multilingually pre-trained LLMs (Fierro and Søgaard, 2022; Weber et al., 2023; Qi et al., 2023; Hupkes et al., 2023). Other work has focused on the consistency of domain-specific QA by assessing whether the questions asked by a certain group of people (Schlicht et al., 2025) or about domain-specific knowledge (Yin et al., 2022; Li et al., 2025) can be correctly answered by LLMs regardless of the query language. Very recently and concurrently with our work, research interest has also risen around the consistency of mRAG pipelines (Wu et al., 2024; Sharma et al., 2024; Park and Lee, 2025).

2.3 Context Utilization in mRAG

Although some studies (Asai et al., 2021; Nie et al., 2023; Stap and Monz, 2023; Chirkova et al., 2024) have demonstrated that cross-lingual retrieval can significantly enhance mRAG answer accuracy, the extent to which LLMs can utilize multilingual contexts consistently remains poorly understood, motivating the present work. The concept of *context utilization* is also not always clearly defined. Recent and concurrent studies (Wu et al., 2024; Sharma

Dataset	QA Task Type	# Languages	# Queries	# Queries (w/ Gold Pass.)	Parallel?			Answer Format
					Query	Answer	Gold Pass.	
XQUAD	Extractive	12	1190	1190	✓	✓	✓	Text
MKQA	Open Domain	24	6758	5951	✓	✓	✗	Text
GMMLU	Multi-Choice	42	14042	4136	✓	✓	✗	A/B/C/D

Table 1: Overall dataset statistics. # Queries (w/ Gold Pass.) refers to the number of queries with at least one gold passage in any language, which is the subset used for our experiments (cf. Section 3.2).

et al., 2024; Park and Lee, 2025) use performance of the complete mRAG pipeline to study context utilization and find that models tend to prefer passages in the query language or Latin scripts. In this paper, we further distinguish between *input understanding* and *decoding capability* as key abilities of an mRAG generator, and disentangle them through our experiments, while strictly controlling for retrieval quality.

3 Experimental Setup

Consider a multilingual QA setup where q^ℓ is a query in language ℓ and a^ℓ is the gold answer in the same language. For each query, a set of relevant passages $P_q = \{p_1, \dots, p_n\}$ in multiple languages is retrieved from a reference multilingual corpus. A relevant passage ($p \in P_q$) is considered gold \hat{p} if it includes the necessary information to answer q^ℓ correctly, or non-gold (‘distracting’) \bar{p} otherwise. To perform mRAG, a subset of relevant passages $C_q \subset P_q$ is selected and provided as extra context to the LLM along with query q^ℓ . In an ideal mRAG setting, the model should answer more accurately when provided with C but it should also be *agnostic to the languages* in which the passages $p \in C$ are provided, in terms of both answer accuracy and feature attribution results. Following Muller et al., 2023, we use the term ‘**in-language**’ for the same language as the user query language, and ‘**out-language**’ for different languages than the user language.

Given this setup, we study LLMs’ ability to handle multilingual context in different retrieval scenarios, which we simulate by varying (i) the number of gold and non-gold (‘distracting’) passages provided in C , and (ii) the languages of those passages.

3.1 Datasets

Question answering datasets can differ across many dimensions. We choose three multilingual QA benchmarks to cover a diverse set of languages, three different types of QA, and different levels

of parallelism (see Table 1) allowing us to isolate different aspects of mRAG in our evaluation.

XQUAD (Artetxe et al., 2020) is an extension of the extractive English QA dataset SQUAD (Rajpurkar et al., 2016), which contains 1190 questions, each provided with a single relevant passage and a gold answer, all translated into 12 languages. While not being originally designed for RAG evaluation, this dataset is the only one allowing us to assess LLMs’ abilities to use *the exact same information* provided in different languages, simulating an impossible scenario where retrieval works perfectly in all languages. **MKQA** (Longpre et al., 2021) is an open domain QA dataset covering 10,000 questions across 24 languages derived from Natural Questions (Kwiatkowski et al., 2019). Removing the questions without any gold answers provided, we work on a total of 6758 paralleled questions in this paper. **Global-MMLU** or **GMMLU** (Singh et al., 2024) is a large multilingual extension of MMLU (Hendrycks et al., 2020) obtained by translating the English instances into 41 languages. Like MMLU, it contains 14042 multi-choice questions that are used to test LLMs’ understanding capability across a range of subjects, like social sciences or medical questions. Each question is provided with four options to choose from. Question examples for all datasets are given in Appendix A.

3.2 Retrieval and Filtering

XQUAD includes a single gold passage for each query, which we can provide to the model without performing any retrieval ($C_q = P_q = \{\hat{p}\}$).

As for **MKQA** and **GMMLU**, we retrieve passages from Multilingual Wikipedia Corpora² using the Cohere Embed Multilingual V3 retriever³, a strong performing multilingual embedding model with balanced language coverage (CohereAI, 2023). Unlike previous work (Asai et al., 2021; Muller

²<https://huggingface.co/datasets/wikimedia/wikipedia>

³<https://huggingface.co/Cohere/Cohere-embed-multilingual-v3.0>

et al., 2023; Chirkova et al., 2024) where the number of studied languages was at most 13, our evaluation covers twice or more languages, making it unfeasible to perform a full cross-lingual retrieval for each query language. As an approximation, we construct the set of relevant passages P_q by performing in-language retrieval for the L parallel versions of q in each language and taking the union of the top-30 ranked passages in each language: $P_q = \bigcup_{\ell=1}^L P_{q^\ell}$.

Then, we tag the gold passages in P_q based on whether they contain the gold answer as a substring, following previous work (Liu et al., 2024, 2025). In our experiments, we only consider queries for which P_q contains at least one gold passage in any of the studied languages, see resulting # Queries (w/ Gold Pass.) in Table 1. While it may be possible to expand this subset by retrieving more than 30 top passages or by improving retriever quality (Chirkova et al., 2024), we believe our setup is appropriate to study LLMs’ ability to use a variety of multilingual context types that are representative of competitive cross-lingual retrieval results.⁴

Detailed statistics on the amount of in-language and out-language gold passages for all queries are shown in Appendix B. As expected, the situation is particularly serious for queries posed in low-resource languages, where only out-language gold passages are available for most of the queries (e.g., 88% in Khmer MKQA and 91% in Yoruba GMMLU), highlighting the importance of ensuring mRAG quality across many languages.

3.3 Evaluation Metrics

For **XQUAD** and **MKQA**, we follow previous work (Asai et al., 2021) and score answers by strict lexical matching, that is, 1 if the entire gold answer string a^ℓ is a substring of the model response $\mathcal{M}(q^\ell)$, or 0 otherwise. Since models in mRAG setups often generate the correct answer in the wrong passage language (Chirkova et al., 2024; Zhang et al., 2024), we also measure the proportion of model answers that contain a gold answer in language ℓ' ($a^{\ell'}$, $\ell' \neq \ell$).⁵ Nevertheless, as exact

⁴Although a large portion of GMMLU queries are filtered out, we argue that the remaining 4136 queries are numerous enough to ensure a robust evaluation. We also verify the diversity of this subset and find a total of 55 covered subjects. See Appendix C for details on the question subjects and categories.

⁵Since we focus on the language of model responses and outright cross-language generation (i.e., whether the gold answer appears in a different language) where small orthographic

matching could be overly strict, we further adopt two complementary metrics (BERTScore and GPT-4.1-nano) on XQUAD. Similar results are observed, providing more insights and enhancing the robustness of our analysis. See Appendix D for more details.

GMMLU is instead designed as a multi-choice task, thus, accuracy can be simply evaluated by checking if the LLM outputs the correct option letter (A/B/C/D). To study the impact of answer generation from that of passage understanding across languages, we also use GMMLU as an open QA task by providing the query without any answer options, and adopting again lexical matching for evaluation. We refer to the original dataset as **GMMLU-Choice**, and the no-options one as **GMMLU-Open**.

3.4 Models

We evaluate four top-performing multilingual LLMs belonging to different model families, which have been used in recent mRAG evaluations (Wang et al., 2024; Thakur et al., 2024), namely: Aya-Expanse-8B (Dang et al., 2024), Llama-3.2-3B-Instruct (Dubey et al., 2024), Gemma-2-9B-it (Team, 2024), and Qwen2.5-7B-Instruct (Yang et al., 2024). Although these models do not officially support some of our studied languages, evidence has shown that LLMs can generalize successfully to unseen languages due to the leak of training data or shared representations (Qi et al., 2023; Budnikov et al., 2024; Lu and Koehn, 2024), which we also observed in preliminary experiments.

4 Single-Passage mRAG

We start from a simple scenario where, for each query q^ℓ , only one gold passage is provided to the model either in the query language (in-language; $C = \{\hat{p}^\ell\}$) or in a different language (out-language; $C = \{\hat{p}^{\ell'}\}$, $\ell' \neq \ell$). As a baseline, we calculate answer accuracy when no context is provided to the model ($C = \emptyset$).

In XQUAD, where gold passages are translated into 12 languages, we iterate over the 11 out-language passage versions for each query and report the average accuracy. We also report accuracy for the passage language that yielded the best (or

variants can be decisive, particularly for phonologically similar languages, we do not adopt the variant of the softer lexical metric (Chirkova et al., 2024) (3-gram recall), which tolerates minor orthographic differences and could blur the distinctions.

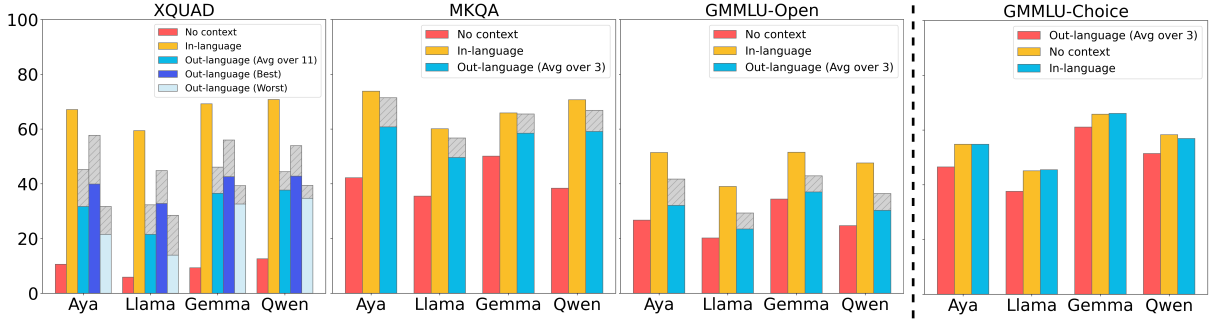


Figure 2: Performance on XQUAD, MKQA, GMLU-Open, and GMLU-Choice, where the LLMs are provided with no retrieved passage or one gold passage in either in-language or out-language. The shading on the bars represents the ratio of questions that can be correctly answered but in the wrong passage language, which does not apply to GMLU-Choice since the evaluation on it is not affected by the generation language.

worst) answer accuracy overall for each query language. By contrast, the gold passages in MKQA and GMLU are retrieved from a Wikipedia corpus as explained in Section 3.2, and are not parallel across languages. As a solution, for each query q^ℓ , we randomly sample 3 different out-language passages from P_q and report accuracy averaged over the 3 single-passages answers. To maximize the chances of obtaining a model response in the query language ℓ , we explicitly mention ℓ in the instruction, which is itself translated into ℓ , following Chirkova et al., 2024; Zhang et al., 2024. The detailed prompts are listed in Appendix E.

4.1 Accuracy Results

Results averaged across all query languages are given in Figure 2, while the full language-specific results are given in Appendix I.

Results on XQUAD We recall that XQUAD is a distinct dataset, originally developed to evaluate extractive QA, rather than open-domain RAG systems. Nevertheless, it is the only dataset where the exact same gold passage is available in different languages, allowing us to isolate the effect of a passage’s language from that of its content. As shown in Figure 2, providing the gold passage in any language strongly improves answer accuracy compared to the **no-context** baseline, which is likely due in part to the extractive nature of QA in this dataset. Looking at the passage language, however, we find that **in-language** passages yield considerably higher accuracy than all **out-language** settings, including out-language (Best). Moreover, a notable portion of questions are answered correctly but in the wrong language even though the models were explicitly prompted to answer in the

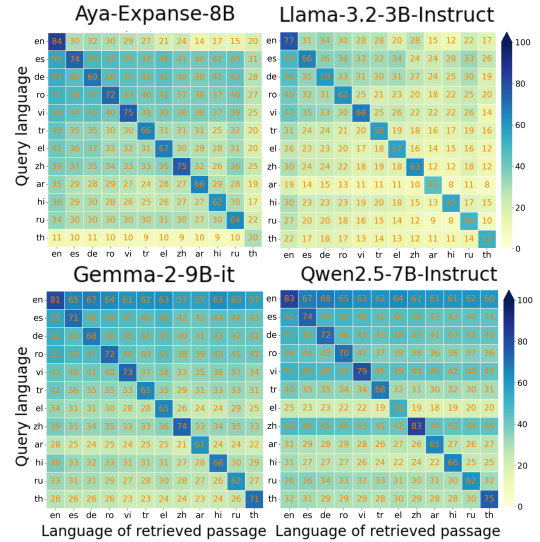


Figure 3: Answer accuracy (%) on XQUAD among different query-passage language combinations. Only model answers in the correct (i.e., query) language are considered as correct.

target language, which is in line with previous findings (Wu et al., 2024; Chirkova et al., 2024). Even when considering these cases, a visible gap remains between in-language and out-language accuracy across the board on XQUAD. We further analyze this gap through manual error analysis and find that missed matches are often due to the use of synonyms or slight paraphrases of the gold answer, or—in the case of languages with different scripts—to transliteration variations (Knight and Graehl, 1997). See Appendix F for more details.

Figure 3 gives a detailed view of how answer accuracy varies with the language of the provided gold passage.⁶ As expected, the highest accuracy

⁶Here we only consider answers in the correct language, see Appendix I for language-specific accuracies when consid-

is always achieved when the retrieved passage is in the same language as the query. Concurrent work (Sharma et al., 2024; Park and Lee, 2025) suggested that models may prefer passage languages that use the same script as the query language, based on a few languages. Because script similarity is a very coarse-grained measure of language similarity that is not informative for many of our language pairs, we turn to finer-grained measures that were previously shown to strongly correlate with cross-lingual consistency of model answers in non-RAG setups (Qi et al., 2023). In particular, we adopt *subword vocabulary overlap* computed on a reference parallel corpus⁷ as this was shown to correlate better with response consistency than various typological similarity measures. We compute Pearson and Spearman correlations between subword overlap and answer accuracy for each query language (excluding the case where query and passage are in the same language), however all correlations are low and not statistically significant. Looking back at Figure 3, we notice that shading (i.e., answer accuracy) is relatively consistent within each row, especially on Gemma and Qwen, more so than within each column. In other words, the query language is much more predictive of accuracy than the passage language, suggesting that generating in the target language is the major bottleneck in our setup, which could dominate, if not hide, the effect of similarity with the passage language.

Additionally, we also investigate if advanced prompts with multi-step instructions (refer to Appendix G) or larger model scales (open-source Gemma3-27B-IT and closed-source GPT-5-nano estimated at 8-18B parameters⁸; Appendix H) can mitigate the language mismatch issue in model answers. However, the problem persists, further reinforcing our finding that multilingual RAG systems face an inherent decoding limitation. Interestingly, we observe that when fed with passages in Thai, which is not officially supported by Aya-Expansive-8B, the model always outperforms the baseline where no context is provided for queries in each language (cf. No-context accuracies in Table 13). This suggests that even though the passages are written in a language that is unseen in the

ering the wrong generation language.

⁷Following Qi et al., 2023, we extract the vocabularies from FLORES-200 (Costa-jussà et al., 2022), a strictly parallel corpus covering 200 languages, and measure their pairwise overlap via Jaccard index (Jaccard, 1912).

⁸<https://www.r-bloggers.com/2025/08/how-many-parameters-does-gpt-5-have/>

pre-training phase, LLMs may be able to utilize them.

Results on MKQA Moving to a more realistic RAG dataset, but without parallel passages, we find a similar trend (Figure 2) where in-language gold passages outperform out-language ones, however the gap is much smaller than in XQUAD and almost disappears when also considering the portion of questions that are answered correctly in the wrong language. These results suggest that the passage language is not a key factor blocking LLMs from understanding and utilizing the context in MKQA.

Results on GMMLU Accuracy results on GMMLU-Open (Figure 2) are in line with the two previous datasets, with an in-/out-language gap falling halfway, that is smaller than in XQUAD but larger than in MKQA. To further disentangle the impact of context understanding from that of target language generation, we compare these results with those of GMMLU-Choice, where the model only has to generate one of the four option letters (A/B/C/D) provided in the prompt. Here, we find that in- and out-language passages yield extremely close accuracy, confirming that input understanding is not the real obstacle for high-quality mRAG. Rather, the main barrier appears to lie on the side of generation, namely, whether models can formulate a proper response *in the correct target language*.

4.2 Interpretability-based Assessment

To further verify our findings that the passage language is not a barrier to LLMs’ understanding capability of the multilingual retrieved passages, we adopt MIRAGE (Qi et al., 2024), a model internal-based method for attributing model responses to the retrieved passages in RAG systems. Generally, it consists of two components: (1) CTI for detecting contextual sensitivity for the generated sentence and (2) CCI for attributing the detected sentences back to each retrieved passage. Given the single-passage setup, in this section we only use the CTI module for evaluating the passage dependency of the model response. For each generated token, this module measures the shift in output probability distribution when no context vs. one passage is provided, measured by KL divergence (Kullback and Leibler, 1951), while keeping the generated sentence prefix fixed. If at least one token is higher than an empirically set CTI threshold, the generated sentence is marked as sensitive to the context

Dataset	AVG+1.0*SD		AVG+1.5*SD		AVG+2.0*SD	
	In.	Out.	In.	Out.	In.	Out.
XQUAD	98	99	97	99	95	98
MKQA	100	100	100	100	100	100

Table 2: Percentage (%) of context-sensitive responses when Aya is provided with in-language (In.) vs. out-language (Out.) gold passages, detected by MIRAGE under different CTI thresholds.

provided in the prompt.

We select Aya-Expansive-8B as the studied model and sample 500 instances separately from XQUAD and MKQA. Table 2 shows the results under different CTI thresholds. We find that nearly all generated responses are tagged as context-sensitive by MIRAGE, even when setting a higher CTI threshold (avg + 2 std_dev) than the one used in the original paper. This confirms that the provided passage significantly drives models’ predictions regardless of its language.

In sum, the results in this section point to the fact that understanding passages in different languages and locating useful information within them is not the main obstacle towards high-quality mRAG, whereas generation abilities in several target languages remain a serious bottleneck. In the next section, we study how models handle more realistic contexts consisting of multiple passages in different languages.

5 Multi-Passage mRAG

Real-world RAG settings are further complicated by the presence of multiple passages $C_q = \{p_1, \dots, p_n\}$, some of which may be related to the query but not functional to answering it correctly (i.e. ‘distracting’ passages \bar{p}). We investigate how the language of different passages in the context affects LLMs’ ability to locate the right information, assuming this is included in at least one passage of the context. In particular, we aim to assess model robustness in a challenging scenario where the important information is only provided in a different language than the query, along with several in-language distractors.

For simplicity, we set the maximum number of passages to 4 and simulate two practical scenarios: (i) a weak retriever finds one out-language gold passage while the other three are distractors; (ii) a strong retriever finds three out-language gold passages while the remaining one is a distractor. In

both cases, we compare accuracies when the distractors are in-language vs. out-language. We conduct experiments on MKQA and GMMLU-Choice. XQUAD is excluded because it is an extractive QA dataset, unsuitable for multi-passage mRAG.

5.1 Accuracy Results

Table 3 presents the results, including the no-context baseline and single in-/out-language gold passage results as computed in Section 4, to enable comparison (see Appendix I for full language-specific results). For this analysis, we also consider as valid the questions that were answered correctly but in the wrong language, as they also reflect a proper understanding of the context by the model. Interestingly, models provided with 3 out-language gold passages achieve higher accuracy than when provided with a single in-language gold passage in the query language, emphasizing the potential of cross-lingual retrieval for mRAG. As expected, the presence of distractors leads to lower accuracy. Notably, this is true for all models, datasets, and setups. However, the effect is considerably stronger in MKQA than in GMMLU-Choice, likely due to the stricter lexical-matching metric adopted for MKQA. We also verify that a higher proportion of distractors (3/4 vs. 1/4) is much more harmful for answer accuracy, which confirms the importance of having access to a high-quality cross-lingual retriever (Chirkova et al., 2024). When comparing the drop between in-language distractors and out-language distractors, we find that in-language distractors have a larger impact in most cases, matching our hypothesis that this is a particularly challenging scenario for LLMs. However, differences are small in many cases, indicating the language of the distractor is not a major issue for multi-passage mRAG.

5.2 Interpretability-based Evaluation

We adopt once again MIRAGE (Qi et al., 2024) to understand how the internal model dynamics are affected by our various simulated multi-passage mRAG scenarios. We sample 50 instances from each dataset and use MIRAGE to attribute Aya-expansive-8B responses to the provided passages via contrastive feature attribution (Yin and Neubig, 2022). Then, we compute **# Contextual**: the average number of distracting passages that contain at least one contextual cue for the produced answer (i.e. a token marked by CCI in MIRAGE), and **# Influential**: the average number of distractors that

Setup	MKQA				GMMLU-Choice			
	Aya	Llama	Gemma	Qwen	Aya	Llama	Gemma	Qwen
No Ctx	41.4	34.9	49.6	37.7	46.6	37.8	61.1	51.4
1 Gold (in)	73.6	59.9	65.5	70.6	55.0	45.2	66.0	58.4
1 Gold (out)	71.1	56.5	65.1	66.6	55.0	45.5	66.2	57.0
+ 3 Dist (in)	47.0	39.4	53.7	49.6	50.8	41.1	65.1	54.5
+ 3 Dist (out)	47.7	38.9	56.1	53.8	51.4	42.5	64.8	54.6
3 Gold (out)	77.7	65.3	75.3	75.9	56.6	47.7	69.1	59.5
+ 1 Dist (in)	68.8	56.0	71.3	70.8	55.8	45.7	68.6	58.4
+ 1 Dist (out)	69.6	57.8	72.9	72.9	56.2	46.6	68.5	58.6

Table 3: Average answer accuracy (%) without context (No Ctx), with a single in-language gold passage (1 Gold (in)), and multi-passages mRAG setups with varying numbers of in-language or out-language gold passages and distracting passages. Results are averaged over all query languages.

AVG Dist.	MKQA		GMMLU	
	In.	Out.	In.	Out.
1 Gold (out) + 3 Distractors				
# Context.	1.77	1.74	1.89	1.82
# Influent.	0.94	0.86	1.13	1.07
3 Gold (out) + 1 Distractor				
# Context.	0.85	0.79	0.92	0.89
# Influent.	0.35	0.25	0.50	0.43

Table 4: Average number of distractors containing contextual cues (# Context.) and receiving a higher sum of CCI scores than all gold passages (# Influent.), for Aya.

receive a higher sum of CCI attribution scores than all gold passages for each query.

The results in Table 4 support our observation that distractors exert a comparable effect regardless of their language, however in-language distractors have a slightly stronger effect. When considering the sum of attribution scores given to the distractors compared with the gold passages, the difference becomes more noticeable (e.g., Aya tends to pay more attention to in-language distractors for MKQA when there is 1 distractor, compared to out-language ones).

Taken together, our results indicate that the number of distractors can be more harmful for mRAG accuracy than the language in which those distractors are provided, when it comes to open-domain QA. On the multi-choice task, the negative effect of distractors is notably smaller and barely dependent on the passage language.

6 Conclusion

In this work, we explored the challenge of consistent context utilization in mRAG systems. Specifically, we assessed the ability of various state-of-the-art LLMs to handle various kinds of multilingual context while strictly controlling for retrieval quality. Our experiments across three diverse QA datasets, using standard accuracy evaluation as well as feature attribution analysis, reveal a remarkable ability of LLMs to understand multilingual contexts and to locate the important information in relevant passages regardless of their language. In fact, models provided with multiple gold passages in languages different from that of the query are more likely to answer correctly than when provided with a single gold passage in the query language, reflecting the potential of retrieving cross-lingually rather than monolingually for mRAG.

At the same time, we also detected some important directions for future improvement. Firstly, poor generation abilities in many languages push the models to respond in a different language than that of the query, resulting in answers that would be deemed useless by most end-users. Importantly, we showed that this also happens when the retrieval works optimally. This suggests that, rather than just trying to optimize the retriever, it may be more effective to invest on the model generation abilities in a specific (set of) user language(s) –for instance by continued pre-training (Fujii et al., 2024; Gao et al., 2024) on generic corpora of those languages– or to apply techniques that push the model to decode in a given language, such as contrastive decoding (Li et al., 2023; O’Brien and Lewis, 2023). Sec-

only, the presence of distracting passages (i.e., relevant to the query topic, but not directly functional to answer it) in the context can have a very negative effect on answer accuracy in open-domain QA. While this effect is rather similar regardless of the distractors’ language, it does highlight the importance of carefully ranking the retrieved passages and to aim for precision when selecting which passages are provided to the model.

To conclude, our work underscores the potential of cross-lingual retrieval in enhancing multilingual QA performance, and stresses the importance of focusing not only on retrieval optimization but also on improving language-specific generation. We believe this dual focus will be key to unlocking more robust and user-friendly mRAG systems that can operate effectively across diverse language settings.

Limitations

The limitations of our work include relying on a strict lexical matching of the answer to compute model accuracy and to detect gold passages. While commonly used, this approach is sensitive to minor variations or rephrasings of the answers and led to a serious underestimation of model performance with out-language gold passages in one of our QA datasets, XQUAD. In our paper, we have tested and reported BERTScore and LLM-based evaluation on XQUAD, as detailed in Section 3.3 to enhance the robustness of our findings. These semantic evaluations mirror the trends observed with the lexical metric, mitigating—if not eliminating—the risk that paraphrasing may influence the results. Nevertheless, future work could incorporate broader metrics and benchmarks to make the assessment more comprehensive.

Additionally, the use of lexical matching in detecting gold passages may overlook passages that provide valuable information but in a slightly rephrased form compared to the gold answer. Nonetheless, Table 3 shows that attaching even a single distracting passage identified by *this* heuristic method substantially degrades model accuracy. Thus, despite its limitations, lexical matching proves to be a practical and effective way for locating distracting passages in our experimental setting. Future work could explore more semantic retrieval methods to capture paraphrased gold evidence.

On the retrieval side, simulating cross-language retrieval by combining results of N in-language retrievers may yield a more comprehensive set of

passages than what we could obtain from a single run of a cross-language retriever. While this does not affect our results on the side of context utilization, it may overestimate retriever performance when our findings are applied to real-world mRAG systems. In terms of datasets, XQUAD was the only one including parallel gold passages, which allowed us to fully isolate the effect of a passage language from that of its content. However, its extractive QA nature makes it less representative of realistic mRAG tasks, highlighting the need to develop better parallel mRAG datasets in future work.

Acknowledgments

The authors have received funding from the Dutch Research Council (NWO): JQ is supported by NWA-ORC project LESSEN (grant nr. NWA.1389.20.183), AB is supported by the above as well as NWO Talent Programme (VI.Vidi.221C.009), RF is supported by the European Research Council (ERC) under European Union’s Horizon 2020 programme (No. 819455).

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A Dataset Examples

Examples of instances in each dataset are shown in Table 5.

B Full Statistics of the Filtered MKQA and GMMLU Datasets

The full statistics of the filtered MKQA and GMMLU datasets are shown in Table 6.

C Subjects Covered by the Filtered GMMLU Set

As shown in Table 7, 55 subjects belonging to 6 categories are covered by the filtered set of Global-MMLU, which ensures the diversity of the instances evaluated in our experiments.

D Extensive Evaluation

Since exact matching could be overly strict for the evaluation, we further adopt two complementary metrics on XQUAD with AYA.

Semantic similarity (BERTScore) We compute BERTScore, serving as a language-agnostic metric, between each model response and its ground-truth

answer based on the semantic similarity of model responses with the gold answer. Table 8 shows that models achieve comparable F1 scores in all query languages when fed gold passages in- or out-language. This finding is in line with our claim that LLMs are capable of understanding the gold passages regardless of their languages.

LLM-based evaluation (GPT-4.1-nano) However, semantic similarity cannot capture language mismatching. Therefore, we prompted GPT-4.1-nano to judge whether each response matches (i) the correct answer and (ii) its translation in the passage language. As shown in Table 8, overall accuracy on board is higher than lexical-matching accuracy in our paper, but the trend remains: models score better on IN than on OUT. If we allow “correct answer in the wrong language” as acceptable, the IN/OUT gap almost disappears.

Taken together, both semantic and LLM-based evaluation support our claim that LLMs are able to understand the multilingual gold passages regardless of their languages, but suffer from decoding the answer correctly in the user query language.

E Prompts and Instructions

To ensure the model responses are always in the query language, we follow previous works (Chirkova et al., 2024; Zhang et al., 2024) and adopt language-specific instructions to explicitly and implicitly guide the model to generate responses in the user-readable language. The examples in English, Spanish, and Chinese are listed in Table 9 and Table 10.

F Error Analysis on XQUAD

While our MKQA and GMMLU results strongly suggest our studied LLMs can understand the provided passages regardless of their language, the in-/out-language gap in XQUAD remains unexplained. To address this, we conduct a manual error analysis on XQUAD with Aya-Expanse-8B, focusing on a random sample of 20 Spanish and 20 Chinese queries that were answered correctly when provided with in-language passages, but wrongly with out-language passages. In most cases, we observe that models successfully understood the context and generated a proper response, however, this response did not perfectly match the gold answer provided in the dataset. This can be due to the presence of synonyms or slight paraphrases of the gold answer, or –in the case of languages

Dataset	Context provided in the dataset	Query	Gold Answer
XQUAD	The Panthers defense gave up just 308 points, ranking sixth in the league, while also leading the NFL in interceptions with 24 and boasting four Pro Bowl selections. ... also racking up 88 tackles and Pro Bowl cornerback Josh Norman, who developed into a shutdown corner during the season and had four interceptions, two of which were returned for touchdowns.	How many points did the Panthers defense surrender?	308
MKQA	-	How long did it take the twin towers to be built?	11.0 years
GMMLU-Open	-	Which god supplanted the earlier Mesopotamian supreme god Enlil?	Marduk
GMMLU-Choice	-	Which god supplanted the earlier Mesopotamian supreme god Enlil? A.Horus B.Inanna C.Marduk D.Isis	C

Table 5: Examples of instances in each dataset.

MKQA (Total 5951 Questions = # Inlang + # Outlang - # Both)														
Query Lang.	en	it	es	de	fr	pt	nl	sv	ru	fi	ja	pl		
# Q. w/ Inlang	5331	4466	4384	4352	4302	4133	4108	3984	3800	3639	3603	3594		
# Q. w/ Outlang	5787	5910	5942	5946	5944	5947	5947	5940	5945	5946	5944	5945		
# Overlap	5167	4425	4375	4347	4295	4129	4104	3973	3794	3634	3596	3588		
Query Lang.	no	tr	hu	da	vi	he	ar	ms	ko	th	zh	km		
# Q. w/ Inlang	3515	3515	3482	3390	3365	3343	2986	2937	2934	2539	2537	703		
# Q. w/ Outlang	5949	5945	5943	5946	5951	5946	5948	5942	5947	5945	5948	5950		
# Overlap	3513	3509	3474	3385	3365	3338	2983	2928	2930	2533	2534	702		
GMMLU (Total 4136 Questions = # Inlang + # Outlang - # Both)														
Query Lang.	en	ja	it	id	ko	nl	zh	vi	sv	pt	de	tr	ro	cs
# Q. w/ Inlang	2588	2054	1864	1778	1725	1712	1695	1689	1688	1679	1611	1583	1513	1512
# Q. w/ Outlang	4040	4064	4118	4115	4097	4125	4094	4116	4124	4118	4111	4121	4126	4116
# Overlap	2492	1982	1846	1757	1686	1701	1653	1669	1676	1661	1586	1568	1503	1492
Query Lang.	ru	es	ms	pl	uk	fr	ar	fa	el	sr	he	hi	fil	lt
# Q. w/ Inlang	1503	1502	1464	1462	1422	1415	1373	1350	1317	1288	1160	1142	1125	1071
# Q. w/ Outlang	4126	4109	4126	4124	4130	4122	4118	4125	4130	4130	4118	4133	4130	4132
# Overlap	1493	1475	1454	1450	1416	1401	1355	1339	1311	1282	1142	1139	1119	1067
Query Lang.	bn	ky	ha	te	sw	ig	si	ne	am	ny	mg	so	sn	yo
# Q. w/ Inlang	1005	985	930	924	923	831	792	746	650	634	625	559	497	389
# Q. w/ Outlang	4125	4121	4123	4130	4129	4125	4132	4132	4135	4129	4133	4129	4134	4129
# Overlap	994	970	917	918	916	820	788	742	649	627	622	552	495	382

Table 6: The statistics of the filtered subset of MKQA and Global-MMLU where each query has gold passages in at least one studied language. For all languages, there is a portion of queries where useful information can only be found in out-language passages, which is particularly evident in low-resource languages. # Inlang: Number of queries having gold passages retrieved from the corpora of the query language. # Outlang: Number of queries having out-language gold passages. I.e. useful information is stored in the corpora of languages other than the query language. # Overlap: Number of queries that have useful information retrieved from both in-language and out-language corpora.

with different scripts—to transliteration variations (Knight and Graehl, 1997). For instance, the gold answer for a Spanish question is ‘*evolución de la lengua y la literatura alemanas*’ (i.e. ‘evolution of the German language and literature’). In the in-language setup, the model manages to generate

this exact string as it is included in the provided Spanish passage. However, when the same passage is provided in English, the model generates the semantically equivalent phrase ‘... *evolución del idioma y la literatura alemana...*’, or ‘...*desarrollo del idioma y la literatura alemana...*’ when the passage

Category	Subject
STEM	high_school_computer_science, high_school_statistics, computer_security, college_biology, college_chemistry, machine_learning, high_school_mathematics, elementary_mathematics, college_mathematics, electrical_engineering, college_physics, astronomy, conceptual_physics, high_school_chemistry, high_school_physics, high_school_biology, college_computer_science, anatomy
Business	business_ethics, management, marketing, professional_accounting
Medical	professional_medicine, virology, college_medicine, clinical_knowledge, human_aging, medical_genetics, nutrition
Social Sciences	high_school_psychology, econometrics, sociology, high_school_microeconomics, high_school_geography, public_relations, security_studies, professional_psychology, high_school_government_and_politics, high_school_macroconomics, human_sexuality, us_foreign_policy
Humanities	international_law, high_school_world_history, moral_disputes, prehistory, world_religions, jurisprudence, high_school_us_history, philosophy, professional_law, formal_logic, logical_fallacies, high_school_european_history
Other	miscellaneous, global_facts

Table 7: The categories and subjects covered by the filtered GMMLU.

Lang.	BERTScore		LLM-Based Score	
	IN.	OUT.	IN.	OUT.
en	90.27	82.58	93.19	81.54 (+12.93)
ar	82.87	81.55	91.93	63.98 (+23.25)
de	81.60	80.69	90.25	71.73 (+14.86)
el	82.38	81.24	92.18	66.00 (+21.04)
es	82.15	81.14	94.37	73.05 (+14.62)
hi	83.31	82.15	89.75	65.78 (+16.71)
ro	81.68	80.65	91.93	69.11 (+18.69)
ru	83.22	81.95	91.51	66.78 (+21.18)
th	84.21	83.23	86.81	57.78 (+23.02)
tr	81.31	80.18	88.40	63.39 (+23.37)
vi	82.81	81.62	89.75	65.81 (+23.05)
zh	84.07	82.95	90.34	65.39 (+21.46)

Table 8: BERTScore (F1) and LLM-based evaluation (Accuracy) on XQUAD with AYA. The numbers between brackets indicate the proportion of queries that are correctly answered but in the wrong language.

is provided in Chinese. Similarly, for a Chinese query with gold answer ‘亚里士多德宇宙学’ (i.e. ‘Aristotelian cosmology’), model responses slightly differ when provided with different out-language passages (e.g. ‘亚里士多德宇宙论’, ‘阿里斯托的宇宙论’, or ‘阿里斯托特利宇宙论’ with English, Arabic, or Greek passage respectively), all of which are correct translations of ‘Aristotelian cosmology’. While this issue can always affect lexical-matching evaluation, it is particularly severe in XQUAD as many answers in this dataset are named entities or sentence segments due to the extractive nature of the task, which in turn causes an underestimation of the models capability.

G Advanced System Prompting

In our main experiments, we follow the previous works (Chirkova et al., 2024; Zhang et al., 2024) and adopt the direct prompt. To test if a stronger prompt could mitigate language-mismatch errors, we add a two-step instruction that first allows the model to answer in any appropriate language, then explicitly translates the answer into the query language. Formally: ‘Write a high-quality answer to the given question using the provided search results. Please respond in English. Specifically, please follow the two steps below. Step 1: Generate a complete answer to the question in any appropriate language. Step 2: Translate your entire answer into clear, natural-sounding English.’

Same as the main experiment in the paper, the prompt is translated into other query languages and explicitly specifies the desired generation language. For instance, the prompt for Spanish queries is:

‘Escriba una respuesta de alta calidad a la pregunta dada utilizando los resultados de búsqueda proporcionados. Por favor responda en español. Específicamente, siga los dos pasos a continuación. Paso 1: Genere una respuesta completa a la pregunta en cualquier idioma apropiado. Paso 2: Traduce toda tu respuesta a un español claro y con sonido natural.’

We run this prompt on XQUAD with AYA and evaluate via GPT-4.1-nano, the same setups and LLM-based evaluation as above in Appendix D. As shown in Table 11, compared to the original prompts, these stronger instructions reduced, but

Language	Setup	Instruction
en	No Ctx	Write a high-quality answer to the given question. Please respond in English.
	Ctx	Write a high-quality answer to the given question using the provided search results. Please respond in English.
es	No Ctx	Escriba una respuesta de alta calidad a la pregunta planteada. Por favor responda en español.
	Ctx	Escriba una respuesta de alta calidad a la pregunta planteada utilizando los resultados de búsqueda proporcionados. Por favor, responda en español.
zh	No Ctx	请对所给问题写出高质量的答案。请使用中文回答。
	Ctx	使用提供的搜索结果对给定的问题写出高质量的答案。请用中文回答。

Table 9: The examples of the adopted instructions for guiding LLMs to generate responses in the user languages on the open QA tasks (XQUAD, MKQA, GMMLU-Open).

Language	Instruction
en	Please choose the most suitable one among A, B, C and D as the answer to the question, and return it in the following format: [choice] where [choice] must be one of [A], [B], [C] and [D].
es	Elija la respuesta más adecuada entre A, B, C y D a la pregunta y devuélvala en el siguiente formato: [opción] donde [opción] debe ser una de [A], [B], [C] y [D].
zh	请在A、B、C和D中选择最合适的一个作为问题的答案，并按照以下格式返回： [choice] 其中[choice]必须是[A]、[B]、[C]和[D]之一。

Table 10: The examples of the adopted instructions for guiding LLMs to generate responses in the user languages on the multi-choice QA task (GMMLU-Choice).

Language	LLM-Based Score	
	IN.	OUT.
en	94.71	82.52 (+11.24)
ar	87.14	64.38 (+24.85)
de	89.92	73.12 (+13.76)
el	90.59	65.11 (+22.05)
es	92.61	73.51 (+14.23)
hi	85.13	63.80 (+20.06)
ro	92.61	67.00 (+19.17)
ru	90.67	69.49 (+19.34)
th	86.89	60.04 (+25.12)
tr	85.46	63.46 (+21.35)
vi	91.34	67.16 (+22.85)
zh	90.84	69.60 (+20.28)

Table 11: LLM-based evaluation score (Accuracy) on XQUAD with Aya, where stronger multi-step reasoning prompts are adopted. Nonetheless, the language-mismatching issue persists.

did not eliminate, the gap between in-language and out-language accuracy. Specifically, many

responses still contained correct answers but remained in the wrong passage language, indicating that even explicitly guiding the LLM to do ‘think then translation’ cannot fully resolve decoding failures. These results underscore that decoding, rather than understanding, remains a substantial bottleneck.

H Extended Evaluation on Larger Models

To enhance the robustness of our experiments, we repeat the XQuAD evaluation (using the same setup) on a 27B open-source model (Gemma3-27B-IT) and a closed-source model estimated at 8-18B parameters (GPT5-nano)⁹. The results in Table 12 show that, although overall accuracy of out-language passages improves, it remains substantially lower than on in-language passages. Moreover, a non-negligible fraction of questions are answered correctly in content but produced in the wrong language when the model receives out-

⁹<https://www.r-bloggers.com/2025/08/how-many-parameters-does-gpt-5-have/>

Language	Accuracy (Gemma3-27B-IT)				
	Non.	In.	Out. (AVG)	Out. (Best)	Out. (Worst)
en	21.3	86.7	67.1 (+4.9)	72.9 (+5.5)	60.3 (+9.4)
es	16.6	72.9	53.2 (+5.8)	59.2 (+9.4)	48.2 (+7.6)
de	17.0	72.5	52.0 (+4.7)	56.9 (+7.2)	48.2 (+7.0)
ro	14.5	76.2	52.0 (+4.3)	56.6 (+8.3)	47.4 (+6.2)
vi	15.1	77.6	49.9 (+7.4)	53.7 (+13.4)	44.3 (+9.7)
tr	12.2	67.4	45.4 (+5.9)	50.5 (+9.8)	42.1 (+5.0)
el	10.4	68.9	40.9 (+8.3)	44.7 (+16.1)	38.2 (+6.8)
zh	13.9	79.2	44.1 (+13.7)	45.7 (+20.7)	41.5 (+7.3)
ar	8.8	65.8	35.5 (+9.5)	37.4 (+19.6)	32.3 (+5.8)
hi	13.3	74.8	42.6 (+6.0)	46.8 (+15.0)	38.7 (+4.2)
ru	11.4	66.6	40.6 (+9.7)	42.6 (+11.8)	36.9 (+6.7)
th	11.1	74.6	35.4 (+14.2)	36.4 (+30.0)	34.5 (+9.8)

Language	Accuracy (GPT5-nano)				
	Non.	In.	Out. (AVG)	Out. (Best)	Out. (Worst)
en	25.6	74.0	55.1 (+7.1)	58.3 (+8.3)	51.8 (+7.8)
es	20.2	64.8	50.2 (+3.6)	55.1 (+7.2)	46.3 (+2.4)
de	20.1	60.2	48.0 (+1.9)	52.0 (+6.2)	44.9 (+0.8)
ro	19.2	59.8	46.1 (+2.6)	49.4 (+7.3)	42.9 (+1.4)
vi	18.3	58.8	45.1 (+4.4)	47.8 (+5.0)	42.4 (+2.1)
tr	15.5	49.2	38.0 (+5.6)	39.8 (+7.4)	35.3 (+2.4)
el	12.5	55.5	35.6 (+6.1)	39.3 (+16.2)	32.9 (+2.1)
zh	16.5	59.6	39.1 (+8.9)	41.4 (+18.2)	37.8 (+3.6)
ar	10.3	48.2	31.3 (+8.8)	33.1 (+7.1)	30.0 (+3.9)
hi	12.8	45.2	29.8 (+10.3)	32.3 (+22.6)	27.0 (+13.3)
ru	12.8	48.9	34.1 (+6.4)	36.4 (+14.0)	31.8 (+3.9)
th	11.9	53.4	32.6 (+10.6)	34.2 (+25.2)	30.4 (+2.1)

Table 12: Language-specific results on XQUAD with larger LLMs (Gemma3-27B-IT and GPT5-nano). Numbers between brackets indicate the proportion of queries that are correctly answered but in the wrong language (i.e., not the query language).

language passages. These findings are consistent with Section 4.1 and further strengthen the generalization of our findings.

I Language-specific Results

The detailed results for each query-passage language pair on XQUAD are given in Figure 4. The detailed single-passage mRAG results for each language on all datasets are provided in Table 13 to 18. The detailed results for each language in the multi-passage mRAG experiments are shown in Table 19 to 22.

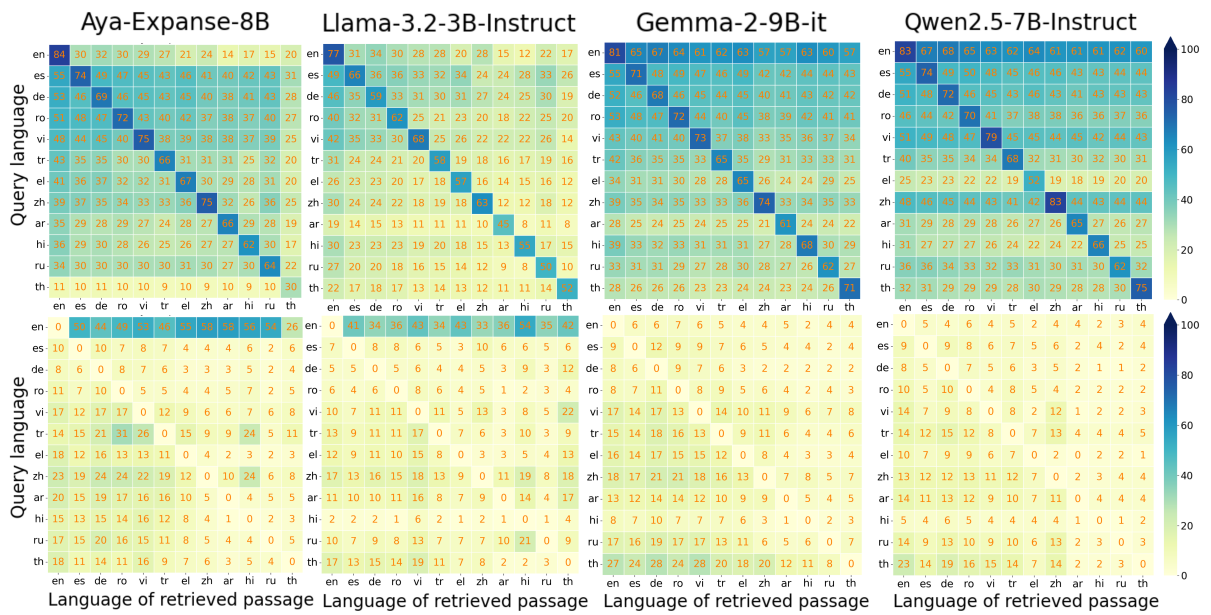


Figure 4: Model performance on XQUAD when the query is concatenated with passage in each studied language. Top: The portion of queries that can be correctly answered in the user language. Bottom: The portion of queries for which the LLMs generate the correct answer but in the wrong (passage) language. For a part of correctly answered queries, the gold answers are the same words in the passage and query languages. In these cases, we only consider them in the above heatmaps to ensure that there is no overlapping between the two vertical heatmaps and that they are addable.

Language	Accuracy (Aya)				
	Non.	In.	Out. (AVG)	Out. (Best)	Out. (Worst)
en	19.4	83.7	23.6 (+49.9)	32.4 (+44.1)	14.0 (+58.5)
es	13.9	73.5	43.7 (+6.3)	54.9 (+10.1)	30.9 (+5.5)
de	12.2	69.2	42.5 (+5.0)	53.4 (+7.6)	28.1 (+4.4)
ro	12.0	72.4	40.9 (+5.8)	51.1 (+10.8)	26.8 (+5.3)
vi	14.3	75.0	39.4 (+10.6)	48.2 (+16.8)	25.5 (+8.4)
tr	9.1	66.1	31.2 (+16.4)	43.0 (+13.9)	19.9 (+10.8)
el	8.5	67.5	31.5 (+8.6)	40.5 (+17.8)	20.0 (+2.6)
zh	12.6	74.6	33.3 (+17.3)	39.0 (+22.6)	25.5 (+8.2)
ar	7.6	66.3	27.4 (+12.1)	35.0 (+19.8)	18.7 (+5.3)
hi	6.1	62.4	27.3 (+9.4)	36.0 (+15.5)	17.2 (+2.6)
ru	9.2	63.8	29.6 (+11.0)	34.1 (+16.7)	22.1 (+5.2)
th	2.1	30.3	10.0 (+9.3)	11.4 (+17.6)	9.1 (+5.8)
AVG	10.6	67.1	31.7 (+13.5)	39.9 (+17.8)	21.5 (+10.2)
Language	Accuracy (Llama)				
	Non.	In.	Out. (AVG)	Out. (Best)	Out. (Worst)
en	14.4	76.8	24.2 (+39.1)	33.7 (+34.1)	12.1 (+53.6)
es	8.8	66.2	32.3 (+6.5)	49.2 (+7.1)	24.0 (+6.0)
de	7.6	59.0	30.1 (+5.5)	45.7 (+5.0)	19.0 (+12.0)
ro	6.6	61.8	25.2 (+4.4)	40.2 (+5.8)	18.2 (+1.4)
vi	8.5	68.4	27.1 (+9.6)	41.8 (+9.7)	14.4 (+21.9)
tr	5.1	57.9	20.5 (+9.2)	30.7 (+13.1)	15.8 (+8.6)
el	2.5	57.5	18.2 (+8.4)	25.8 (+12.4)	11.8 (+12.5)
zh	5.2	62.9	18.9 (+14.2)	30.3 (+16.6)	11.8 (+18.0)
ar	2.0	45.3	12.0 (+10.7)	18.7 (+10.5)	8.2 (+17.5)
hi	2.7	55.3	19.6 (+2.3)	29.6 (+2.4)	13.4 (+0.8)
ru	4.1	49.8	15.3 (+9.8)	26.8 (+10.0)	7.6 (+20.7)
th	2.9	51.8	14.6 (+10.1)	21.6 (+16.9)	11.0 (+1.8)
AVG	5.9	59.4	21.5 (+10.8)	32.8 (+12.0)	13.9 (+14.6)

Table 13: Language-specific results on XQUAD with single-passage mRAG setup. Numbers between brackets indicate the proportion of queries that are correctly answered but in the wrong language (i.e., not the query language).

Language	Accuracy (Gemma)				
	Non.	In.	Out. (AVG)	Out. (Best)	Out. (Worst)
en	17.9	80.6	61.5 (+5.0)	67.1 (+6.5)	56.6 (+5.3)
es	12.4	70.8	46.3 (+6.6)	54.5 (+9.4)	41.7 (+4.1)
de	12.1	67.7	44.1 (+4.4)	52.0 (+7.6)	39.8 (+2.3)
ro	12.1	72.1	43.3 (+6.2)	52.9 (+8.5)	37.8 (+5.9)
vi	10.8	73.4	37.7 (+11.3)	43.0 (+16.8)	33.1 (+10.8)
tr	8.4	65.2	33.7 (+10.5)	41.8 (+15.0)	29.1 (+11.1)
el	5.0	65.0	28.2 (+10.1)	34.0 (+15.7)	23.7 (+4.0)
zh	9.3	73.8	34.5 (+13.7)	38.9 (+17.6)	32.9 (+6.9)
ar	4.9	61.3	24.3 (+9.8)	27.6 (+12.9)	20.7 (+9.0)
hi	6.1	67.7	31.2 (+5.5)	38.9 (+7.6)	26.7 (+3.4)
ru	7.4	62.1	28.9 (+12.1)	32.9 (+16.8)	26.1 (+5.5)
th	5.4	71.3	24.9 (+20.0)	28.2 (+26.7)	22.8 (+11.6)
AVG	9.3	69.2	36.5 (+9.6)	42.6 (+13.4)	32.6 (+6.7)

Language	Accuracy (Qwen)				
	Non.	In.	Out. (AVG)	Out. (Best)	Out. (Worst)
en	23.5	82.7	63.1 (+3.9)	67.6 (+4.4)	60.3 (+3.7)
es	17.2	74.3	46.6 (+5.7)	55.2 (+9.3)	42.5 (+2.4)
de	15.2	72.0	44.9 (+4.1)	51.2 (+8.3)	41.4 (+1.7)
ro	13.7	70.1	39.1 (+4.9)	46.2 (+9.8)	35.5 (+1.9)
vi	15.7	79.1	45.7 (+6.2)	50.5 (+14.2)	42.1 (+2.4)
tr	9.8	68.4	32.9 (+8.9)	40.1 (+13.5)	29.8 (+3.5)
el	4.8	51.6	20.9 (+5.0)	25.1 (+9.7)	18.1 (+0.4)
zh	18.9	83.0	43.9 (+8.5)	47.7 (+12.9)	41.2 (+12.4)
ar	9.1	65.3	27.7 (+9.1)	31.0 (+14.5)	25.7 (+10.3)
hi	5.5	66.1	25.6 (+3.7)	30.8 (+5.5)	22.1 (+0.6)
ru	9.1	62.2	32.4 (+8.5)	36.1 (+9.0)	29.6 (+2.9)
th	8.5	75.1	29.5 (+11.7)	32.2 (+22.6)	27.6 (+14.4)
AVG	12.6	70.8	37.7 (+6.7)	42.8 (+11.1)	34.7 (+4.7)

Table 14: Extension: Language-specific results on XQUAD with single-passage mRAG setup. Numbers between brackets indicate the proportion of queries that are correctly answered but in the wrong language (i.e., not the query language).

Language	Accuracy (Aya)			Accuracy (Llama)		
	Non.	In.	Out.	Non.	In.	Out.
en	58.0	87.5	69.4 (+15.3)	61.8	82.4	63.9 (+10.2)
it	53.0	86.9	78.5 (+4.6)	44.7	70.6	63.6 (+3.7)
es	54.6	85.7	77.9 (+4.2)	46.9	72.1	66.8 (+3.1)
de	52.8	84.4	78.2 (+3.2)	46.0	70.6	65.3 (+2.2)
fr	55.4	86.9	79.1 (+3.1)	48.8	74.2	67.3 (+2.6)
pt	54.4	84.7	76.2 (+5.4)	45.0	70.1	63.8 (+3.9)
nl	55.9	85.6	76.8 (+4.2)	50.3	70.3	64.3 (+2.8)
sv	39.1	76.7	66.7 (+5.3)	44.9	69.7	63.3 (+3.4)
ru	43.6	79.6	59.7 (+14.0)	23.7	56.8	37.7 (+10.1)
fi	17.0	72.4	58.3 (+7.4)	27.2	62.4	53.9 (+4.2)
ja	46.8	82.1	54.9 (+23.3)	21.7	57.5	36.1 (+12.3)
pl	50.1	79.2	68.0 (+6.1)	35.3	60.6	51.5 (+4.4)
no	39.9	76.4	64.1 (+7.9)	43.6	66.4	58.3 (+5.3)
tr	52.0	82.3	72.2 (+7.6)	38.2	66.3	55.5 (+5.5)
hu	26.7	67.5	52.6 (+8.3)	34.4	59.3	49.2 (+5.1)
da	42.9	75.8	66.2 (+6.1)	46.4	66.5	60.3 (+4.2)
vi	54.4	79.0	71.2 (+6.5)	47.0	67.3	60.2 (+5.1)
he	36.2	78.5	46.5 (+25.4)	5.9	25.6	17.1 (+20.3)
ar	38.8	72.5	50.4 (+19.5)	17.2	46.4	27.2 (+10.7)
ms	53.6	78.4	68.4 (+7.7)	46.8	62.5	55.5 (+5.0)
ko	15.3	30.7	25.8 (+25.3)	19.2	52.9	30.2 (+17.6)
th	15.0	40.5	25.8 (+16.7)	24.2	46.9	32.0 (+13.3)
zh	48.4	78.0	56.6 (+20.2)	27.8	52.4	37.4 (+16.3)
km	7.8	19.2	14.9 (+8.2)	6.0	13.0	9.4 (+0.2)
AVG	42.2	73.8	60.8 (+10.6)	35.5	60.1	49.6 (+7.1)

Language	Accuracy (Gemma)			Accuracy (Qwen)		
	Non.	In.	Out.	Non.	In.	Out.
en	65.0	79.8	75.7 (+1.3)	55.6	86.0	81.7 (+1.1)
it	59.6	80.3	75.4 (+3.7)	44.5	81.2	72.7 (+4.1)
es	61.4	78.0	73.3 (+3.8)	48.4	80.9	73.5 (+3.6)
de	58.3	75.9	73.7 (+2.4)	44.6	78.2	70.5 (+2.9)
fr	61.8	80.7	74.8 (+2.6)	49.0	82.3	74.9 (+2.6)
pt	60.1	76.5	70.5 (+5.0)	48.5	78.6	71.4 (+4.2)
nl	64.5	74.8	71.1 (+3.3)	45.7	79.0	71.1 (+3.3)
sv	59.9	73.5	70.2 (+3.6)	43.7	75.4	68.0 (+4.6)
ru	42.8	68.8	50.6 (+10.6)	30.7	71.0	51.2 (+10.3)
fi	44.6	68.3	62.4 (+4.6)	23.9	72.5	60.9 (+5.7)
ja	42.7	69.9	47.9 (+13.7)	31.1	75.2	46.3 (+17.5)
pl	55.0	67.8	62.0 (+4.6)	36.9	68.9	59.1 (+5.4)
no	59.3	68.6	63.9 (+5.8)	42.3	73.8	63.8 (+6.9)
tr	56.7	66.8	62.8 (+4.7)	36.4	72.4	64.4 (+5.7)
hu	51.2	64.9	61.9 (+5.5)	27.4	67.1	55.9 (+6.9)
da	61.1	66.8	64.4 (+4.9)	44.8	72.7	65.8 (+5.1)
vi	54.4	66.5	64.1 (+5.3)	50.9	74.3	69.3 (+4.9)
he	29.7	65.3	39.5 (+16.6)	19.9	66.6	34.3 (+18.2)
ar	30.0	61.1	42.8 (+9.9)	27.9	64.8	42.3 (+12.7)
ms	60.5	63.8	62.3 (+6.9)	47.1	68.1	63.4 (+6.4)
ko	12.2	17.5	19.7 (+9.7)	23.3	59.0	39.1 (+16.6)
th	40.0	55.9	38.2 (+18.6)	34.6	56.6	40.2 (+16.6)
zh	45.0	61.9	47.8 (+14.7)	49.5	70.0	58.5 (+12.2)
km	26.2	28.7	27.9 (+5.9)	14.0	23.2	21.1 (+6.6)
AVG	50.1	65.9	58.5 (+7.0)	38.4	70.7	59.1 (+7.7)

Table 15: Language-specific results on MKQA with single-passage mRAG setup. Numbers between brackets indicate the proportion of queries that are correctly answered but in the wrong language (i.e., not the query language).

Language	Accuracy (Aya)			Accuracy (Llama)		
	Non.	In.	Out.	Non.	In.	Out.
en	47.9	70.4	32.7 (+30.8)	48.5	65.7	38.8 (+15.9)
ja	38.9	68.3	43.4 (+11.7)	19.9	46.9	23.4 (+6.6)
it	40.4	66.8	49.3 (+6.2)	26.9	51.9	34.7 (+6.1)
id	40.6	68.2	48.1 (+8.2)	27.2	46.7	30.4 (+6.0)
ko	12.4	25.7	16.6 (+11.7)	18.8	43.6	21.1 (+7.5)
nl	38.5	64.6	44.4 (+7.5)	29.2	50.2	31.0 (+5.7)
zh	40.7	65.2	47.8 (+10.8)	27.6	45.1	30.1 (+6.5)
vi	34.6	60.5	39.6 (+11.2)	26.1	45.4	28.1 (+8.6)
sv	22.4	55.6	32.7 (+8.0)	28.3	49.4	33.2 (+5.4)
pt	40.5	72.3	50.1 (+7.4)	27.3	53.7	33.7 (+6.1)
de	41.1	67.1	48.8 (+5.5)	32.0	53.4	37.6 (+5.1)
tr	36.0	65.7	39.0 (+13.7)	21.0	47.3	24.0 (+8.6)
ro	40.2	60.8	45.7 (+5.3)	26.5	44.2	32.5 (+4.6)
cs	34.2	57.2	39.0 (+7.7)	22.0	42.1	26.2 (+6.0)
ru	34.1	63.0	39.3 (+8.1)	21.0	43.3	23.3 (+6.5)
es	34.4	58.5	41.5 (+7.0)	25.7	48.4	34.3 (+5.4)
ms	35.8	64.1	44.0 (+8.7)	27.2	45.8	32.3 (+5.9)
pl	33.3	58.1	37.9 (+6.9)	20.6	39.1	24.8 (+6.3)
uk	32.8	59.4	37.4 (+6.7)	16.0	38.8	20.0 (+5.4)
fr	38.5	62.5	44.9 (+7.5)	23.8	50.7	31.5 (+5.5)
ar	29.2	59.9	36.0 (+9.4)	10.4	32.7	11.4 (+6.1)
fa	29.6	61.1	35.8 (+10.1)	15.2	43.6	16.9 (+8.7)
el	31.4	53.3	34.6 (+7.0)	15.5	35.6	17.7 (+8.1)
sr	13.4	38.4	18.9 (+7.7)	12.3	33.6	17.7 (+6.8)
he	30.9	60.6	36.6 (+9.3)	12.3	24.7	17.4 (+10.5)
hi	21.3	43.3	26.6 (+6.3)	17.9	39.0	23.4 (+1.5)
fil	23.4	44.9	30.2 (+8.7)	25.5	39.3	28.0 (+6.1)
lt	16.7	46.7	21.6 (+9.1)	14.8	35.9	19.0 (+4.9)
bn	5.1	23.9	8.2 (+5.4)	10.0	25.8	13.7 (+2.2)
ky	14.5	36.1	22.7 (+2.6)	13.9	27.4	16.6 (+5.9)
ha	15.0	43.9	24.3 (+16.0)	13.7	31.1	19.8 (+6.5)
te	4.8	15.5	6.2 (+2.9)	13.2	20.0	13.9 (+0.4)
sw	16.6	56.1	25.5 (+9.1)	20.1	34.7	25.8 (+4.7)
ig	15.5	34.9	20.8 (+13.5)	16.2	27.6	17.6 (+3.5)
si	6.1	13.3	4.4 (+3.3)	8.5	13.9	8.3 (+3.1)
ne	8.4	28.3	10.8 (+13.7)	9.2	27.7	10.2 (+14.4)
am	8.0	18.9	16.5 (+23.3)	8.5	10.3	5.8 (+0.3)
ny	21.5	44.2	29.6 (+13.8)	17.9	28.2	19.9 (+3.5)
mg	18.3	44.6	24.4 (+10.0)	20.1	40.4	22.1 (+4.6)
so	23.7	54.9	31.7 (+8.2)	19.9	40.0	22.7 (+4.6)
sn	27.5	60.2	31.9 (+15.7)	19.0	40.1	22.2 (+3.8)
yo	24.1	40.2	29.4 (+7.0)	20.2	32.9	24.7 (+1.1)
AVG	26.7	51.4	32.1 (+9.6)	20.2	39.0	23.5 (+5.8)

Table 16: Language-specific results on GMMLU-Open with single-pass mRAG setup when the model is given no options and forced to output an open answer as the response. Numbers between brackets indicate the proportion of queries that are correctly answered but in the wrong language (i.e., not the query language).

Language	Accuracy (Gemma)			Accuracy (Qwen)		
	Non.	In.	Out.	Non.	In.	Out.
en	54.4	69.2	61.1 (+2.6)	56.1	73.2	63.4 (+2.2)
ja	43.0	67.5	47.7 (+5.1)	33.1	66.0	41.4 (+6.9)
it	47.2	65.7	54.0 (+4.7)	36.3	64.5	45.3 (+6.1)
id	46.8	66.8	50.6 (+7.4)	38.5	63.3	44.4 (+6.5)
ko	13.2	20.4	18.4 (+6.7)	23.7	43.7	28.3 (+7.4)
nl	45.0	63.2	46.6 (+6.8)	31.9	58.4	38.8 (+6.7)
zh	48.3	66.4	54.3 (+5.1)	52.3	67.2	57.7 (+4.1)
vi	38.5	58.1	39.6 (+9.8)	34.9	59.6	41.0 (+8.1)
sv	43.6	62.5	47.0 (+5.7)	28.4	60.0	35.6 (+7.2)
pt	47.3	68.9	51.8 (+6.3)	38.6	68.5	48.7 (+5.6)
de	47.2	66.8	54.2 (+4.2)	36.8	62.9	44.4 (+5.3)
tr	40.1	59.7	42.1 (+7.3)	24.2	56.2	32.2 (+10.1)
ro	43.2	58.3	46.6 (+5.2)	30.1	52.1	36.0 (+5.7)
cs	34.7	54.1	37.1 (+6.9)	23.2	47.9	28.5 (+5.7)
ru	38.1	55.7	38.4 (+8.2)	31.3	56.2	36.0 (+6.0)
es	39.8	57.7	45.5 (+6.2)	37.0	60.5	44.0 (+5.4)
ms	44.6	61.4	46.1 (+8.8)	32.5	57.4	39.7 (+7.2)
pl	36.3	54.0	38.9 (+6.8)	25.6	51.2	30.6 (+7.2)
uk	33.3	53.1	36.5 (+7.1)	18.3	45.8	23.8 (+5.4)
fr	39.5	62.1	47.7 (+5.8)	36.5	65.1	44.8 (+6.0)
ar	24.2	56.4	29.1 (+6.9)	22.4	57.8	29.2 (+7.3)
fa	31.4	61.2	36.3 (+7.7)	14.2	48.9	19.8 (+9.0)
el	29.4	48.1	29.2 (+7.4)	10.2	25.7	11.4 (+4.8)
sr	32.1	48.9	32.1 (+5.7)	17.5	43.4	23.8 (+5.6)
he	30.4	56.4	34.9 (+8.6)	18.8	53.3	26.7 (+7.9)
hi	35.1	52.2	35.7 (+2.9)	15.5	39.2	20.0 (+2.6)
fil	45.2	52.6	44.9 (+7.3)	30.0	45.9	33.4 (+9.7)
lt	31.4	51.0	29.9 (+8.0)	16.3	42.0	20.6 (+7.4)
bn	24.4	46.9	24.7 (+6.6)	11.0	35.5	15.0 (+5.2)
ky	28.2	43.5	30.9 (+3.3)	15.7	33.7	21.1 (+4.6)
ha	29.8	42.0	31.6 (+5.6)	19.2	41.4	24.4 (+8.9)
te	24.7	43.2	29.0 (+4.4)	7.7	17.7	6.9 (+1.6)
sw	35.6	48.7	37.4 (+6.1)	17.2	44.2	23.7 (+6.8)
ig	23.7	36.1	25.9 (+4.4)	17.4	35.7	24.1 (+7.7)
si	17.0	32.1	19.9 (+1.6)	9.5	15.7	8.8 (+1.0)
ne	24.1	38.4	25.8 (+11.7)	6.1	24.0	8.0 (+13.2)
am	15.6	24.6	16.9 (+2.2)	11.9	20.8	14.1 (+4.2)
ny	29.0	35.6	29.0 (+3.2)	18.0	29.9	24.0 (+4.7)
mg	26.7	33.0	24.2 (+4.2)	19.9	40.5	27.1 (+6.0)
so	29.2	40.6	28.6 (+4.1)	23.6	42.3	27.4 (+6.1)
sn	34.3	42.6	29.2 (+5.3)	20.2	37.4	26.4 (+5.2)
yo	21.2	35.3	25.4 (+2.5)	26.7	42.7	34.1 (+2.5)
AVG	34.4	51.5	37.0 (+5.9)	24.7	47.6	30.3 (+6.1)

Table 17: Extension: Language-specific results on GMLU-Open with single-passage mRAG setup when the model is given no options and forced to output an open answer as the response. Numbers between brackets indicate the proportion of queries that are correctly answered but in the wrong language (i.e., not the query language).

Language	Accuracy (Aya)			Accuracy (Llama)			Accuracy (Gemma)			Accuracy (Qwen)		
	Non.	In.	Out.	Non.	In.	Out.	Non.	In.	Out.	Non.	In.	Out.
en	70.2	77.3	75.5	69.7	76.6	72.6	80.5	83.3	81.0	81.6	84.3	82.8
ja	61.5	71.1	71.4	44.3	58.1	57.9	69.9	77.2	75.9	66.2	74.0	71.4
it	64.6	70.7	70.7	59.2	65.8	64.6	75.5	78.6	78.9	72.2	74.9	75.1
id	61.8	69.7	68.9	50.7	57.6	57.9	72.5	76.7	75.4	69.8	74.5	73.2
ko	58.8	64.6	65.8	39.3	47.1	47.7	66.7	72.6	71.9	64.4	70.7	69.2
nl	61.7	68.8	67.9	54.3	63.6	61.5	73.2	75.9	74.9	71.0	73.6	74.3
zh	60.3	66.2	68.8	52.3	61.5	59.2	71.0	74.0	75.3	73.2	72.2	72.5
vi	55.5	62.2	62.4	48.5	57.8	56.0	65.8	71.1	70.9	66.9	70.7	69.8
sv	52.7	65.3	65.2	47.3	60.3	58.5	72.3	76.4	76.4	67.0	73.6	72.9
pt	70.1	75.5	75.0	35.1	60.7	53.3	78.2	83.2	81.6	78.6	83.0	82.1
de	67.9	75.2	74.2	60.2	70.3	69.0	78.3	81.6	81.9	74.9	80.4	78.5
tr	59.1	67.4	68.1	46.4	57.7	56.1	69.1	73.4	74.0	57.5	67.0	66.4
ro	61.8	66.2	66.5	51.4	59.2	58.4	70.9	72.8	73.0	64.9	70.2	68.3
cs	60.9	70.2	68.0	47.1	56.6	56.9	72.1	75.0	74.4	65.2	71.9	69.6
ru	60.9	70.6	70.0	40.3	49.2	50.5	72.3	77.8	77.4	74.2	76.4	76.0
es	63.9	69.5	69.7	57.5	65.8	64.0	73.5	76.3	76.4	72.4	76.9	76.0
ms	56.3	65.4	64.4	47.0	54.4	54.9	70.1	73.2	72.7	66.2	72.3	70.8
pl	59.4	68.9	67.7	47.9	55.2	51.5	71.7	75.1	74.9	67.2	71.6	70.5
uk	58.9	68.4	67.2	29.1	34.8	37.0	70.5	75.3	74.9	64.8	72.4	70.6
fr	69.5	78.1	77.1	62.3	67.2	67.0	80.4	84.1	82.8	77.9	82.0	81.0
ar	60.7	74.3	73.4	41.2	61.4	58.0	66.1	77.5	76.7	63.2	75.9	73.2
fa	58.4	68.9	69.2	38.8	53.2	53.3	69.3	78.6	78.1	58.3	71.3	68.4
el	58.1	65.0	65.2	27.8	40.8	45.1	64.7	72.4	71.9	47.3	61.4	58.0
sr	41.0	58.2	55.8	14.5	8.8	21.3	65.1	70.6	70.5	58.4	67.7	66.5
he	54.3	64.0	62.7	19.4	18.8	24.5	59.7	69.6	69.8	28.1	35.4	40.1
hi	51.0	58.3	60.8	39.1	49.1	49.7	64.4	66.8	68.6	49.0	61.2	59.1
fil	41.9	48.0	50.7	37.2	39.1	40.7	66.6	68.7	70.0	58.0	60.4	59.1
lt	39.9	55.0	50.9	34.0	48.5	46.6	65.4	71.4	70.7	46.6	61.3	56.9
bn	26.7	48.9	46.6	30.2	45.4	49.1	61.0	67.6	67.8	52.3	62.1	61.5
ky	26.4	37.1	41.9	20.4	24.3	28.5	48.2	53.5	54.1	38.7	49.9	48.2
ha	29.4	38.3	33.7	26.6	30.8	31.8	35.4	32.8	38.9	25.6	35.5	30.4
te	11.9	21.6	28.7	29.8	44.2	42.4	56.8	61.2	62.6	25.9	33.4	32.2
sw	28.5	39.8	35.7	32.0	37.0	40.9	55.2	57.4	60.1	27.2	37.2	32.8
ig	28.0	35.8	33.3	25.1	30.0	28.7	33.2	40.2	39.6	22.7	31.0	29.7
si	7.1	12.6	12.5	22.6	32.1	26.7	35.9	40.6	49.9	10.7	15.7	15.8
ne	35.6	40.7	44.1	26.5	25.7	31.9	56.2	55.9	59.6	36.7	38.7	40.7
am	3.2	5.9	17.3	15.4	5.5	8.2	36.1	45.4	44.0	10.3	25.0	17.9
ny	22.2	24.6	23.6	21.5	21.5	26.4	37.8	46.0	43.8	19.3	28.1	25.5
mg	22.5	32.5	27.4	19.3	22.1	23.7	36.5	37.0	36.2	21.1	28.2	26.2
so	28.1	38.3	34.7	24.1	27.0	26.0	26.4	35.9	36.7	25.2	36.4	31.6
sn	21.2	22.6	24.9	23.0	23.0	27.1	39.4	44.2	46.1	19.8	21.0	23.5
yo	21.7	19.8	25.7	20.7	25.0	25.0	32.7	38.7	37.1	17.0	19.2	21.5
AVG	46.5	54.8	54.8	37.6	45.1	45.5	61.1	65.8	66.1	51.4	58.3	56.9

Table 18: Language-specific results on GMMLU-Choice with single-passage mRAG setup when the model is given options and the answer accuracy is evaluated by whether the model outputs the correct option letter. This setup eliminates the effect of generation language on the performance evaluation.

Accuracy (Aya)														
Setups	en	ja	it	id	ko	nl	zh	vi	sv	pt	de	tr	ro	cs
No Ctx	70.3	61.4	64.8	61.9	58.8	61.7	60.1	55.6	53.1	70.5	68.1	59.5	61.9	61.2
1o	75.2	71.3	71.0	69.1	65.8	68.3	67.1	63.4	65.6	75.0	74.7	67.4	66.3	68.4
1o3i	72.9	68.1	68.8	64.8	62.4	63.4	62.8	57.7	61.3	64.5	70.2	64.0	62.4	65.6
1o3o	72.2	68.0	68.4	63.7	62.9	64.6	62.8	56.6	61.6	68.7	70.3	63.0	61.1	64.6
3o	78.3	74.5	73.6	72.2	69.2	70.4	70.7	63.3	68.4	73.9	77.5	69.9	67.0	71.2
3o1i	77.2	73.5	73.5	70.9	68.7	69.3	69.0	62.0	67.7	71.2	76.0	68.7	66.8	70.8
3o1o	77.4	73.9	73.5	71.0	69.3	69.6	69.5	61.6	67.3	74.3	76.5	69.3	67.0	71.0
Setups	ru	es	ms	pl	uk	fr	ar	fa	el	sr	he	hi	fil	lt
No Ctx	60.9	64.0	56.4	59.6	59.1	69.6	60.9	58.3	58.2	41.3	54.3	51.0	41.6	39.7
1o	70.3	70.3	64.2	68.6	68.0	76.8	71.7	68.9	65.4	56.6	63.7	60.0	52.1	51.7
1o3i	65.1	66.6	59.3	65.6	64.4	73.6	68.0	64.6	61.9	52.5	60.6	57.7	44.3	46.3
1o3o	64.9	65.5	60.0	64.8	63.8	72.3	67.0	64.7	62.1	53.2	62.0	57.8	49.4	47.3
3o	71.9	72.3	66.8	70.4	69.8	79.7	75.8	71.8	68.7	60.3	66.9	65.0	53.5	53.1
3o1i	70.8	71.0	65.6	70.2	69.4	77.7	74.7	71.4	67.9	58.8	65.7	64.0	51.9	52.8
3o1o	71.8	71.4	66.2	70.2	68.9	78.3	74.3	70.7	68.2	59.4	66.0	64.3	52.4	52.5
Setups	bn	ky	ha	te	sw	ig	si	ne	am	ny	mg	so	sn	yo
No Ctx	26.7	26.5	28.2	12.2	28.3	28.1	6.6	35.3	3.2	22.3	23.5	28.1	22.4	23.5
1o	47.1	39.8	33.9	28.9	37.0	34.2	12.7	44.5	17.3	24.8	28.5	35.9	23.5	24.5
1o3i	42.6	34.2	33.1	14.7	31.9	30.1	12.1	41.1	9.0	21.2	25.2	33.9	23.8	23.0
1o3o	46.1	37.5	32.7	17.7	33.5	31.1	11.7	43.4	10.1	20.9	26.4	33.0	23.5	26.2
3o	53.5	44.4	34.3	22.1	38.0	33.0	12.0	47.2	11.7	21.9	27.6	38.2	23.8	25.5
3o1i	51.4	40.2	35.8	20.4	37.0	34.0	13.3	44.5	7.8	22.6	30.1	36.0	26.9	25.8
3o1o	53.5	41.9	34.5	22.0	39.0	33.7	11.7	47.2	10.3	20.5	28.4	37.0	26.0	28.0

Table 19: Full performance on GMMLU-Choice with multiple-passage mRAG setup.

Accuracy (Llama)														
Setups	en	ja	it	id	ko	nl	zh	vi	sv	pt	de	tr	ro	cs
No Ctx	70.0	43.6	58.9	51.1	39.4	54.7	52.2	48.7	47.8	34.2	60.3	46.4	51.4	48.1
1o	73.0	57.5	64.5	58.7	48.1	62.2	58.9	56.6	59.2	51.0	69.3	56.6	58.4	57.1
1o3i	72.5	56.7	63.5	52.8	45.4	61.0	57.7	53.9	48.6	48.7	65.5	52.5	56.5	54.3
1o3o	71.3	55.2	60.1	53.7	45.5	60.6	56.5	54.9	53.1	49.3	66.3	53.3	56.8	54.3
3o	75.5	63.9	68.3	59.4	52.2	65.4	63.6	61.1	59.0	53.0	73.6	60.0	62.8	60.3
3o1i	75.7	62.7	67.4	56.8	50.3	64.8	62.7	59.2	55.7	49.6	73.1	58.4	61.4	58.4
3o1o	75.2	63.1	66.6	58.1	51.8	65.3	62.4	60.4	57.8	53.1	73.3	58.5	61.3	59.5
Setups	ru	es	ms	pl	uk	fr	ar	fa	el	sr	he	hi	fil	lt
No Ctx	41.0	57.2	47.3	48.2	29.1	62.9	41.2	38.6	27.3	14.5	20.6	39.2	37.6	34.5
1o	49.7	64.2	55.0	53.0	36.7	67.3	59.0	52.5	46.4	22.6	25.8	48.4	41.5	45.7
1o3i	33.1	64.6	49.4	36.7	16.5	65.4	58.3	46.1	21.9	5.1	28.2	46.1	39.5	36.9
1o3o	41.9	62.1	52.3	46.6	19.7	65.0	57.8	45.0	30.3	11.6	26.9	48.1	38.4	42.7
3o	49.1	68.6	58.7	52.7	25.0	71.5	67.3	52.6	39.9	14.3	35.4	54.7	42.6	49.2
3o1i	41.1	67.7	56.0	47.1	18.4	71.9	65.8	51.7	30.0	6.7	34.8	51.8	43.3	45.6
3o1o	47.3	67.6	56.6	52.5	21.6	70.9	65.5	50.2	33.8	12.5	32.0	53.6	42.6	47.9
Setups	bn	ky	ha	te	sw	ig	si	ne	am	ny	mg	so	sn	yo
No Ctx	30.3	21.1	26.2	28.7	32.3	25.0	22.1	26.8	15.9	22.3	19.8	23.9	24.8	21.4
1o	48.2	28.7	30.6	42.6	41.7	29.0	25.1	30.2	8.1	26.0	24.0	28.5	26.2	24.4
1o3i	49.3	23.3	28.6	43.1	42.3	28.2	25.8	21.4	7.8	22.0	21.0	24.9	20.7	29.5
1o3o	48.7	20.3	30.6	40.0	45.2	28.0	26.9	24.5	8.5	27.6	22.5	27.1	28.3	26.1
3o	55.9	21.5	34.1	47.3	49.4	28.7	28.9	29.3	8.6	26.9	25.5	28.8	29.2	28.3
3o1i	56.4	19.6	32.4	49.5	48.1	26.9	30.2	27.5	9.2	24.1	22.6	28.2	26.2	30.3
3o1o	56.0	21.8	33.9	47.7	50.4	28.7	28.7	27.5	9.1	26.8	23.3	27.9	29.9	26.5

Table 20: Extension: Full performance on GMMLU-Choice with multiple-passage mRAG setup.

Accuracy (Gemma)														
Setups	en	ja	it	id	ko	nl	zh	vi	sv	pt	de	tr	ro	cs
No Ctx	80.6	69.8	75.6	72.8	66.7	73.1	71.0	65.9	72.3	78.3	78.4	69.0	71.0	72.3
1o	81.2	76.4	78.6	75.9	72.1	74.6	75.1	71.7	76.1	82.1	81.7	74.3	73.8	74.7
1o3i	80.4	76.3	78.2	74.8	71.4	74.8	73.2	70.1	75.1	78.2	80.1	72.9	72.6	74.3
1o3o	80.2	74.4	77.1	74.2	71.4	73.4	72.6	68.7	73.9	74.7	80.4	71.5	71.7	73.1
3o	83.1	78.6	80.8	78.6	75.9	76.8	77.1	73.7	77.8	81.7	83.7	76.4	74.7	77.7
3o1i	82.9	78.9	81.2	78.3	75.8	77.4	76.9	72.4	77.6	80.5	83.1	76.2	75.4	77.3
3o1o	82.9	78.7	80.8	78.4	76.1	76.7	76.3	73.1	77.5	79.5	84.1	75.8	74.5	76.9
Setups	ru	es	ms	pl	uk	fr	ar	fa	el	sr	he	hi	fil	lt
No Ctx	72.2	73.5	70.4	72.0	70.7	80.5	66.1	69.3	64.9	65.3	59.5	64.4	66.9	65.6
1o	77.6	76.8	72.5	75.5	75.4	83.2	75.8	77.4	72.4	70.3	70.2	68.2	69.8	70.2
1o3i	75.6	76.2	71.1	74.8	73.1	81.9	74.8	75.3	71.3	70.5	68.7	67.5	69.5	69.3
1o3o	75.5	75.0	70.8	73.4	73.2	82.0	72.6	75.2	71.0	68.7	69.1	67.3	67.3	66.5
3o	80.1	78.9	74.8	76.9	77.8	85.8	79.2	79.9	75.1	73.6	73.8	71.9	71.7	72.2
3o1i	79.3	78.4	74.7	76.8	76.8	85.2	78.9	80.0	74.1	74.0	73.7	71.4	71.7	72.7
3o1o	79.5	78.4	74.1	76.7	76.5	85.1	78.5	79.9	74.3	72.9	72.8	71.0	71.5	71.3
Setups	bn	ky	ha	te	sw	ig	si	ne	am	ny	mg	so	sn	yo
No Ctx	61.1	48.1	34.6	56.8	55.2	33.3	36.2	56.2	35.5	38.1	36.5	25.7	39.8	32.5
1o	69.3	53.3	39.0	62.2	59.4	41.5	51.0	58.0	45.1	44.2	35.9	34.6	45.1	38.5
1o3i	68.3	52.3	35.4	60.1	58.8	35.7	49.5	58.7	44.1	45.4	30.7	42.7	44.2	37.9
1o3o	68.2	52.4	44.1	60.4	56.9	37.1	53.4	56.1	47.6	42.3	32.7	44.2	45.7	37.7
3o	73.3	59.8	45.5	66.7	61.8	40.8	59.2	59.9	48.9	45.8	34.3	49.3	49.0	41.2
3o1i	72.2	58.0	41.1	66.0	61.3	39.0	53.9	60.3	48.4	47.7	34.4	49.1	48.1	40.5
3o1o	72.8	58.2	45.4	65.8	62.2	40.1	57.2	59.5	49.6	44.1	34.4	48.9	47.8	38.6

Table 21: Extension: Full performance on GMMLU-Choice with multiple-passage mRAG setup.

Accuracy (Qwen)														
Setups	en	ja	it	id	ko	nl	zh	vi	sv	pt	de	tr	ro	cs
No Ctx	81.6	66.2	72.4	70.1	64.4	71.2	73.7	66.8	67.0	78.8	75.0	57.7	65.0	65.4
1o	83.0	71.2	75.4	73.6	69.9	73.7	72.4	69.8	72.7	81.9	77.8	66.8	69.0	70.1
1o3i	80.8	70.3	74.4	72.0	68.8	70.9	69.0	65.3	71.0	79.5	76.1	65.0	65.3	68.8
1o3o	80.2	69.3	75.9	71.5	66.9	71.5	68.6	65.2	71.2	79.2	75.4	64.9	64.4	67.3
3o	83.9	75.4	78.2	75.8	72.6	75.5	74.1	70.8	76.1	83.5	81.3	71.2	70.4	73.0
3o1i	83.7	74.7	77.7	75.3	71.9	74.9	74.1	69.9	75.9	83.8	81.3	69.2	69.3	72.9
3o1o	83.9	74.9	78.2	75.9	71.8	75.7	73.0	70.7	75.4	83.4	80.6	69.7	69.8	72.7
Setups	ru	es	ms	pl	uk	fr	ar	fa	el	sr	he	hi	fil	lt
No Ctx	74.3	72.5	66.5	67.3	65.0	77.9	63.2	58.2	47.3	58.3	28.6	48.9	58.0	46.7
1o	76.1	75.7	70.2	71.8	70.8	81.4	72.6	68.4	58.1	66.6	40.5	57.9	59.4	56.1
1o3i	72.0	74.4	67.0	69.2	68.4	79.1	69.8	63.9	57.0	64.0	41.2	55.5	57.2	54.3
1o3o	72.2	74.6	67.9	67.9	68.5	78.6	67.6	62.9	54.8	63.9	40.4	56.9	56.5	54.3
3o	78.5	78.1	73.3	72.8	73.2	83.5	75.3	73.4	62.4	69.6	44.2	63.5	62.4	60.0
3o1i	77.5	77.0	72.0	73.4	71.9	82.9	74.0	71.0	59.7	69.1	41.5	62.4	60.6	58.9
3o1o	77.2	77.4	72.5	73.1	72.6	83.4	73.4	70.6	60.4	68.5	42.4	62.3	61.1	59.5
Setups	bn	ky	ha	te	sw	ig	si	ne	am	ny	mg	so	sn	yo
No Ctx	52.2	38.9	26.0	25.6	27.3	22.5	9.8	36.5	9.4	18.9	21.3	26.2	19.7	15.8
1o	61.6	48.0	30.8	33.2	33.2	29.0	15.5	41.0	18.6	27.4	25.4	31.5	24.5	20.5
1o3i	52.4	45.0	29.4	23.9	30.4	26.5	16.1	40.1	16.0	26.5	22.0	26.8	22.9	21.7
1o3o	49.7	43.6	31.6	20.2	29.7	28.8	19.4	42.5	18.1	28.9	24.9	29.0	27.4	22.7
3o	60.8	50.1	33.3	28.5	35.0	31.5	20.7	48.9	20.7	29.5	26.2	31.4	27.2	24.7
3o1i	55.2	46.6	32.5	23.1	33.3	29.3	20.8	45.9	22.1	29.5	25.8	30.0	26.9	25.3
3o1o	55.0	47.2	33.1	25.0	34.2	29.5	21.1	48.1	20.7	29.0	25.2	30.7	27.6	23.5

Table 22: Extension: Full performance on GMMLU-Choice with multiple-passage mRAG setup.

CLIRudit: Cross-Lingual Information Retrieval of Scientific Documents

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Abstract

Cross-lingual information retrieval (CLIR) helps users find documents in languages different from their queries. This is especially important in academic search, where key research is often published in non-English languages. We present CLIRudit, a novel English-French academic retrieval dataset built from Érudit, a Canadian publishing platform. Using multilingual metadata, we pair English author-written keywords as queries with non-English abstracts as target documents, a method that can be applied to other languages and repositories. We benchmark various first-stage sparse and dense retrievers, with and without machine translation. We find that dense embeddings without translation perform nearly as well as systems using machine translation, that translating documents is generally more effective than translating queries, and that sparse retrievers with document translation remain competitive while offering greater efficiency. Along with releasing the first English-French academic retrieval dataset, we provide a reproducible benchmarking method to improve access to non-English scholarly content.

1 Introduction

Cross-lingual information retrieval (CLIR) helps users find documents written in languages different from their search queries. This removes the need for proficiency in multiple languages and makes it easier to access valuable information that might otherwise be missed because of language barriers.

CLIR is especially important for academic research. While English is the main language for scientific communication, important work often exists in other languages, particularly in certain fields and historical contexts (Pölonen, 2020; Beigel and Di-
giampietri, 2022; Khanna et al., 2022). Researchers

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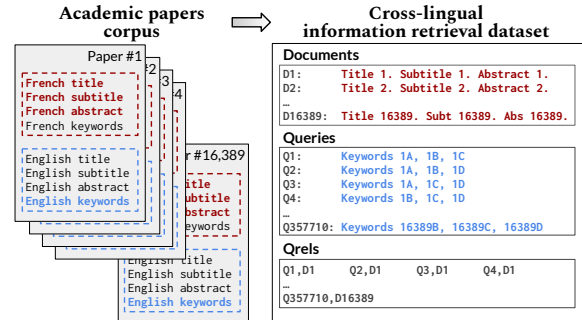


Figure 1: The CLIRudit dataset. We use articles with abstracts and keywords in both French and English. English keywords form the queries, with relevance judged by their presence in each article. Documents consist of the French title, subtitle, and abstract.

may overlook key work if they cannot search across languages, especially if they're unfamiliar with technical terms. English is also often used due to the expectation of finding more results, reinforcing bias against documents in other languages.

Modern information retrieval (IR) systems often use bi-encoder architectures for first-stage retrieval, separately encoding documents and queries as dense embeddings (Devlin et al., 2019; Karpukhin et al., 2020; Xiong et al., 2021). Multilingual extensions of these methods have been effective in general-domain CLIR (Artetxe and Schwenk, 2019; Conneau et al., 2020; Anastasopoulos and Neubig, 2020; Asai et al., 2021a; Nair et al., 2022; Zhang et al., 2023a). Another common approach is to use machine translation (MT) to convert queries or documents to the same language before searching (Galuščáková et al., 2022; Lin et al., 2022; Huang et al., 2023; Lawrie et al., 2024).

Technical texts often use specialized vocabulary and styles that present challenges for MT and multilingual embeddings (Lawrie et al., 2024; Litschko et al., 2025). However, research on CLIR in technical domains is limited (Xu et al., 2016; Zavorin

et al., 2020), and studies focusing specifically on academic content are even scarcer, typically relying on small, curated datasets (Lawrie et al., 2024). As a result, the effectiveness of CLIR methods for academic retrieval remains underexplored.

We address this gap by introducing a dataset for cross-lingual academic search and benchmarking first-stage retrieval methods. Our contributions are:

- A new method for creating academic CLIR datasets using multilingual metadata. We use English keywords as queries and non-English abstracts as documents, allowing evaluation of IR methods on retrieving original-language documents based on author-provided English keywords. This method can be applied to other academic databases and language pairs.
- The release of CLIRudit, a dataset based on Érudit, a Quebec-based non-profit publishing platform (Fig. 1).¹ To our knowledge, this is the first dataset for English-French academic retrieval.
- A thorough empirical comparison of first-stage CLIR methods, including query and document translation, and state-of-the-art dense and sparse retrievers.
- Practical insights to improve the discoverability of non-English scholarly content, which is especially relevant for academic publishing platforms.

Our results show that dense embeddings without translation perform nearly as well as those using MT. Document translation generally improves retrieval more than query translation. While sparse retrievers combined with document translation may not surpass the best dense multilingual methods, they remain competitive and offer advantages in search speed and indexing efficiency.

2 Related work

This section reviews relevant research on academic CLIR, focusing on first-stage retrieval methods, datasets, and bilingual academic corpora.

2.1 Cross-lingual retrieval

Lin et al. (2022) proposed a conceptual framework for CLIR, outlining three main strategies for first-stage retrieval: **document translation** (DT), translating documents into the query language; **query**

translation (QT), translating queries into the document language; and **language-independent representations**, encoding queries and documents into a shared vector space for direct retrieval. Since we focus on single-stage retrieval, we do not address later steps of a retrieval pipeline, such as re-ranking or results fusion.

Translation-based methods have been widely used and generally effective, although their success has varied across domains and language pairs. DT combined with neural ranking has shown strong performance in general-domain tasks (Lin et al., 2022; Lawrie et al., 2023b; Lassance et al., 2023), often outperforming QT, which struggles with short, ambiguous queries and limited training data (Galuščáková et al., 2022). However, DT is not a clear winner, with QT performing better in domains like healthcare (Saleh and Pecina, 2020) and in high-resource languages (Huang et al., 2023).

Alternative approaches like probabilistic structured queries (PSQ) generate multiple plausible translations per term using alignment models, offering more flexibility than standard machine translation (Darwish and Oard, 2003; Yang et al., 2024c).

Early studies found a strong link between translation quality and retrieval effectiveness (Zhu and Wang, 2006), but later work found that better MT doesn't always improve retrieval, particularly in specialized domains (Pecina et al., 2014). Recent research suggests a weak positive correlation (Bonifacio et al., 2022) with diminishing returns beyond a certain MT quality level (Zhang and Misra, 2022).

Multilingual bi-encoders avoid MT entirely by using multilingual pretrained models (Jiang et al., 2020; Bonifacio et al., 2022; Nair et al., 2022, 2023). These methods can reduce indexing costs but often perform worse than MT-based retrieval, with QT or DT followed by monolingual retrieval frequently achieving better first-stage results (Litschko et al., 2019; Asai et al., 2021a; Lin et al., 2022; Nair et al., 2023; Lawrie et al., 2023b).

Recent methods like translate-train (Nair et al., 2022) and translate-distill (Yang et al., 2024b) integrate MT into training, allowing bi-encoders to jointly learn retrieval and translation; unlike translate-test methods like DT and QT, which translate only at test-time. Translate-distill further uses distillation from cross-encoders, achieving strong results across multiple languages. Additionally, large decoder-only language models (LLMs) have been adapted as bi-encoders for dense retrieval (Lee et al., 2024; Li et al., 2025).

¹<https://hf.co/datasets/ftvalentini/clirudit>

2.2 CLIR datasets

Well-documented and diverse datasets are crucial for advancing CLIR because they enable training and evaluation across languages and domains.

Shared evaluation initiatives like TREC (Voorhees, 2005) and CLEF (Chen, 2002) provide manually curated test collections with human-generated queries and relevance judgments gathered by pooling top-ranked results. NeuCLIR (TREC 2022) focuses on neural CLIR, alongside other datasets such as BETTER (Soboroff, 2023) and HC4 (Lawrie et al., 2022). While these collections are usually carefully designed, they are typically small, often with fewer than 1,000 queries. Galuščáková et al. (2022) provide a comprehensive survey of such resources.

Sentence-level retrieval datasets are also common, such as BUCC, Tatoeba (Siddhant et al., 2020), and STS17/STS22 (Cer et al., 2017; Chen et al., 2022), which focus on matching similar sentences across languages.

To address scale limitations, recent work has explored automatic dataset creation. For example, Mayfield et al. (2023) used LLMs to generate English queries from target-language documents. Wikipedia’s multilingual, structured content has also been used for automatic dataset creation, as seen in MuSeCLIR (Li et al., 2022), MKQA (Longpre et al., 2021), WikiCLIR (Sasaki et al., 2018), CLIRMatrix (Sun and Duh, 2020), and AfriCLIRMatrix (Ogundepo et al., 2022).

2.3 Academic datasets

Some prior datasets address CLIR in technical domains. For example, Xu et al. (2016) study cross-language technical question retrieval, CLEF eHealth simulates medical search by non-experts (Galuščáková et al., 2022), and MATERIAL covers law, security, and health topics (Zavorin et al., 2020). A close reference to our work is NeuCLIR 2023’s technical track, which contains 40 English queries to retrieve Chinese academic abstracts across Chemistry, Economics, Physics, Biology, and Medicine (Lawrie et al., 2024). NeuCLIR 2024 also featured a technical task but their proceedings were unavailable at the time of writing.

Beyond CLIR-specific datasets, some parallel academic corpora similar to the one we use include academic metadata aligned across languages. SciPar (Roussis et al., 2022) compiles bilingual titles and abstracts from theses and dissertations.

Other examples mentioned in Roussis et al. (2022) include SciELO (Neves et al., 2016, English, Portuguese, Spanish), ASPEC (Nakazawa et al., 2016, English, Japanese, Chinese), CAPES (Soares et al., 2018, Brazilian academic works), and EDP (Névéol et al., 2018, English-French biomedical texts). In the biomedical domain, MEDLINE (Wu et al., 2011) and BVS (Soares and Krallinger, 2019) provide multilingual aligned abstracts. Niu and Jiang (2024) introduce a dataset of translated abstracts from journals in translation studies.

These corpora mainly support MT by providing parallel abstracts and titles, often with aligned sentences. Our work differs by using keywords as queries of a CLIR dataset. Among existing corpora, only CAPES and BVS include multilingual keywords suitable for this task, but they are not publicly available at the time of writing.

3 Evaluation data

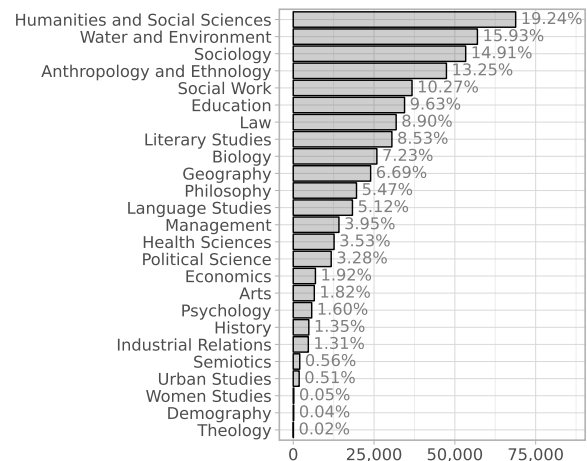


Figure 2: Number of queries per disciplines in the CLIRudit dataset. A query inherits the disciplines of the articles containing its keywords. Since queries can originate from multiple articles and articles can have multiple disciplines, percentages do not sum to 100%.

To evaluate academic CLIR methods, we built CLIRudit using data from Érudit², a Quebec-based Canadian platform that publishes research in the arts, humanities, and social sciences. Érudit’s journals are selected by a scientific committee and meet national quality standards, ensuring the relevance and quality of the content.

We focused exclusively on research articles that included both English and French abstracts and keywords, provided by the authors. From each

²<https://www.erudit.org/en/>

article’s metadata, we extracted the title, subtitle, abstract, and keywords.

Following the standard CLIR task setup, with English queries targeting non-English documents (Lawrie et al., 2023a, 2024), we built the dataset as follows (see Fig. 1 for an overview):

- **Queries.** Created by combining all possible groups of three English keywords from each article; e.g., an article with keywords $\{A, B, C, D\}$ generates the queries: “ A, B, C ”, “ A, B, D ”, “ A, C, D ”, and “ B, C, D ”.
- **Relevance judgments.** A document was marked relevant to a query if its English keyword metadata included all three query keywords. This is based on the assumption that authors try to make their work discoverable via those terms.
- **Document collection.** Each document or retrieval unit was built as the concatenation of its French title, subtitle, and abstract.

We chose three-keyword combinations for queries based on preliminary observations. Using only two keywords produced overly broad queries which could apply to many documents even if those specific terms weren’t used by the authors; e.g., “*family dynamics, gender identity*” or “*canada, québec*”. In contrast, using more than three keywords led to overly narrow queries that were unlikely to reflect realistic user search behavior.

The final dataset contains 357,710 queries derived from 41,594 unique English keywords, with an average query length of 4.8 words ($SD = 1.7$); and 16,389 French documents from 124 journals across 25 disciplines, with an average document length of 176.7 words ($SD = 82.4$). Because of the way the dataset was built, all documents in the collection are relevant to at least one query. 99.3% of queries have only one relevant document, showing that most three-keyword combinations are unique to a single article, which highlights the specificity of the queries.

84.9% of the abstracts in the dataset come from articles whose primary language is French, 14.3% from English, and 0.9% from other languages. The most frequent disciplines in the queries are Humanities and Social Sciences, Water and Environment, Sociology, and Anthropology and Ethnology (full distribution in Fig. 2).

CLIRudit simulates a scenario where users know only the relevant terms in English, while the per-

tinent documents are only in French, with no direct translations available. Our pipeline offers a reproducible method to build CLIR datasets for academic search. Rather than relying on complex heuristics, it leverages the inherent bilingual structure of scientific publications. While this work focuses on English-French retrieval, the method can be extended to other databases and language pairs, facilitating research in cross-lingual scientific retrieval.

4 Models and methods

This section describes the retrieval and MT methods, and evaluation metrics used for benchmarking.

4.1 Retrievers

We tested lexical, sparse, and dense first-stage retrievers, all operating as bi-encoders, encoding queries and documents separately. Due to our relatively small document collection, we used exhaustive nearest-neighbor search. We prioritized well-documented, open-source models.

Dense multilingual retrievers. We evaluated three state-of-the-art bi-encoders for direct CLIR without translation, as they are pretrained and fine-tuned on multilingual data: **mE5**³ (Wang et al., 2024), **mGTE-dense**⁴ (Zhang et al., 2024), and **BGE-m-gemma2**⁵ (Li et al., 2025). While mGTE-dense and BGE-m-gemma2 are fine-tuned on some cross-lingual tasks involving mixed-language inputs, mE5 is trained on multilingual but not explicitly cross-lingual data, which may affect CLIR performance.

Dense English retrievers. We included English-focused models to assess two approaches: (1) retrieving French documents translated to English, or (2) leveraging cross-lingual transfer, where models, fine-tuned mainly on one language, perform well on other languages for the same task (Artetxe and Schwenk, 2019; Asai et al., 2021b; Zhang et al., 2023a). We assessed two top English MTEB (Muennighoff et al., 2023) performers as of early 2025: **NV-Embed-v2**⁶ (Lee et al., 2024), and **BGE-EN-ICL**⁷ (Li et al., 2025). Though targeting English, these models have some multilingual fine-tuning (including French), and their Mistral-7B backbone (Jiang et al., 2023) may also have had

³intfloat/multilingual-e5-large

⁴Alibaba-NLP/gte-multilingual-base

⁵BAAI/bge-multilingual-gemma2

⁶nvdiia/NV-Embed-v2

⁷BAAI/bge-en-icl

multilingual pretraining. but this information is not publicly available.

French-specialized dense retrievers. Few dense retrievers specialize in non-English languages, and those that do are developed by open source communities and lack thorough documentation. We considered these top performers on the MTEB French benchmark (Ciancone et al., 2024): **Croissant**⁸ (from CroissantLLM, Faysse et al., 2024), **Solon**⁹, and **Lajavaness**¹⁰, all of which are bilingual at some degree as they include English data in pre-training or fine-tuning.

Dense multi-vector retrievers. ColBERT-style models encode queries and documents into token-level embeddings, enabling fine-grained late interaction and pre-computation of document representations, with strong performance in out-of-domain retrieval (Khattab and Zaharia, 2020; Santhanam et al., 2022b). PLAID (Santhanam et al., 2022a) improves speed using clustering and centroid-based interaction. We tested **PLAID-X**¹¹ (Yang et al., 2024a), a multilingual ColBERT variant trained via translate-distill, distilling signals from an English cross-encoder and translated passages. It uses multilingual batching to support English queries and French, German, and Spanish documents.

Sparse retrievers. These encode queries and documents as term-weighted vectors, enabling efficient retrieval with inverted indexes (Formal et al., 2022). We tested **BM25** (Robertson et al., 2009), a strong exact-match baseline (Thakur et al., 2021), used on inputs translated into a common language.

Learned sparse models improve retrieval by expanding terms through supervised training (Lin et al., 2022). We assessed **SPLADE++**¹² (monolingual, requires MT into English); and the multilingual **mGTE-sparse** (Zhang et al., 2024) and **BGE-M3-sparse** (Chen et al., 2024), which allow cross-lingual retrieval but lack term expansion, limiting performance when queries and documents share few tokens. We excluded BLADE (Nair et al., 2023), a cross-lingual SPLADE variant with term expansion, due to the lack of an English-French version. Additionally, BLADE has demonstrated lower effectiveness compared to PLAID-X, which we included in our evaluation.

Finally, we tested **PSQ** (Yang et al., 2024c),

which enables sparse CLIR without conventional MT by indexing documents in query language tokens using a probabilistic alignment matrix (Yang et al., 2024b).

See Appendix A for further details on the models and their implementations.

4.2 Machine translation

We tested three machine translation models:

- **GPT-4o-mini**¹³. Recent work shows LLMs perform well on document-level MT (Kocmi et al., 2023; Zhang et al., 2023b; Pang et al., 2025). We used a cost-efficient proprietary model which performed competitively on high-resource language pairs (Hendy et al., 2023; Zhu et al., 2024).
- **Llama-3.2**. We used the 3.2B-parameter version as an open-source LLM alternative to GPT, with strong zero-shot capabilities in French to English translation (Zhang et al., 2023b). Open-source models can be advantageous for cost-efficiency and for the ability to fine-tune on domain-specific data.
- **OpusMT**, a 75M-parameter French-English MarianMT encoder-decoder model (Tiedemann et al., 2023) trained on Opus parallel data¹⁴. While designed for sentence-level MT, we applied it at the document level following Cui et al. (2024). It supports up to 512 tokens, far fewer than the 100k+ limits of GPT and Llama.

For LLM translation we used a zero-shot prompt suited for instruction-tuned LLMs (details in Appendix B). We did not test other strong proprietary translators due to lack of cost-efficient APIs.

Finally, as **gold standard** translations, we used the English translations of the French titles, subtitles, and abstracts provided by the article authors. These reflect the potential performance of each retrieval method using human translations. We did not use the actual French keywords as “gold standard” queries since they do not map one-to-one to the English keywords; using them would alter the original set of evaluation queries and introduce noise into the analysis.

4.3 Evaluation metrics

To measure retrieval performance, we use Recall@100 and Mean Average Precision with a 1000 cutoff rank (MAP), which have been widely used (Nair et al., 2023; Lawrie et al., 2024; Yang et al., 2024c). Whereas Recall@100 is useful to assess

⁸manu/sentence_croissant_alpha_v0.3

⁹OrdalieTech/Solon-embeddings-large-0.1

¹⁰Lajavaness/bilingual-embedding-large

¹¹plaidx-large-clef-mtd-mix-passages-mt5xxl-engeng

¹²naver/splade-cocondenser-ensembledistil

¹³gpt-4o-mini

¹⁴Helsinki-NLP/opus-mt-fr-en

the effectiveness of methods when used as first-stage retrievers, MAP is more appropriate for measuring overall performance of a method used as a single-stage system (Yang et al., 2024c). We compute 95% bootstrap confidence intervals with 1,000 resamples to assess statistical significance.

To evaluate document translation quality, we used three metrics used in recent works (Sun et al., 2022; Zhang et al., 2022; Zhuocheng et al., 2023): BLONDE (Jiang et al., 2022), document-BLEU (d-BLEU, Liu et al., 2020), and document-chrF (d-chrF, Zhuocheng et al., 2023).

5 Results and analysis

This section analyzes the performance of retrieval and translation models on CLIRudit (Table 1). Due to the large sample size, no confidence interval width exceeded 0.003. Intervals are omitted here for readability (see Appendix C). To account for input length effects, we evaluated each method both at its native input limit and with the same 512-token limit. Results differed by no more than 0.005 from the reported values, small enough to not affect general trends.

We now discuss key findings from the results.

1. Without translation, dense retrievers excel, even without multilingual retrieval fine-tuning. NV-Embed-v2 and PLAID-X achieved the highest MAP, while BGE-m-gemma2 led in Recall@100. Interestingly, NV-Embed-v2 is not reported to have multilingual capabilities; though its fine-tuning data, which is English-only for retrieval, includes French in STS17 and STS22 sentence pairs (Cer et al., 2017; Chen et al., 2022).

BM25 with the French analyzer performed poorly without MT due to the query-document language mismatch, but still had non-zero results. This shows CLIRudit has some query-document lexical overlap; manual inspection revealed shared terms like proper nouns, Latin terms, and acronyms.

Among sparse models, SPLADE++ outperformed mGTE-sparse and BGE-M3-sparse, likely thanks to query expansion mitigating the language mismatch. PSQ addresses this mismatch via probabilistic translation, reaching MAP comparable to larger dense models like mE5 and mGTE-dense.

2. Document translation can improve dense retrievers. DT with GPT-4o-mini improved dense retriever MAP by up to 10% and Recall@100 by up to 5% (Fig. 3, left). The highest MAP overall came from NV-Embed-v2+DT and PLAID-X+DT with

GPT-4o-mini. However, translation sometimes hurt performance, especially with QT, affecting models like mE5, BGE-EN-ICL, and even top-performing ones like NV-Embed-v2 and PLAID-X.

Manual review showed QT can reduce recall by mistranslating proper nouns with identical cross-language spelling. For example, “*Goose Bay*” (a Canadian town) was incorrectly translated as “*Baie aux Oies*” instead of remaining unchanged.

3. Document translation usually outperformed query translation for sparse retrievers. Translation had a modest effect on dense models but significantly boosted sparse retrieval. Moreover, DT consistently outperformed QT (Fig. 3 right), especially for BM25 and SPLADE++, with SPLADE++ plus DT nearing the top dense retriever MAP, and also outperforming the PSQ probabilistic translation method (Table 1).

While DT may offer richer context than QT (Galuščáková et al., 2022; Lin et al., 2022), DT outperforming QT is expected for SPLADE++ since it’s trained only in English. In contrast, mGTE-sparse and BGE-M3-sparse performed similarly with QT and DT.

Manual inspection of BM25 cases where DT outperformed QT shows that DT can preserve key terms better. For example, “*fair innings*” correctly remains unchanged with DT to English, but translating the query to French yields “*juste part*”, which isn’t in the original document. Similarly, the term “*beck*” in a query about the surname of a social scientist is correctly preserved in DT, but mistranslated as “*appel*” in the query (French for “call”), making the document irretrievable.

4. Document translation quality correlated with retrieval performance. GPT-4o-mini led in document translation quality (BLEU=34.41, BLONDE=49.32, chrF=63.83), followed closely by Llama (BLEU=31.27, BLONDE=46.52, chrF=61.56), with OpusMT trailing far behind (BLEU: 10.77, BLONDE: 19.35, chrF: 36.15). This ranking mirrors their retrieval performance, where GPT-4o-mini systematically outperformed Llama, which in turn outperformed OpusMT (Table 1). While these results indicate a correlation between translation and retrieval quality, quantifying MT’s exact contribution requires further study beyond the scope of this paper.

5. Top dense retrievers approached gold translation recall. Models like NV-Embed-v2, BGE-m-gemma2, BGE-EN-ICL, and PLAID-X, performed close to their gold translation recall (Fig.

Machine Trans. (\rightarrow) Retriever (\downarrow)	MAP						Recall@100					
	None	Query (GPT4)	Doc.			Gold	None	Query (GPT4)	Doc.			Gold
			Opus	Llama	GPT4				Opus	Llama	GPT4	
mE5	0.434	0.412	0.448	0.480	0.490	0.526	0.784	0.760	0.790	0.817	0.823	0.840
mGTE-dense	0.450	0.445	0.452	0.459	<u>0.468</u>	0.496	0.820	0.813	0.820	0.834	<u>0.837</u>	0.849
BGE-m-gemma2	<u>0.571</u>	0.543	0.533	0.548	0.560	0.571	0.903	0.895	0.894	0.908	0.910	0.917
NV-Embed-v2	0.580	0.575	0.541	0.569	0.586	0.600	<u>0.895</u>	0.889	0.866	0.887	0.892	0.894
BGE-EN-ICL	<u>0.507</u>	0.441	0.411	0.486	0.501	0.535	<u>0.857</u>	0.810	0.760	0.831	0.837	0.861
Croissant	0.358	<u>0.365</u>	0.325	0.345	0.357	0.376	0.793	<u>0.794</u>	0.748	0.773	0.781	0.794
Solon	0.507	0.516	0.502	0.520	<u>0.536</u>	0.555	0.856	0.858	0.845	0.860	<u>0.866</u>	0.870
Lajavaness	<u>0.472</u>	0.454	0.431	0.457	0.470	0.486	<u>0.848</u>	0.838	0.817	0.836	0.843	0.849
PLAID-X	0.578	0.548	0.539	0.572	0.586	0.605	0.870	0.854	0.845	0.869	<u>0.874</u>	0.879
SPLADE++	0.284	0.426	0.530	0.548	<u>0.572</u>	0.609	0.604	0.753	0.836	0.853	<u>0.864</u>	0.875
mGTE-sparse	0.169	<u>0.434</u>	0.401	0.405	0.428	0.487	0.443	0.763	0.737	0.760	<u>0.771</u>	0.805
BGE-M3-sparse	0.177	0.458	0.413	0.434	<u>0.460</u>	0.511	0.449	<u>0.781</u>	0.738	0.763	0.778	0.807
BM25	0.181	0.390	0.488	0.513	<u>0.549</u>	0.611	0.417	0.706	0.789	0.815	<u>0.832</u>	0.861
PSQ	<u>0.440</u>	-	-	-	-	-	<u>0.756</u>	-	-	-	-	-

Table 1: MAP and Recall@100 in CLIRudit. Best column scores are in bold; best row scores per metric are underlined, excluding gold translation. Statistical significance is shown in Appendix C for better readability.

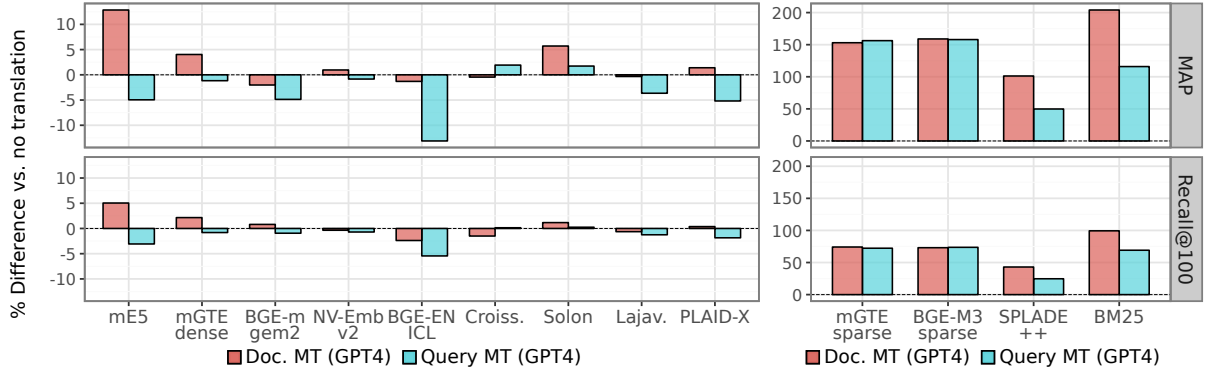


Figure 3: % difference in MAP and Recall@100 of document translation (red) and query translation (blue) compared to no translation. Positive (negative) values indicate improvement (degradation) with translation. For ease of visualization, sparse models are shown with a different scale and only GPT translation is considered.

4). Except for BGE-m-gemma2, gaps in MAP were larger, indicating potential for better ranking.

Sparse models BM25 and SPLADE++ achieved the highest MAP with gold translations (Table 1), highlighting the impact of translation quality. Because CLIRudit queries are keywords and documents are abstracts, sparse models naturally perform well with accurate translations. SPLADE’s smaller gap to gold as compared to other sparse methods suggests greater robustness to translation errors, likely due to query expansion.

6. Performance varies significantly across disciplines. Considering the best-performing approach for each retriever, MAP was on average higher in Industrial Relations, Theology, Women’s Studies, Psychology, Management, and Economics, and lower in Philosophy and Law (Fig. 5). While Croissant was typically the weakest across disci-

plines, no translation-retriever combination consistently outperformed the others.

6 Discussion

Dense single-vector retrievers based on large decoder-only models (e.g., NV-Embed-v2, BGE-m-gemma2) achieve near gold translation-augmented performance without additional training, which may result from pretraining on large corpora and cross-lingual transfer capabilities. A smaller, CLIR-specialized model, PLAID-X, also performed competitively; at the expense of needing language- and task-specific training data and having higher search latency due to its multi-vector design (Santhanam et al., 2022a). Both dense approaches avoid the overhead of translating the entire corpus, but large models may incur high index-

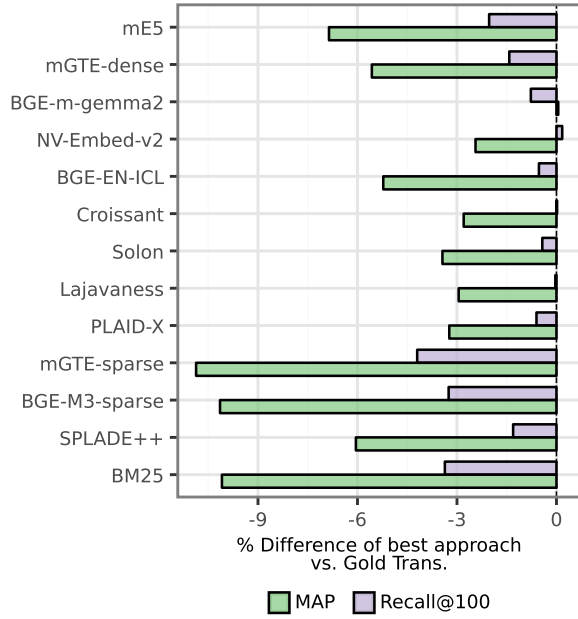


Figure 4: % difference in MAP (green) and Recall@100 (purple) for the best-performing approach of each retriever, relative to gold-standard translations.

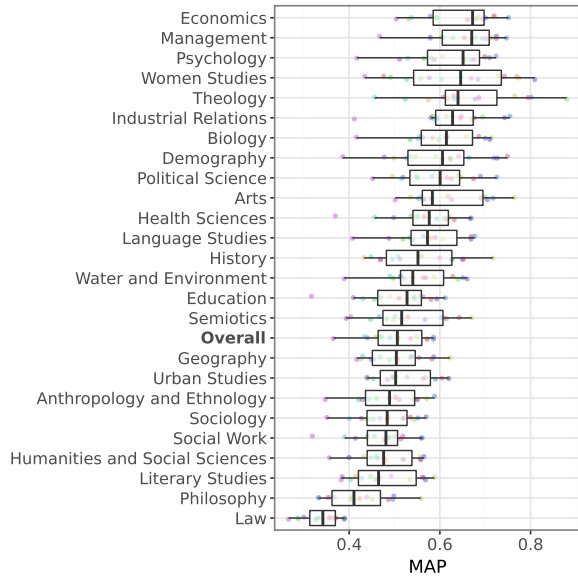


Figure 5: MAP of retrievers across CLIRudit disciplines. Each dot represents a method’s MAP in a discipline’s queries, using its best translation method (excluding gold). Dot colors indicate retrievers: Croissant (pink) often performs worst, while the best varies by discipline.

ing costs on large collections.

Sparse retrievers, lexical or learned, offer faster indexing and search, but need translation to narrow the gap with dense methods, and still fall short in overall performance. DT outperformed QT, likely because it provides richer context; and it can be done offline, which is important when using

costly MT systems. QT enables quicker experimentation by avoiding corpus reindexing with each new model, but usually with lower accuracy (Lin et al., 2022; Galuščáková et al., 2022). Ultimately, the choice of method comes down to balancing retrieval performance, indexing and search latency, and translation costs.

Our dataset uses keyword-based queries, reflecting how authors describe their work to make it discoverable. This assumes users know the right keywords, shifting the dataset challenge to language differences in a technical domain rather than query formulation. This allows meaningful analysis, though it’s unclear how system rankings might change with other types of queries, e.g., natural language questions. Our approach aligns with other datasets using non-natural or generated queries, such as SCIDOCs, DBPedia (Thakur et al., 2021), WikiCLIR (Sasaki et al., 2018), and CLIRMatrix (Sun and Duh, 2020).

Like all IR datasets, ours has limitations in scope and collection method, so we encourage evaluation on many, diverse datasets. As the first English-French academic retrieval dataset, CLIRudit adds to this diversity and complements existing resources.

7 Conclusions

We introduced a method for building CLIR datasets from bilingual metadata in scientific publications. By using keywords as queries and abstracts as documents, this approach enables automated, scalable creation of large evaluation resources without manual annotation or complex heuristics. We applied it to produce CLIRudit, the first English-French CLIR dataset for academic search, based on a real-world database.

Evaluations of single-stage methods on CLIRudit showed that: (1) state-of-the-art dense bi-encoders achieved strong cross-lingual performance without translation, nearing monolingual retrieval with gold translations; (2) sparse retrievers with document translation were competitive; and (3) document translation generally outperformed query translation, likely due to richer context.

These results have practical implications for academic search systems. Large dense retrievers deliver the best performance, but the strong results of sparse retrievers with document translation suggest a viable alternative that may be more practical to implement at scale. This is particularly relevant

for academic publishing platforms like Érudit that aim to make their content more discoverable to researchers.

Our method can be applied to other academic databases and language pairs, supporting broader research in cross-lingual access to scientific knowledge.

Limitations

Our dataset’s document collection includes only relevant documents, unlike in real applications where relevant documents might coexist with a much larger collection. The values reported may not be representative of real-world settings. The reported metrics should be used to compare methods rather than to provide absolute performance estimates, which is standard practice in IR research (Thakur et al., 2021).

Our dataset may also contain some false negatives: some relevant documents may not be labeled as such if some authors did not include some suitable keywords in the metadata, while others did. However, because queries consist of three keywords, they are relatively specific, likely reducing false negatives, as it is unlikely that there is more than one document in the collection relevant to a narrow query.

We found that the proprietary GPT-4o-mini LLM outperformed the open-source Llama 3.2 and the smaller OpusMT encoder-decoder for zero-shot translation. Further exploration with few-shot prompting or fine-tuning may improve the performance of the open-source models. In addition, OpusMT is not optimized for document translation, so using sentence-level translation may be more optimal. However, this approach requires a more complex pipeline with sentence splitting and risks losing cross-sentence coherence.

Possible data contamination is a concern for fair evaluation: our test set may appear in the training data of pre-trained models, especially LLMs used for translation and retrievers initialized from LLMs, such as NV-Embed-v2 and BGE-m-gemma2. This could lead to inflated results, but is difficult to verify due to the lack of information about the exact training data of these models (Sainz et al., 2023; Oren et al., 2024).

Our dataset is limited to keyword-based queries and metadata-only documents. Results may differ with other query types, e.g. natural language questions, or full-text documents. Future work could

explore approaches that use other types of queries or full-text representations. We also focused on French, a high-resource language; performance may vary in low-resource settings due to lower translation quality and limited training data for retrievers.

We tested single-stage retrieval without re-ranking, fusion, or pseudo-relevance feedback (Lin et al., 2022). Including these techniques could enhance performance and reveal additional insights into CLIR system design. We also did not analyze the computational costs of translation, retrieval, or indexing, as explored in prior work (Rosa et al., 2021; Nair et al., 2023). Such analysis would be valuable for assessing the trade-offs between effectiveness and efficiency in practical deployment. Additionally, we did not fine-tune or train any retrieval models on our dataset. Training on domain-specific data could potentially lead to better performance, both on our dataset and on others.

Acknowledgments

This project was funded by the Social Science and Humanities Research Council of Canada Pan-Canadian Knowledge Access Initiative Grant (Grant 1007-2023-0001), and the Fonds de recherche du Québec-Société et Culture through the Programme d’appui aux Chaires UNESCO (Grant 338828).

We used computational resources from NodoIA San Francisco (Ministry of Science and Technology of the Province of Córdoba, Argentina).

We thank Érudit for their support and access to data.

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A Retrievers

Table 2 provides an overview of the retrievers evaluated in our study.

Inference with neural models was run using 16-bit floating point (fp16) inference on two NVIDIA A30 GPUs, each with 24GB of memory.

BGE-EN-ICL, BGE-m-gemma2, and NV-Embed-v2 require appending task-specific instructions before encoding the queries, which we did following the authors’ templates. BGE-EN-ICL (Li et al., 2025) was used in its zero-shot mode, i.e., without in-context examples appended to the queries.

We also experimented with BGE-M3-dense¹⁵ (Chen et al., 2024), which we excluded from the body of the paper because it did not show improved performance or valuable insights.

We implemented BM25 using Pyserini with default parameters and language-specific analyzers (Lin et al., 2021). For PSQ, we used the fast_psq implementation by Yang et al. (2024c)¹⁶ with default parameters. We used the English-French matrix trained on 17.6M parallel sentences provided by Yang et al. (2024c).

B Translation

For LLM-based translation, we used a zero-shot prompt inspired by established best practices for

¹⁵<https://hf.co/BAAI/bge-m3>

¹⁶<https://github.com/hltcoe/PSQ>

Retriever	Type	Pre-train. Lang.	Fine-tuning Lang.	#Params.	Emb. Dim.	Max. Len.
mE5	Dense (single-vector)	Multilingual	Mostly English	560M	1024	512
mGTE-dense			Mostly English, Chinese	305M	768	8192
BGE-m-gemma2			Mostly English, Chinese	9.2B	3584	8192
Solon			French	560M	1024	512
Lajavaness			French-English	560M	1024	512
Croissant		French-English	French-English	1.3B	2048	2048
NV-Embed-v2		Unknown	Mostly English	7.8B	4096	32768
BGE-EN-ICL			Mostly English	7.1B	4096	512
PLAID-X	Dense (multi-vector)	Multilingual	English, French, German, Spanish	560M	128 per token	512
mGTE-sparse	Sparse (Learned)	Multilingual	Mostly English, Chinese	305M	250,000*	8192
BGE-M3-sparse			Mostly English, Chinese	568M	250,000*	8192
SPLADE++		English	English	110M	30,522*	512
BM25	Sparse	–	–	–	49,144*	–
PSQ	(Lexical)	–	–	–	715,837*	–

Table 2: Retrievers used in the study. #Params.: Number of parameters. Emb. Dim.: Document embedding dimension. Max. Len.: Maximum number of input tokens allowed by the model. The values in the pretraining and fine-tuning language columns mentioned are approximations; in many cases, intermediate steps are involved, such as initializing from a pretrained model, followed by training with weak supervision and supervised fine-tuning. However, in all cases, fine-tuning data includes some degree of French data. The specific checkpoints used are given in footnotes in section 4.1.

*The embedding dimension of sparse methods is the underlying vocabulary size.

instruction-tuned LLMs¹⁷. The complete prompt is provided in Table 3. We used sampling with 0.1 temperature and 1.0 top-p.

You are a highly skilled translator from French to English.
Your task is to accurately translate the French text I provide into English.
You will be provided with a text, and you will output a JSON object containing the following information:

```
{
  translation: string // the translated text
}
```

Preserve the meaning, tone, and nuance of the original text.

Please maintain proper grammar, spelling, and punctuation in the translated version.

Table 3: Prompt used for document translation with LLMs. We used a slight variation of this prompt for query translation.

C Statistical significance

Tables 4 and 5 show the 95% bootstrap confidence intervals for MAP and Recall@100, respectively, for each retrieval method and translation method.

¹⁷<https://docs.anthropic.com/en/prompt-library/polyglot-superpowers>,
<https://platform.openai.com/docs/examples/default-translation>.

Retriever	Translation		MAP	Retriever	Translation		MAP
BM25	Gold	1	0.611 ²	mGTE-sparse	Gold	40	0.487 ^{38,39,41,42}
SPLADE++	Gold	2	0.609 ¹	BGE-EN-ICL	Docs. (L3)	41	0.486 ^{39,40,42}
PLAID-X	Gold	3	0.605	Lajavaness	Gold	42	0.486 ^{39,40,41}
NV-Embed-v2	Gold	4	0.600	mE5	Docs. (L3)	43	0.480
PLAID-X	Docs. (G4)	5	0.586 ⁶	Lajavaness	None	44	0.472 ⁴⁵
NV-Embed-v2	Docs. (G4)	6	0.586 ⁵	Lajavaness	Docs. (G4)	45	0.470 ^{44,46}
NV-Embed-v2	None	7	0.580 ⁸	mGTE-dense	Docs. (G4)	46	0.468 ⁴⁵
PLAID-X	None	8	0.578 ^{7,9}	BGE-M3-sparse	Docs. (G4)	47	0.460 ^{48,49,50}
NV-Embed-v2	Query (G4)	9	0.575 ⁸	mGTE-dense	Docs. (L3)	48	0.459 ^{47,49,50}
SPLADE++	Docs. (G4)	10	0.572 ^{11,12,13}	BGE-M3-sparse	Query (G4)	49	0.458 ^{47,48,50}
PLAID-X	Docs. (L3)	11	0.572 ^{10,12,13,14}	Lajavaness	Docs. (L3)	50	0.457 ^{47,48,49}
BGE-m-gemma2	None	12	0.571 ^{10,11,13,14}	Lajavaness	Query (G4)	51	0.454
BGE-m-gemma2	Gold	13	0.571 ^{10,11,12,14}	mGTE-dense	Docs. (Op)	52	0.452 ⁵³
NV-Embed-v2	Docs. (L3)	14	0.569 ^{11,12,13}	mGTE-dense	None	53	0.450 ^{52,54}
BGE-m-gemma2	Docs. (G4)	15	0.560	mE5	Docs. (Op)	54	0.448 ⁵³
Solon	Gold	16	0.555	mGTE-dense	Query (G4)	55	0.445
BM25	Docs. (G4)	17	0.549 ^{18,19,20}	BGE-EN-ICL	Query (G4)	56	0.441
SPLADE++	Docs. (L3)	18	0.548 ^{17,19,20}	BGE-M3-sparse	Docs. (L3)	57	0.434 ^{58,59,60}
PLAID-X	Query (G4)	19	0.548 ^{17,18,20}	mGTE-sparse	Query (G4)	58	0.434 ^{57,59,60}
BGE-m-gemma2	Docs. (L3)	20	0.548 ^{17,18,19}	mE5	None	59	0.434 ^{57,58,60}
BGE-m-gemma2	Query (G4)	21	0.543 ²²	Lajavaness	Docs. (Op)	60	0.431 ^{57,58,59}
NV-Embed-v2	Docs. (Op)	22	0.541 ^{21,23}	mGTE-sparse	Docs. (G4)	61	0.428 ⁶²
PLAID-X	Docs. (Op)	23	0.539 ²²	SPLADE++	Query (G4)	62	0.426 ⁶¹
Solon	Docs. (G4)	24	0.536 ²⁵	BGE-M3-sparse	Docs. (Op)	63	0.413 ^{64,65}
BGE-EN-ICL	Gold	25	0.535 ^{24,26}	mE5	Query (G4)	64	0.412 ^{63,65}
BGE-m-gemma2	Docs. (Op)	26	0.533 ^{25,27}	BGE-EN-ICL	Docs. (Op)	65	0.411 ^{63,64}
SPLADE++	Docs. (Op)	27	0.530 ²⁶	mGTE-sparse	Docs. (L3)	66	0.405
mE5	Gold	28	0.526	mGTE-sparse	Docs. (Op)	67	0.401
Solon	Docs. (L3)	29	0.520	BM25	Query (G4)	68	0.390
Solon	Query (G4)	30	0.516 ³¹	Croissant	Gold	69	0.376
BM25	Docs. (L3)	31	0.513 ^{30,32}	Croissant	Query (G4)	70	0.365
BGE-M3-sparse	Gold	32	0.511 ³¹	Croissant	None	71	0.358 ⁷²
BGE-EN-ICL	None	33	0.507 ³⁴	Croissant	Docs. (G4)	72	0.357 ⁷¹
Solon	None	34	0.507 ³³	Croissant	Docs. (L3)	73	0.345
Solon	Docs. (Op)	35	0.502 ³⁶	Croissant	Docs. (Op)	74	0.325
BGE-EN-ICL	Docs. (G4)	36	0.501 ³⁵	SPLADE++	None	75	0.284
mGTE-dense	Gold	37	0.496	BM25	None	76	0.181
mE5	Docs. (G4)	38	0.490 ^{39,40}	BGE-M3-sparse	None	77	0.177
BM25	Docs. (Op)	39	0.488 ^{38,40,41,42}	mGTE-sparse	None	78	0.169
				PSQ	None	79	0.123

Table 4: 95% bootstrap confidence intervals for MAP, using 1000 resamples. Numbers in subscripts indicate the 95% interval of the system of the row overlaps with the interval of the systems in the subscripts.

G4: GPT-4o-mini. L3: Llama-3.2. Op: OpusMT.

Retriever	Translation		Recall@100	Retriever	Translation		Recall@100
BGE-m-gemma2	Gold	1	0.917	SPLADE++	Docs. (Op)	40	0.836 ^{36,37,38,39,41}
BGE-m-gemma2	Docs. (G4)	2	0.910	mGTE-dense	Docs. (L3)	41	0.834 ^{39,40,42}
BGE-m-gemma2	Docs. (L3)	3	0.908	BM25	Docs. (G4)	42	0.832 ^{41,43}
BGE-m-gemma2	None	4	0.903	BGE-EN-ICL	Docs. (L3)	43	0.831 ⁴²
NV-Embed-v2	None	5	0.895 ^{6,7,8}	mE5	Docs. (G4)	44	0.823
BGE-m-gemma2	Query (G4)	6	0.895 ^{5,7,8}	mGTE-dense	None	45	0.820 ⁴⁶
BGE-m-gemma2	Docs. (Op)	7	0.894 ^{5,6,8}	mGTE-dense	Docs. (Op)	46	0.820 ⁴⁵
NV-Embed-v2	Gold	8	0.894 ^{5,6,7,9}	mE5	Docs. (L3)	47	0.817 ^{48,49}
NV-Embed-v2	Docs. (G4)	9	0.892 ⁸	Lajavaness	Docs. (Op)	48	0.817 ^{47,49}
NV-Embed-v2	Query (G4)	10	0.889	BM25	Docs. (L3)	49	0.815 ^{47,48,50}
NV-Embed-v2	Docs. (L3)	11	0.887	mGTE-dense	Query (G4)	50	0.813 ⁴⁹
PLAID-X	Gold	12	0.879	BGE-EN-ICL	Query (G4)	51	0.810
SPLADE++	Gold	13	0.875 ¹⁴	BGE-M3-sparse	Gold	52	0.807 ⁵³
PLAID-X	Docs. (G4)	14	0.874 ¹³	mGTE-sparse	Gold	53	0.805 ⁵²
PLAID-X	None	15	0.870 ^{16,17}	Croissant	Query (G4)	54	0.794 ^{55,56}
Solon	Gold	16	0.870 ^{15,17}	Croissant	Gold	55	0.794 ^{54,56}
PLAID-X	Docs. (L3)	17	0.869 ^{15,16}	Croissant	None	56	0.793 ^{54,55}
Solon	Docs. (G4)	18	0.866 ¹⁹	mE5	Docs. (Op)	57	0.790 ⁵⁸
NV-Embed-v2	Docs. (Op)	19	0.866 ^{18,20}	BM25	Docs. (Op)	58	0.789 ⁵⁷
SPLADE++	Docs. (G4)	20	0.864 ¹⁹	mE5	None	59	0.784
BGE-EN-ICL	Gold	21	0.861 ^{22,23}	Croissant	Docs. (G4)	60	0.781 ⁶¹
BM25	Gold	22	0.861 ^{21,23}	BGE-M3-sparse	Query (G4)	61	0.781 ⁶⁰
Solon	Docs. (L3)	23	0.860 ^{21,22,24}	BGE-M3-sparse	Docs. (G4)	62	0.778
Solon	Query (G4)	24	0.858 ^{23,25,26}	Croissant	Docs. (L3)	63	0.773 ⁶⁴
BGE-EN-ICL	None	25	0.857 ^{24,26}	mGTE-sparse	Docs. (G4)	64	0.771 ⁶³
Solon	None	26	0.856 ^{24,25,27}	mGTE-sparse	Query (G4)	65	0.763 ^{66,67}
PLAID-X	Query (G4)	27	0.854 ^{26,28}	BGE-M3-sparse	Docs. (L3)	66	0.763 ^{65,67,68}
SPLADE++	Docs. (L3)	28	0.853 ²⁷	mGTE-sparse	Docs. (L3)	67	0.760 ^{65,66,68,69}
mGTE-dense	Gold	29	0.849 ^{30,31}	BGE-EN-ICL	Docs. (Op)	68	0.760 ^{66,67,69}
Lajavaness	Gold	30	0.849 ^{29,31}	mE5	Query (G4)	69	0.760 ^{67,68,70}
Lajavaness	None	31	0.848 ^{29,30}	PSQ	None	70	0.757 ⁶⁹
PLAID-X	Docs. (Op)	32	0.845 ³³	SPLADE++	Query (G4)	71	0.753
Solon	Docs. (Op)	33	0.845 ^{32,34}	Croissant	Docs. (Op)	72	0.748
Lajavaness	Docs. (G4)	34	0.843 ³³	BGE-M3-sparse	Docs. (Op)	73	0.738 ⁷⁴
mE5	Gold	35	0.840	mGTE-sparse	Docs. (Op)	74	0.737 ⁷³
Lajavaness	Query (G4)	36	0.838 ^{37,38,39,40}	BM25	Query (G4)	75	0.706
mGTE-dense	Docs. (G4)	37	0.837 ^{36,38,39,40}	SPLADE++	None	76	0.604
BGE-EN-ICL	Docs. (G4)	38	0.837 ^{36,37,39,40}	BGE-M3-sparse	None	77	0.449
Lajavaness	Docs. (L3)	39	0.836 ^{36,37,38,40,41}	mGTE-sparse	None	78	0.443
				BM25	None	79	0.417

Table 5: 95% bootstrap confidence intervals for Recall@100, using 1000 resamples. Numbers in subscripts indicate the 95% interval of the system of the row overlaps with the interval of the systems in the subscripts
G4: GPT-4o-mini. L3: Llama-3.2. Op: OpusMT.

TenseLoC: Tense Localization and Control in a Multilingual LLM

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Abstract

Multilingual language models excel across languages, yet how they internally encode grammatical tense remains largely unclear. We investigate how decoder-only transformers represent, transfer, and control tense across eight typologically diverse languages: English, German, French, Italian, Portuguese, Hindi, Spanish, and Thai. We construct a synthetic tense-annotated dataset and combine probing, causal analysis, feature disentanglement, and model steering to LLaMA-3.1 8B. We show that tense emerges as a distinct signal from early layers and transfers most strongly within the same language family. Causal tracing reveals that attention outputs around layer 16 consistently carry cross-lingually transferable tense information. Leveraging sparse autoencoders in this subspace, we isolate and steer English tense-related features, improving target-tense prediction accuracy by up to 11% in a downstream cloze task¹.

1 Introduction

Recent transformer-based large language models (LLMs) learn high-dimensional contextual embeddings that yield state-of-the-art performance on multilingual tasks. However, these vectors conflate multiple linguistic features (Jawahar et al., 2019; Tenney et al., 2019; Belinkov, 2022), and as yet it remains unclear how these models represent tense internally. Grammatical tense, how languages mark past, present, and future, is fundamental to accurate human communication, reasoning and natural language processing (NLP) alike. Linguistic theories, from Reichenbach’s tripartite model of event, reference, and speech time (Prior, 1967; Kamp, 1968) to later typological surveys, show that languages employ varied morphological and syntactic strategies, morphological inflections (e.g., “-ed”), auxiliaries

¹We release our data and code publicly at <https://github.com/ariunerdenetum/tenseloc>

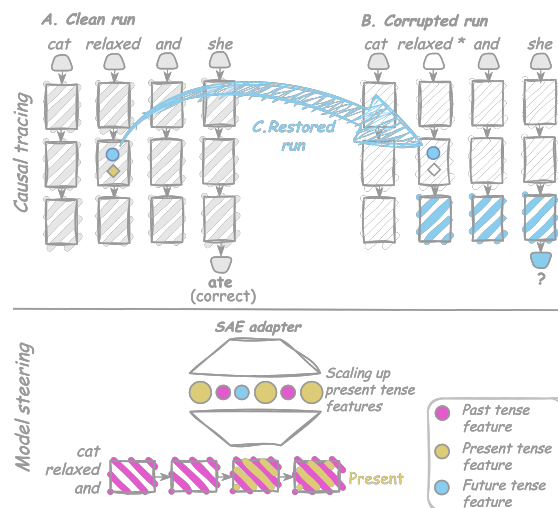


Figure 1: Main findings. Tense resides in a compact, causally active decoder subspace. **(Top)** Causal tracing shows that restoring a small projected subspace recovers tense probabilities across languages. **(Bottom)** SAE-based steering shows that scaling interpretable tense features in the residual stream shifts cloze completions toward the target tense, with minimal impact on other tenses at moderate scaling. These effects hold without temporal adverbials, indicating an internalized tense representation rather than surface-cue reliance.

(e.g., “will”), or adverbial cues (e.g., “Yesterday”), to situate events temporally.

Despite this foundational importance, the ways in which multilingual LLMs internally encode tense remain largely uncharted. Prior probing work (Li and Wisniewski, 2021) shows that morphological cues can predict tense in cross-lingual settings (i.e., French and Chinese), and large-scale studies report that multilingual encoders reliably encode morphological information including tense (Acs et al., 2023). Yet, these studies rely on correlation and cannot show whether the identified subspaces are functionally used by the model.

Along a related line of research, Sparse Autoencoders (SAEs) have been proposed to disentangle monosemantic features, hidden dimensions aligned with human-interpretable concepts (Tem-

pleton et al., 2024; Gao et al., 2024). If successful, SAEs offer not only interpretability but also control, enabling researchers to steer model outputs by scaling these features (O’Brien et al., 2024; Härle et al., 2024). However, their application to grammatical tense remains under-explored. In particular, it is still unknown whether sparse tense features identified by SAEs, if they exist, are functionally necessary or sufficient for influencing model predictions.

In this work, we present a comprehensive analysis of **LLaMA-3.1 8B to examine how it encodes and uses grammatical tense across typologically diverse languages, and to determine whether these encodings are causally necessary, sufficient, and manipulable via sparse-feature interventions**. We show that targeted interventions on identified subspaces produce predictable changes in generation accuracy, providing a functional (not merely correlational) account of tense representation.

We combine probing, causal tracing, pre-trained SAEs, and targeted residual-stream interventions grounded in mechanistic interpretability to (i) locate tense subspaces, (ii) identify tense-carrying streams and layers (Section 3), (iii) disentangle human-interpretable, monosemantic tense features (Section 4), and (iv) test controllability via feature scaling (Section 5). We show our main findings in Figure 1.

Our contributions are fourfold:

1. We curate and release a multilingual, tense-annotated dataset of simple past, present, and future-tensed sentences in eight languages, with and without explicit temporal adverbials.
2. We show that linear tense signals are consistent throughout layers, generalize within language families in mid-layers, and that a causal bottleneck in attention-output around layer 16 (i.e., mid-layer) mediates functional use.
3. We extract monosemantic SAE features for each tense in English and check if those features are human interpretable, by validating their alignment with surface tense markers (e.g., “did”, “will”).
4. We manipulate the model’s generation output via SAE features, showing that moderate scaling of target-tense features improves English cloze accuracy by up to 11% and transfers to German.

Language	UD Treebank
English (en)	UD_English-EWT (*)
German (de)	UD_German-GSD (*)
French (fr)	UD_French-GSD (*)
Italian (it)	UD_Italian-ISDT (*)
Spanish (es)	UD_Spanish-GSD (*)
Portuguese (pt)	UD_Portuguese-GSD (**)
Hindi (hi)	UD_Hindi-HDTB (***)
Thai (th)	UD_Thai-PUD (***)

Table 1: UD corpora and curation methods for eight languages. Inflection method is denoted by asterisk (“*”): (*) - PatternLite; (**) - mlconjug3; (***) - custom rules.

2 Methods

2.1 Overview of our Approach

By combining probing, causal analysis, and feature disentanglement, we investigate how complex grammatical categories are represented in large multilingual transformers and establish a methodology for precise and interpretable control over temporal generation.

1. **Identification and isolation of tense representation:** We apply layer-wise probes and causal interventions to hidden activations to identify which layers and output streams carry tense signals and which are functionally necessary for tense prediction.
2. **Identifying human-interpretable tense features:** We apply pre-trained SAEs to these tense-bearing activations to disentangle tense to monosemantic features that align with human-readable tense markers (e.g., “did,” “will”), and validate these features against probing and causal-tracing results.
3. **Steering tense generation:** We test whether SAE-derived features provide causal leverage by scaling them during inference. Through controlled interventions in the residual stream, we evaluate whether such scaling predictably steers tense generation in downstream cloze task.

2.2 Dataset

We build a controlled, multilingual, tense-annotated dataset from Universal Dependencies (UD) v2 (Consortium, 2021) and focus on languages that differ in morphological tense marking (curation in Table 1 and examples in Table 2). Dataset construction proceeds in two stages: (i) extraction of subject-verb-object clauses (SVO; SOV for Hindi; see Table 6 in Appendix; (ii) generation

Lang.	Tense	no_temp	with_temp
English	Past	We lacked sufficient information of an investigation.	<i>Yesterday</i> , we lacked sufficient information of an investigation.
	Present	We lack sufficient information of an investigation.	<i>Usually</i> , we lack sufficient information of an investigation.
	Future	We will lack sufficient information of an investigation.	<i>Tomorrow</i> , we will lack sufficient information of an investigation.
German	Past	Sie hatte eine Länge von Metern.	<i>Gestern</i> , hatte sie eine Länge von Metern.
	Present	Sie hat eine Länge von Metern.	<i>Normalerweise</i> , hat sie eine Länge von Metern.
	Future	Sie wird eine Länge von Metern haben .	<i>Morgen</i> , wird sie eine Länge von Metern haben .

Table 2: Synthetic sentence examples in past, present, and future tenses for two datasets (“no_temp” and “with_temrep”). Each sentence is generated via subject–verb–object extraction and verb inflection, producing three tense variants per sentence.

of three tense variants per sentence by automatically inflecting the main verb of the sentence using language-specific tools and rules.

Verb conjugation is performed with existing libraries and targeted rule sets: PatternLite (Smedt and Daelemans, 2012) for Romance and Germanic languages, mlconjug3 (Diao, 2023) for Portuguese (to capture irregular forms), and custom rule-based scripts for Hindi² and Thai³ (see Table 1). Each example is annotated with language, tense, sentence, main_verb, and verb_index. The full corpus comprises 18,580 training and 4,646 test examples. To separate reliance on additional lexical temporal adverbials from internal verbal tense representations, we maintain two parallel splits: no_temp (i.e., temporal adverbials removed) and with_temp.

We select our target languages (Table 3) to cover typological diversity in tense marking (e.g., morphological inflection, auxiliaries, adverbials) and permit evaluation of within-family transfer. A per-language breakdown of tense-marking strategies and extraction configurations is provided in the Appendix C.

Language	Family	Writing system
English	Germanic	Latin
German	Germanic	Latin
French	Romance	Latin
Italian	Romance	Latin
Portuguese	Romance	Latin
Spanish	Romance	Latin
Hindi	Indo-Aryan	Devanagari
Thai	Kra-Dai	Thai script

Table 3: Target languages, families, and scripts. All languages are Indo-European except Thai.

²<https://en.wikibooks.org/wiki/Hindi/Verbs>

³https://en.wikipedia.org/wiki/Thai_language

2.3 Model

We use Meta LLaMA-3.1-8B (Meta, 2024), an autoregressive decoder-only transformer with byte-pair encoding. For each input sentence, we extract the hidden representation of the main-verb token (excluding auxiliaries) at every layer $\ell = \{0, \dots, 32\}$. Model weights remain frozen for all experiments.

Sparse Autoencoders. We use two distinct pre-trained SAEs for our analyses. (i) We employ LLaMA Scope (He et al., 2024) TopK-8x SAEs, which comprise 256 SAE components applied at each layer and stream (residual, attention, MLP), trained on the SlimPajama corpus (He et al., 2024). However, LLaMA Scope exhibits relatively high reconstruction loss, which restricts steering capabilities. Since it was trained on a primarily English dataset, we expect extreme sparse English features, which can limit interpretability and stability when applied cross-lingually⁴.

To address these issues, (ii) we train multilingual SAEs of TopK-8x variants (expanding the hidden space by “factor 8”) on Wikipedia text from seven languages: English, Spanish, French, Indonesian, Vietnamese, Chinese, and Japanese. Unlike LLaMA Scope’s English-centric and highly sparse representations, our multilingual SAEs are designed to achieve lower reconstruction loss while producing sparse, language-agnostic features that enable more reliable cross-lingual comparison and steering within the same model architecture.

3 Identification and isolation of tense representation

We systematically probe how tense is encoded in LLaMA-3.1 8B, examining which layers and com-

⁴https://huggingface.co/Yusser/multilingual_llama3.1-8B_saes/tree/main

ponents represent tense and to what extent. To complement this, we use causal tracing to identify which layers are functionally responsible for carrying and applying tense signals during generation. In the body of the paper, we mainly focus on causal tracing, with additional detailed results on probing reported in Appendix D.

Causal Tracing of Tense Signals. As a preliminary experiment to ascertain if the tense representation is linearly decodable, we perform linear probing (Hewitt and Manning, 2019; Tenney et al., 2019; Chi et al., 2020) and find that tense representation resides throughout all the layers emerging from early layers and most robust in later layers (Figure 7 in Appendix D).

However, probing alone only shows where information is encoded and thus demonstrates correlation rather than causal influence; to address this, we test causality by intervening in intermediate activations to verify that the representations in question directly drive syntactic tense production. We adopt the causal tracing method introduced by Meng et al. (2022), implementing layerwise intervention and patching in our target model using the Pyvene library (Wu et al., 2024). In causal tracing, we care about the activations (i.e., hidden signals) as they travel through the network, which in our case, are tense signals.

Prompting. Each of our trials uses a one-shot prompt consisting of (i) a full sentence in the target tense and (ii) a truncated version of that sentence ending just before the verb:

Template

<partial-X-tense-ending-before-verb>

Example

Lily the cat relaxed on the mat and she ate an apple.
Lily the cat relaxed on the mat and she

The truncated sentence is fed to the model, forcing prediction of the verb and exposing how tense is internally represented. Since verbs may span multiple subtokens, we compute log-probabilities until the full sequence is generated.

Subspace Intervention. On this prompting setup, we apply a clean–corrupt–restore cycle at each transformer block to identify subspaces critical for tense encoding. We intervene across four activation streams S : attention output, MLP acti-

vation, MLP output, and post-residual block output. (i) In the **clean** step, we record the probability p_{gold} of the gold next token. (ii) In the **corrupt** step, Gaussian noise $\epsilon \sim \mathcal{N}(0, \delta^2 I)$ is injected into tense-bearing embeddings at layer 0. (iii) In the **restore** step, noisy activations at layer ℓ and stream S are overwritten with their clean counterparts.

We measure recovery as

$$\Delta p_{\text{restored}}^{\ell, S} = p_{\text{restored}}^{\ell, S} - p_{\text{corrupt}}$$

Averaging over prompt variants, noise seeds (Colas et al., 2018), and languages yields a recovery curve with Standard Error of the Mean (\pm SEM; Wooldridge, 2023) as a function of layer ℓ . Following Meng et al. (2022), we report the indirect effect, i.e., the change in output probability when a single state is restored. More details are in Appendix E.

Results. By corrupting and selectively restoring hidden-state activations, we observe that across the evaluated languages and tenses the **attention-output** stream shows a clear recovery peak around layer 16 (Figure 2); restoring the projected subspace at this layer yields a measurable increase in target-tense probability. This localizes mid-layers as **functionally necessary** for tense prediction, consistent with our preliminary probing results (Figure 7 Appendix D). Per-stream breakdowns are shown in Figure 12 in Appendix F.

Layer wise analysis indicates a processing progression: tense information emerges in the MLP activations near layer 15, is read by attention in layers 15-18, and then is propagated forward (Figure 13 in Appendix F). Recovery magnitudes in the MLP stream are smaller than in attention but indicate a measurable tense signal. This pattern is consistent with prior layer-wise intervention studies on other phenomena (e.g., factual knowledge in Meng et al. (2022)).

4 Identifying human-interpretable tense features.

Having identified critical layers ℓ^* for tense representation, we next ask whether features extracted by SAEs can be used to steer the model’s outputs. Specifically, we test whether activating or inhibiting these features systematically shifts the predicted verb tense. This allows us to evaluate not only the interpretability of SAE features but also their causal influence on generation. To this end, we use SAEs to discover latent features in the model’s hidden states that align with grammatical

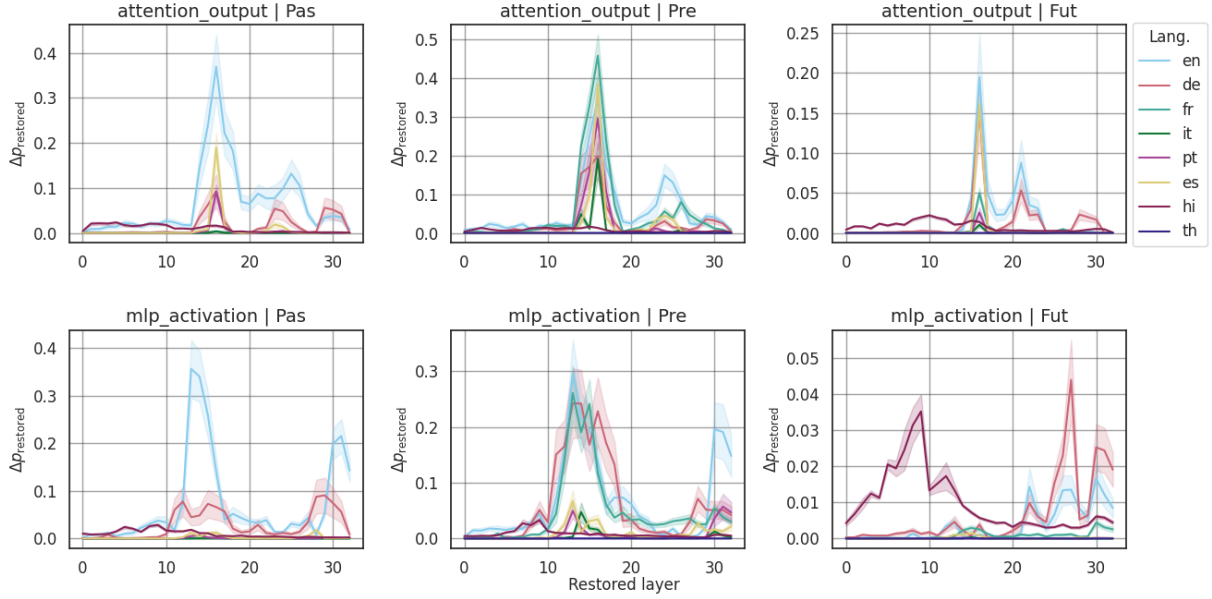


Figure 2: layerwise recovery curves $\Delta p_{\text{restored}}(\ell, S)$ in each language, faceted by stream and tense in attention output and MLP activation. High values indicate that restoring the corrupted token activations at that layer and stream most effectively recovers the correct verb-tense prediction.

tense in English. Our goals are twofold: (i) to validate that SAE-derived features are consistent with the probing and causal-tracing results (Figures 2 in Section 3 and 7 in Appendix D), and (ii) to identify monosemantic tense features that reliably map to tense labels and localize to the critical transformer layers ℓ^* identified earlier. Experiments are conducted on our curated datasets `no_temp` and `with_temp`.

Hidden-state extraction. Each sentence is fed individually through the original LLaMA model via the HookedTransformer interface in the `sae_lens` library (Bloom et al., 2024). We capture the hidden activations at the attention, MLP, and residual output streams for critical layers 15-31 (Figure 2 in Section 3). We extract the activation vector corresponding to the main verb token in each sentence.

SAE inference. We feed the hidden states to our trained multilingual SAEs and the LLaMA Scope SAEs (He et al., 2024) and obtain feature activations and corresponding decoder weights. We compute the reconstruction mean-squared error (MSE) on activations to identify which SAE best compresses the original signal with minimal loss (Figure 3). This helps us select the SAE whose low MSE guarantees fidelity to the model’s internal representations (Shu et al., 2025; Engels et al., 2025).

However, since SAEs are trained with two loss functions for reconstruction and sparsity, there is

a trade between having sparse monosemantic features and the steerability of the SAE (Bayat et al., 2025; Härle et al., 2024). Bayat et al. (2025) address this problem by adding a reconstruction error term to the SAE output while we propose training a new model that preforms better on reconstruction loss.

To assess how well each SAE isolates tense, we perform clustering on the encoder outputs at each layer and calculate the V-measure (v_ℓ) (Rosenberg and Hirschberg, 2007) against true tense labels⁵. We flatten the feature activations across all examples, use K-means with $k = 3$ (i.e., assumes 3 clusters and equal weight per class) for the past, present, and future tenses, and compute v_ℓ for each layer ℓ (Figure 4).

Extracting tense features at critical layers ℓ^* .

After determining the optimal ℓ^* , we shortlist candidate features by intersecting two rankings. First, we rank each latent dimension based on the cosine similarity with static token embeddings from the model’s unembedding matrix (He et al., 2024), which relies on the linear representation hypothesis (Nanda, 2023a; Bereska and Gavves, 2024). Second, we train *one-vs-rest linear probes* with LogisticRegression from scikit-learn on the encoder

⁵V-measure quantifies clustering quality as the harmonic mean of homogeneity (i.e., each cluster contains only members of a single class) and completeness (i.e., all members of a class are assigned to the same cluster).

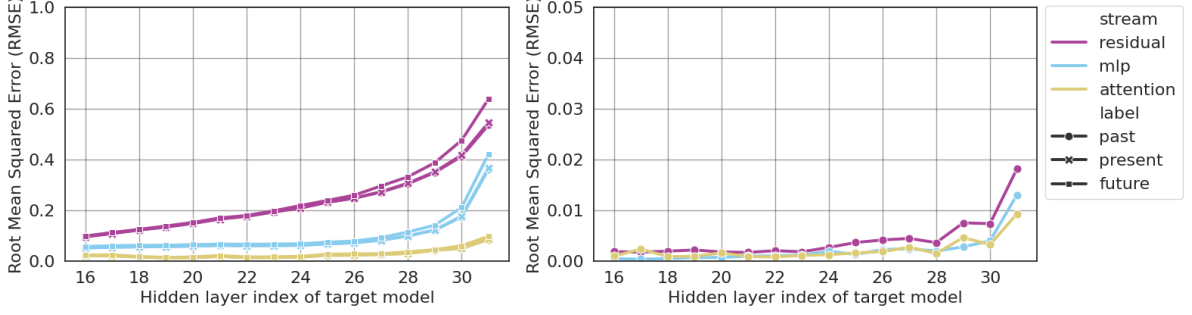


Figure 3: Layerwise MSE trends. **Left:** LLaMA Scope error grows. **Right:** Flat, near-zero error with Multilingual SAE.

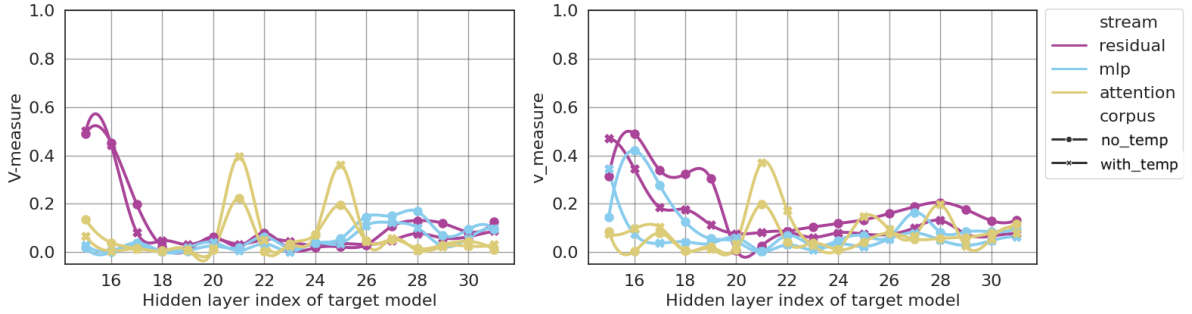


Figure 4: V-measure by layer for SAEs on corpora with/without temporal cues. Tense features are most distinct at layers 15–16.

outputs to predict temporal states.

Features are then ranked by their absolute probe weights to identify those that align with tense tokens and drive tense classification. However, this intersection might overlook weaker valid features or retain spuriously correlated ones if noise is agreed upon in both rankings. To address this, we conduct additional experiments in the steering experiment detailed in Section 5.

Results. Our multilingual SAE attains low mean-squared reconstruction error across layers (Figure 3), supporting $\ell^* \approx \{15, 16\}$ as the tense-critical layers where tense distinctions are most sharply encoded. This underscores the importance of intermediate layers for tense representation and aligns with our previous results in Figure 2 in Section 3. The intersected SAE feature set corresponds to human-readable tense markers (e.g., “did,” “does,” “will”; Figure 5), validating the interpretability of these features and their suitability for downstream steering. Additional visualizations appear in Figures 14 and 15 (Appendix G).

Visualizing high-dimensional SAE activations at ℓ^* via UMAP provides an intuitive snapshot of how the model’s latent space isolates tense information (Figure 16 in Appendix G).

Baselines	
A	Original model, no adapter.
B1	LLaMA Scope SAE adapter applied at ℓ^* , with $\alpha = 1.0$ (i.e., no scaling).
B2	Our Multilingual SAE adapter applied at ℓ^* , with $\alpha = 1.0$ (i.e., no scaling).
Steering	
Excitation	Multiply each selected feature f by $\alpha > 1.0$ (positive intervention).
Inhibition	Multiply each selected feature f by $\alpha < 1.0$ (negative intervention).

Table 4: Definitions of baselines and feature-steering settings.

We find that in both SAE frameworks, future tense forms a distinct cluster while having more subtle distinctions between past and present tenses. This pattern suggests that SAEs capture a stronger, more uniform signal for the future tense than for the more subtle distinctions between past and present forms.

5 Steering Tense Generation

After identifying tense-sensitive features, we test whether these features can be used directly to control model behavior. Following an adapter-based steering paradigm Kissane et al. (2024b), we integrate SAE-derived “tense axes” into the residual stream and scale them during generation (McGrath

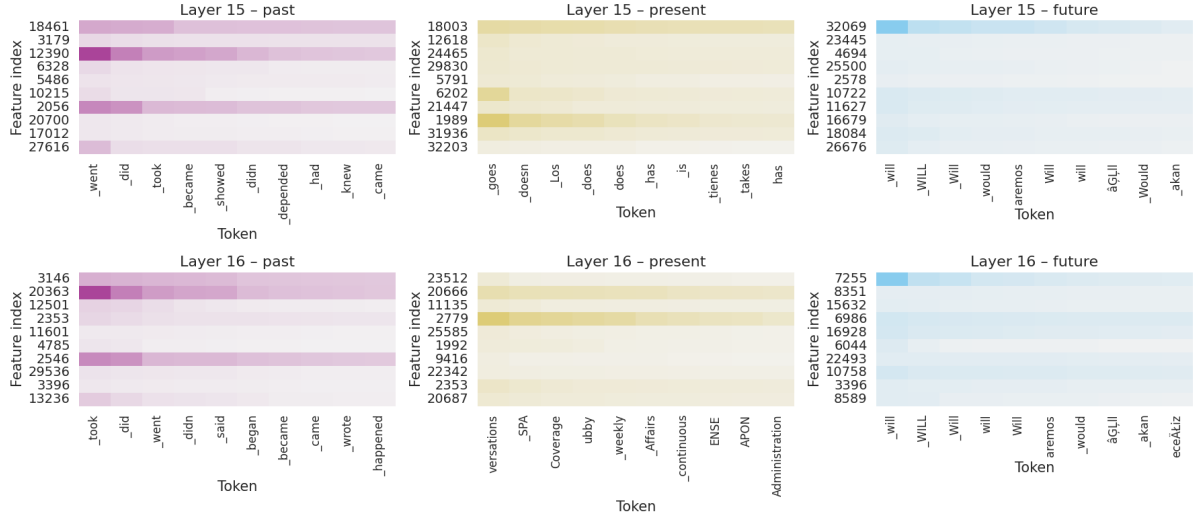


Figure 5: Token–feature heatmaps from the model’s input embeddings at $\ell^* = 15$ (LLaMA Scope). Rows correspond to features, columns show the top ten tokens by cosine similarity.

et al., 2024; O’Brien et al., 2024; Härle et al., 2024). This mirrors prior steering work on syntactic and factual pathways and enables fine-grained tense control without retraining.

Specifically, we evaluate the causal impact of tense features by steering LLaMA-3.1 8B’s hidden activations in a cloze task, which is explained below. Using feature scaling, we multiply selected latent dimensions by a factor α at critical layers ℓ^* , with $\alpha > 1$ for excitation and $\alpha < 1$ for inhibition on the cloze task.

Cloze task. We use a **cloze fill-in-the-blank** evaluation. Each prompt consists of a temporal cue (e.g., “Yesterday”), a sentence with a missing verb, three verb-form options (one per tense), and an answer placeholder. For instance:

Example

Yesterday, the dog ___ at the mailman.
A) barks
B) barked
C) will bark
Answer:

The model must output the correct option (“A”, “B”, or “C”). For each tense, we construct a balanced development set of 30 prompts and a test set of 500. Prompts pair diverse subjects/objects (e.g., “I”, “we”, “the mailman”) with base verbs conjugated (including irregulars) into target tenses using PatternLite (Smedt and Daelemans, 2012); correct option order is randomized. We run the task in English and German and report accuracy.

Steering procedure. We compare three baselines and multiple steering configurations (Table 4).

SAE adapter combinations. We explore SAE adapters at individual layers (e.g., $\ell^* = 15$ then $\ell^* = 16$ separately), and both layers combined. For each combination, we apply the same feature set (Table 9 in Appendix H) and scaling α across all prompts in one run. This setup enables us to observe how scaling the SAE features, either individually or jointly across layers, affects the model’s predictions in the downstream task.

Feature selection and scaling. Our SAE observation analysis (Section 4) yields a pool of features, but we need to ensure that these human-interpretable features are functional in the downstream task. Thus, we perform a grid search on the dev set to identify which features and α values work best for each tense. Specifically, for each candidate feature f in the combined pool, we run steering on the dev-prompts for each label, record the change in accuracy relative to baselines, and retain only those feature combinations that improve the target-label accuracy. This fine-grained search allows us to isolate the most effective features and scaling factors before the final test-set evaluation. The features determined in this fashion are listed in Table 9 in Appendix H.

Results. We evaluate cloze-task accuracy on the test set and find that moderate excitation ($\alpha = 5.0$) of tense features reliably enhances correct-tense

Language	Target tense	A	B1	B2	15			16			Both		
		-	1.0	1.0	2.0	5.0	0.1	2.0	5.0	0.1	2.0	5.0	0.1
English	Past	0.81	0.13	0.81	0.82	0.84	0.80	0.80	0.82	0.81	0.80	0.80	0.81
	Present	0.39	0.09	0.39	0.41	0.36	0.39	0.42	0.48	0.38	0.50	0.38	0.37
	Future	0.76	0.14	0.77	0.80	0.85	0.74	0.78	0.81	0.77	0.81	0.77	0.75
German	Past	0.63	-	0.63	0.64	0.68	0.63	0.65	0.65	0.67	0.62	0.63	0.63
	Present	0.60	-	0.61	0.62	0.66	0.64	0.71	0.66	0.72	0.60	0.60	0.57
	Future	0.44	-	0.43	0.43	0.44	0.42	0.38	0.43	0.36	0.44	0.45	0.45

Table 5: Test-set steering results. Baselines: A = original; B1 = LLaMA Scope SAEs (15–16); B2 = Multilingual SAEs (15–16). $F_{\ell^*} \in \{15, 16, \text{Both}\}$ is the Multilingual SAE hook layer(s); subheader shows α ($\alpha > 1$: excitation). (Highlighted) cells mark excitation that outperforms the baselines. In inhibition settings, lower accuracy indicates successful downward control.

predictions. Inhibition produces only small accuracy reductions, suggesting the model compensates for partial suppression via redundant or alternative features. A likely mechanistic explanation is that tense encoding is partially distributed and overlapping, so that inhibiting only a subset of target features may not have an effect as intended (McGrath et al., 2024). In line with McGrath et al. (2024), positive interventions are more effective than negative ones.

English tense features transfer to German for past and present (Table 5), but not for future tense. This finding suggests partial cross-lingual alignment and the presence of language-specific attention heads. We hypothesize that the observed English \rightarrow German non-transfer primarily reflects distinct syntactic encodings (e.g., German verb-second and verb-final patterns) that alter where tense cues are represented across layers and components. The layer-wise causal differences reported in Figure 2, Section 3 align with this interpretation.

We do not rule out potential effects of tokenization or corpus frequency; confirming whether syntax alone explains the pattern will require targeted tests such as tokenization normalization, auxiliary alignment interventions, and controlled frequency experiments, which we leave for future work.

Moreover, since SAE features can partially overlap semantically, interventions on one tense may also influence others. We present these cross-label effects in Tables 10 and 11 in Appendix H.

6 Conclusion

We present a four-phase diagnostic pipeline: probing, causal tracing, SAE disentanglement, and steering that links where tense information is linearly readable in latent representations to where it is functionally necessary and controllable. Lin-

ear probes show that LLaMA-3.1 8B (Meta, 2024) internally represents simple past, present, and future tenses in low-dimensional subspaces that are detectable across layers; with crosslingual transfer peaking in layers 20 to 30, suggesting a language agnostic encoding. Causal interventions (Meng et al., 2022) localize a functionally necessary subspace at around layers 15-16, primarily within the attention stream (with contributions from MLP activations and outputs), and restoring this small subspace recovers tense probability.

Applying SAEs (Kissane et al., 2024b; O’Brien et al., 2024; Härle et al., 2024) to activations at layers 15-16 yields monosemantic tense features that align with human-readable tense markers. Scaling these features in the residual stream systematically shifts cloze completions toward the target tense, improving correct-tense accuracy by up to 11% points with modest degradation. Crucially, the effect persists even without temporal adverbs (for example, “yesterday”), showing that the model internally encodes tense rather than relying on surface cues. English derived features transfer to German past and present but not future tense, suggesting that the model captures an abstract crosslingual temporal structure, though some future constructions may remain language specific or data limited.

To our knowledge, this is the first evidence in a multilingual LLM of a causally active, language agnostic tense subspace whose disentangled, interpretable features can steer generation. The finding holds across eight languages for simple tense forms, but broader generalization to richer aspectual patterns, other model families, and naturalistic contexts remains open. Future work should extend this framework to more complex temporal systems and finer grained circuit level analyses of cross-lingual temporal representation.

Limitations

This study operates in a controlled diagnostic setting that enables causal intervention but may limit generalization. Our experiments rely on automatically inflected sentences from UD treebanks, which simplify discourse context and may not mirror natural tense use. Rule-based inflections for Hindi and Thai add minor noise. We analyze only one decoder-family model and focus on basic tense forms—past, present, and future. While our interventions reveal clear mechanistic signals, we do not claim generalization to richer discourse contexts, morphologically complex or low-resource languages, other architectures, or compound aspectual tenses.

Future work should extend to human-annotated, naturalistic corpora with explicit tense labels, replicate analyses across architectures and tokenizers, and apply finer-grained causal probes and steering methods. Evaluating longer contexts and downstream tasks will further test whether the recovered features capture robust, generalizable temporal representations.

Acknowledgments

YG is supported by the German Federal Ministry of Research, Technology and Space (BMFTR) as part of the project TRAILS (01IW24005). DM is supported by the project “Human-centred AI for a Sustainable and Adaptive Society” (reg. no.: CZ.02.01.01/00/23_025/0008691), co-funded by the European Union. KDC is supported by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) – SFB 1102 Information Density and Linguistic Encoding.

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A Ethical Considerations

This work investigates how multilingual large language models represent and transfer grammatical tense across languages through causal and interpretability analyses. All experiments were conducted on open-weight models and publicly available datasets, including synthetically generated, tense-annotated corpora derived from existing treebanks. No human or private data were used. All model and data artifacts were used in full compliance with their respective licenses.

B Related work

This section addresses our study within interconnected research areas: linguistic theory of tense, interpretability methods used in our work, and current progress of linguistic analysis in mechanistic interpretability.

B.1 Tense in linguistics

Early linguistic work characterizes tense as the grammatical marking that locates an event in time. From a *syntactic perspective*, tense operates as a feature on a clause head that triggers morphological inflections (Partee, 1973). In contrast, *semantic*

frameworks treat tense morphemes as operators that shift a reference time relative to the utterance time (Dahl and Velupillai, 2011). A further distinction arises between absolute tense, which ties events to the moment of speaking (e.g., simple past vs. present), and relative tense, which relates one event time to another (e.g., perfect or pluperfect) (Comrie, 1985).

B.2 Mechanistic interpretability

Superposition hypothesis. Superposition posits that internal vectors store more distinct features than their dimensionality by overlapping feature directions. Overlap causes crosstalk when recovering a single feature, because directions are not all orthogonal. This cost is acceptable when features are sparse (i.e., few active features per input) and when nonlinear readouts or learned decoders excite true signals and inhibit overlap (Bereska and Gavves, 2024; Olah, 2023).

Linear representation hypothesis. This hypothesis proposes that neural networks often depict high-level features as linear trajectories within the activation space (Bereska and Gavves, 2024). Linear representation can ease the comprehension and adjustment of neural network representations (Nanda, 2023b).

Relevant studies. Mechanistic interpretability has progressed through complementary observation and intervention methods. Linear and structural probes (Tenney et al., 2019; Hewitt and Manning, 2019; Jawahar et al., 2019) reveal that transformer layers encode syntactic and semantic categories. Multilingual probing of mBERT and XLM-R shows recoverable tense signals across dozens of languages (Acs et al., 2023; Li and Wisniewski, 2021). However, high-capacity probes risk spurious correlations and probing accuracy can be misleading (Hewitt and Manning, 2019; Belinkov, 2022). Consistent with Tenney et al. (2019) and Jawahar et al. (2019), we expect syntax is represented in early layers and higher-level abstractions in mid layers. Temporal semantics research—timeline inference and event ordering corpora (UzZaman et al., 2012; Yahiaoui and Atanassova, 2023)—and aspectual probes (Metheniti et al., 2022) target factual time relations rather than internal tense morphology. Causal tracing techniques (Abnar and Zuidema, 2020; Meng et al., 2022; Zhang and Nanda, 2024), have begun to link hidden activations to model behaviors, but have not

yet been applied to tense. Finally, SAEs demonstrate that enforcing sparsity extracts monosemantic units for linguistic features (Bricken et al., 2023), offering a promising path to disentangle tense from other representations. Unlike prior work on encoders (e.g., mBERT probes), our work unifies these strands—probing, causal analysis, and SAE disentanglement—to fill the current gap in understanding and controlling tense in decoder-only multilingual transformers.

C Tense Typologies

We survey the target languages in terms of family, script, word order, and tense marking strategies:

English (Indo-European, Germanic; Latin alphabet; SVO): English has a strong past/non-past distinction (Parsons, 2002). The simple past is marked by the suffix “-ed” (i.e., plus irregular forms), and the present is unmarked or marked by “-s” for a third person. Future time is typically expressed periphrastically using auxiliaries (e.g., “will”, “going to”) rather than an inflection (Parsons, 2002). Thus, English encodes tense morphologically for past and present but uses modal auxiliaries for future.

German (Indo-European, Germanic; Latin alphabet; Verb-Second order): German also marks tense morphologically. Present-tense verb forms (e.g., *geht* (“war”)) contrast with a simple past (i.e., Präteritum) typically marked by suffixes or vowel ablaut (e.g., *ging* (“went”)). German uses auxiliaries (e.g., “werden”, “sein”, “haben”) to form periphrastic tenses, including the future and perfect. In subordinate clauses, it can use *wird gehen* (“will go”) as a future. Overall, German has a two-way distinction (i.e., present vs. past) with optional future auxiliaries.

French (Indo-European, Romance; Latin alphabet; SVO): French has rich tense inflection on verbs. The present tense (e.g., *parle* (“speaks”)) is marked, as is the simple past (i.e., passé simple, e.g. *parla*) and imperfect (e.g., *parlait*). The “passé composé” uses “avoir/être” + past participle to express past. French also has a true future suffix (e.g., “-ra”, as in *parlera* (“will speak”)) (Dryer and Haspelmath, 2013). Thus, tense is marked by a variety of suffixes and auxiliary constructions.

Italian (Indo-European, Romance; Latin alphabet; SVO): Italian, like other Romance lan-

guages, uses inflectional suffixes to mark tense. For example, “-ò” and “-ai” in *parlerò* (“I will speak”) signal future tense, while “-ai” or “-i” mark past forms. The present tense is marked by suffixes on the verb stem (e.g., “-o”, “-i”, “-a”, “-iamo”, etc.). Compound tenses (i.e., passato prossimo) use “avere/essere” + participle for past reference. Thus, Italian distinguishes past, present, and future with a mix of suffixal and auxiliary marking.

Portuguese (Indo-European, Romance; Latin alphabet; SVO): Portuguese similarly marks tense on verbs. Present tense forms (e.g., *falo* (“speak”)) contrast with a past preterite (e.g., *falei*) and a future suffix (e.g., *falarei*). There is also an imperfect (e.g., *falava*). The future tense can be formed analytically (i.e., using auxiliary “ir” + infinitive) or synthetically (i.e., “-rei” endings). Overall, Portuguese verb morphology encodes multiple tense distinctions.

Spanish (Indo-European, Romance; Latin alphabet; SVO): Spanish marks tense on verbs with multiple inflections. The simple past (i.e., preterite, e.g., *hablé* (“speak”)) and imperfect (e.g., *hablaba*) are distinct suffixes, as are present (e.g., *hablo*) and future (e.g., *hablaré*) forms (Dryer and Haspelmath, 2013). The future tense is a suffix (i.e., usually “-ré”) attached to the infinitive. Compound tenses use auxiliaries (i.e., “haber” + participle). Overall, Spanish has separate affixes for past, present, and future on the verb.

Hindi (Indo-European, Indo-Aryan; Devanagari script; SOV): Hindi’s tenses are typically marked by verb inflections and auxiliaries. The simple present and past tenses are distinguished by different participial stems and agreement. For example, “-taa/-ti” suffixes for present continuous vs. “-yaa” participles for perfective past (e.g., *khaataa/khaatii* (“eating”), *khaayaa/khaayi* (“ate”)). Hindi does not have a grammatical future inflection on the verb itself. Instead, periphrastic futures are formed with modal auxiliaries (e.g., *hoga* (“will be”)) or with the verb *nikalnaa* (“to leave”) implying future intent. Thus, Hindi effectively contrasts past vs. non-past, with future marked by particles or context.

Thai (Kra-Dai, Tai branch; Thai script; SVO): Thai is often described as a tenseless language. Thai verbs do not inflect for tense. Instead, time reference is conveyed by aspect markers and temporal adverbs. For example, particles such as *lăew*

Language	NP Modifiers	VP Auxiliaries	PP Modifiers
en, de, fr, it, pt, es	det, amod, compound, poss, nummod	aux, aux:pass, compound:prt	det, amod, compound
hi	det, amod, compound, poss, nummod	aux, aux:pass, compound:prt	det, amod, compound
th	det, amod, compound, nummod	aux, aux:pass, compound:prt	det, amod, compound

Table 6: Simplified dependency-modifier configuration used for NP, VP, and PP extraction per language.

(“already”) or *jà* (“will”) and context words (e.g., “yesterday” or “tomorrow”) indicate past or future tense. Typologically, Thai lacks any inflectional future tense. It falls in the Southeast Asian area that does not mark future morphologically (Dryer and Haspelmath, 2013).

D Preliminary Linear Probing

We check if tense information is stored linearly by training classifiers on the model’s hidden states. We follow the probing framework of Hewitt and Manning (2019) for layer-wise analysis and the multilingual transfer evaluation of Chi et al. (2020). We conduct a series of experiments to assess internal tense representation after having observed strong diagonal accuracy from final layer (Figure 6). We utilize layerwise probes, where we train a separate probe for each layer on the dataset labeled as “no_temp” with a learning rate set at 1e-3.

$$\hat{y} = \text{softmax}(W_{\ell} h_{\ell}(x) + b), \mathcal{L} = H(\hat{y}, y) + \lambda \|W\|_1$$

where $y \in \{\text{past, present, future}\}$, x is the main verb in the input and $\lambda \in \{0.01, 0.003, 0.001\}$.

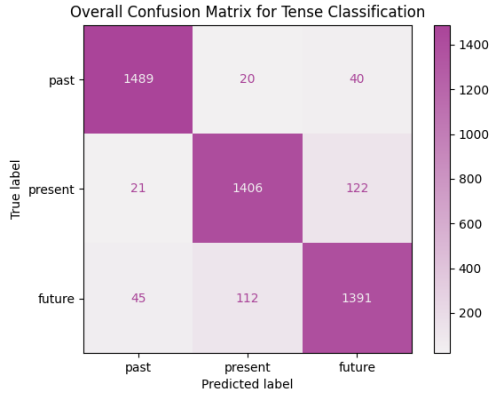


Figure 6: Confusion matrix of classification performance at the final layer of Llama-3.1 8B. Rows are true tense labels, and columns are predicted labels. Strong diagonal values relative to the off-diagonal values confirm linear separability. It is measured on the main verb token (i.e., can be multiple tokens) embeddings.

D.1 Cross-lingual transfer

We adapt the layerwise paradigm to assess language-agnostic encoding by following the

framework established by Chi et al. (2020) conducting two strategies: direct and hold-one-out transfer. This approach tests whether grammatical tense is encoded in a language-agnostic subspace or vary by language morphology. High transfer accuracy indicates a shared tense representation, while low accuracy suggests language-specific patterns. In the direct transfer approach, we train our model on one language and then test it on other languages, and in the hold-one-out method, we train the model on seven other languages while reserving one language for testing.

D.2 Results

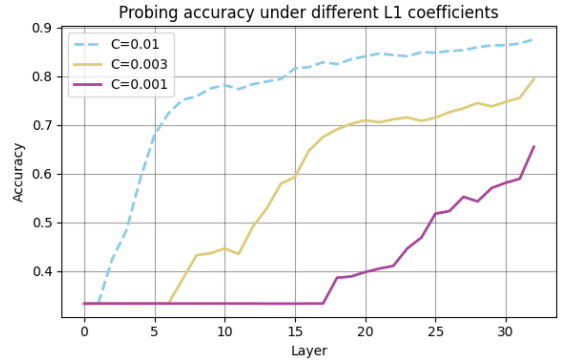


Figure 7: Probes trained with L1 regularization ($\lambda = 0.01, 0.003, 0.001$) show that tense is recoverable from early layers under weak regularization. Stronger penalties delay emergence to later layers, indicating that tense develops in early layers but strengthens in deeper ones, aligning with previous findings on syntactic feature emergence (Kissane et al., 2024a; Tenney et al., 2019). Early detection may also relate to morphology.

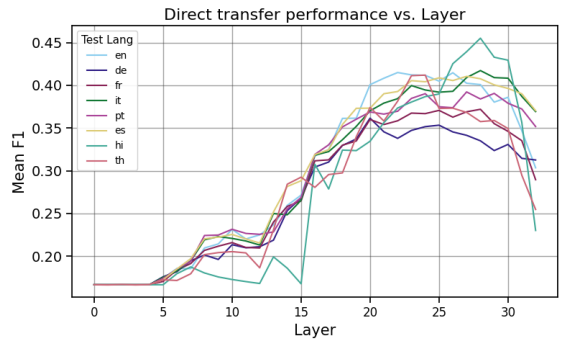


Figure 8: Direct-transfer performance across languages.

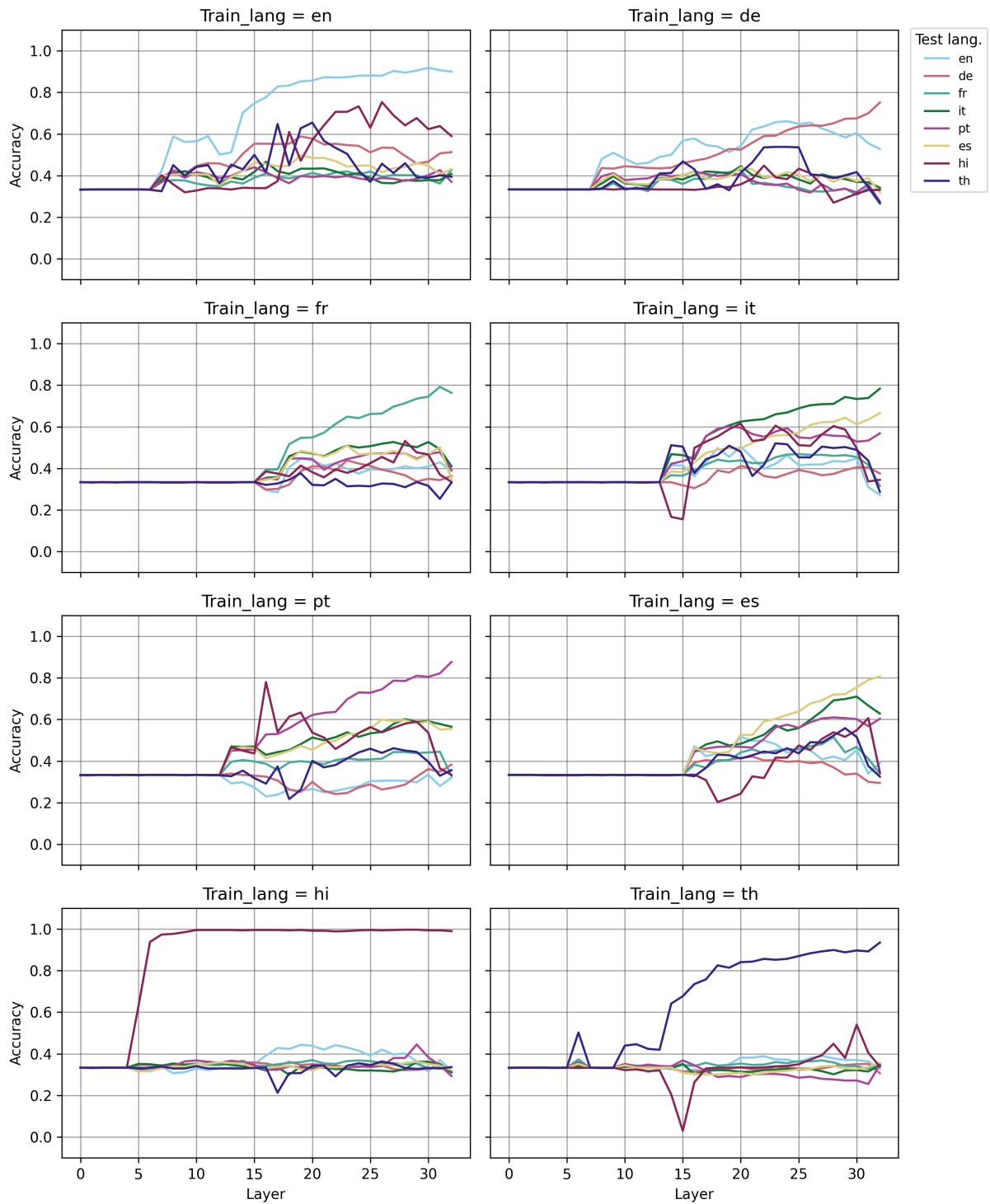


Figure 9: Direct-transfer accuracy by layer. Each subplot shows, for a fixed train language, the probe’s accuracy on all test languages at each layer. Languages within the same family transfer more effectively to one another, with peak transfer performance in the mid-to-late layers. Romance languages exhibit strong within-group transfer, although French yields the weakest performance among them. Hindi and Thai show poor cross-transfer from most other languages, indicating distinct tense encoding, likely attributable to their divergent typology, writing systems, and language families. English and German nonetheless transfer moderately well into Hindi and Thai, possibly because auxiliary constructions in Hindi and future-tense markers in Thai partially align with Germanic and Romance patterns.

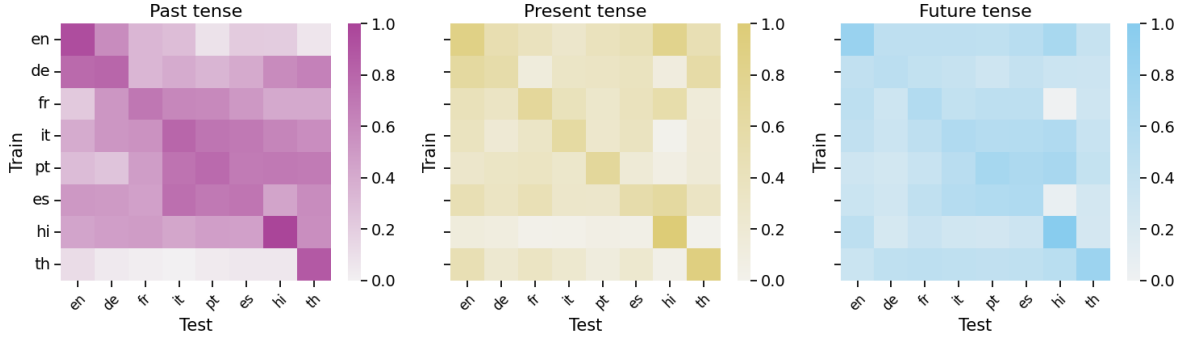


Figure 10: Direct transfer performance broken down into tense at layer 25, where the transfer performance peaks. Transfer between languages within the same family is noticeable, while self-transfer is also distinguishable.

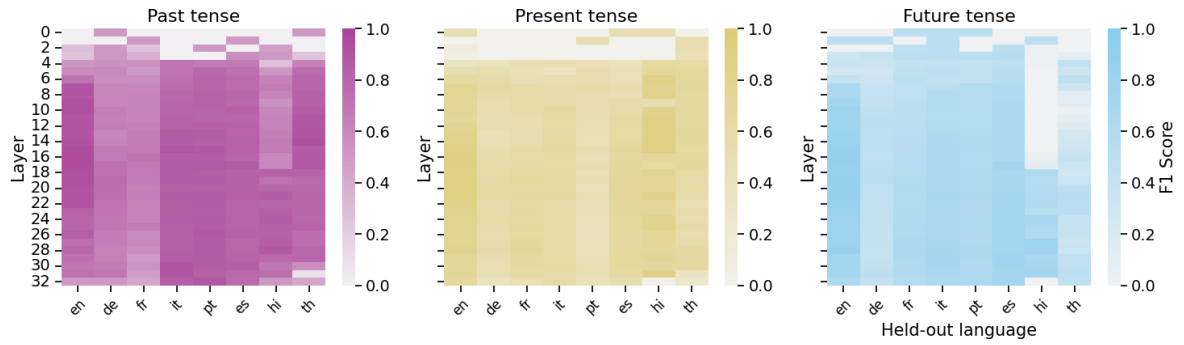


Figure 11: Hold-one-out transfer probing performance across layers and languages, broken down by tense. A single hyperplane trained on all languages except the held-out target still separates tense above chance for most languages, signifying language-agnostic features—past tense yields the highest hold-out F1-macro across all held-out languages, with English highest and German lowest. In the Romance group, only the past tense remains robust; present and future collapse toward chance, especially for French. Hindi’s past/future peaks in late layers; present emerges earlier. Thai’s past-tense transfer peaks mid-layers; present/future remain near chance.

Language	Past	Present	Future
English	Lily the cat relaxed on the mat and she ate an apple.	Lily the cat relaxes on the mat and she eats an apple.	Lily the cat will relax on the mat and she will eat an apple.
German	Lily die Katze entspannte sich auf der Matte und sie aß einen Apfel.	Lily die Katze entspannt sich auf der Matte und sie isst einen Apfel.	Lily die Katze wird sich entspannen auf der Matte und sie wird einen Apfel essen .

Table 7: Semantically minimal, tense-varying template example in English and German.

E Causal Tracing

E.1 Prompt design

We construct semantically minimal sentence frames that differ only in verbal inflection (i.e., past, present, or future) across eight languages.

Few-shot. We create prompts with two identical full-tense sentences separated by a distractor of alternate tense. We inject noise in the verb positions of the first and last sentences to assess whether causal tracing method can flip the generated tense.

Template

```
<full-X-tense-sentence>
<full-Y-tense-sentence>
<partial-X-tense-ending-before-verb>
```

Example

Lily the cat relaxed on the mat and she ate an apple.
Lily the cat relaxes on the mat and she eats an apple.
Lily the cat relaxed on the mat and she
Original generation: ate. After noise injection: eats.

One-shot. To confirm cross-language validity, we generate five variants per tense by varying subjects (e.g., “I,” “Aki the dog”), verbs, and objects while preserving argument structure. English templates were manually drafted, translated using Google Translate, and validated through back-translation. Table 7 shows representative templates.

Template

```
<full-X-tense-sentence>
<partial-X-tense-ending-before-verb>
```

Example

Lily the cat relaxed on the mat and she ate an apple.
Lily the cat relaxed on the mat and she
Original generation: ate. After noise injection: is.

E.2 Experimental setup

1. **Prompts.** Five prompts per tense and language, varying subject/pronoun and verb-object lexemes.

2. **Noise Seeds.** $M_{noise} = 5$, seeds to ensure independent Gaussian draws for reproducibility.
3. **Window Size.** $Window = 3$, restoring layer ℓ activations at some token positions with its previous and next layers.
4. **Streams.** Four sub-components per layer: attention output, MLP activation, MLP output, block output.

Restoration positions In the few-shot prompt experiment, we perform restoration on all token positions. Based on the results, we decided to focus on critical token positions where restoration is most effective in the one-shot experiment (Table 8).

Position	Description
< begin_of_text > (pos 0)	The very first token embedding.
Pre-verb	The token immediately preceding the first main-verb subtoken.
Tense-bearing subtokens	All subtokens of the auxiliary + main-verb.
Final token	The last token in the “partial ... ending” line.

Table 8: Critical token positions.

E.3 Evaluation metrics

We interpret higher $\Delta p_{restored}$ values as more substantial evidence that a given layer and stream are critical for tense generation. We report means with Standard Error of Mean (SEM) across different seeds. The Standard Error of the Mean (SEM) quantifies the precision with which we have estimated the true mean of $\Delta p_{restored}$ across noise-seed replicates. Formally, if $\{x_i\}_{i=1}^M$ are the $\Delta p_{restored}$ values for M independent seeds, and $\bar{x} = \frac{1}{M} \sum_i x_i$ with sample standard deviation $\sqrt{\frac{1}{M-1} \sum_i (x_i - \bar{x})^2}$, then

$$SEM = \frac{s}{\sqrt{M}}. \quad (1)$$

F Layer-wise Recovery Analysis

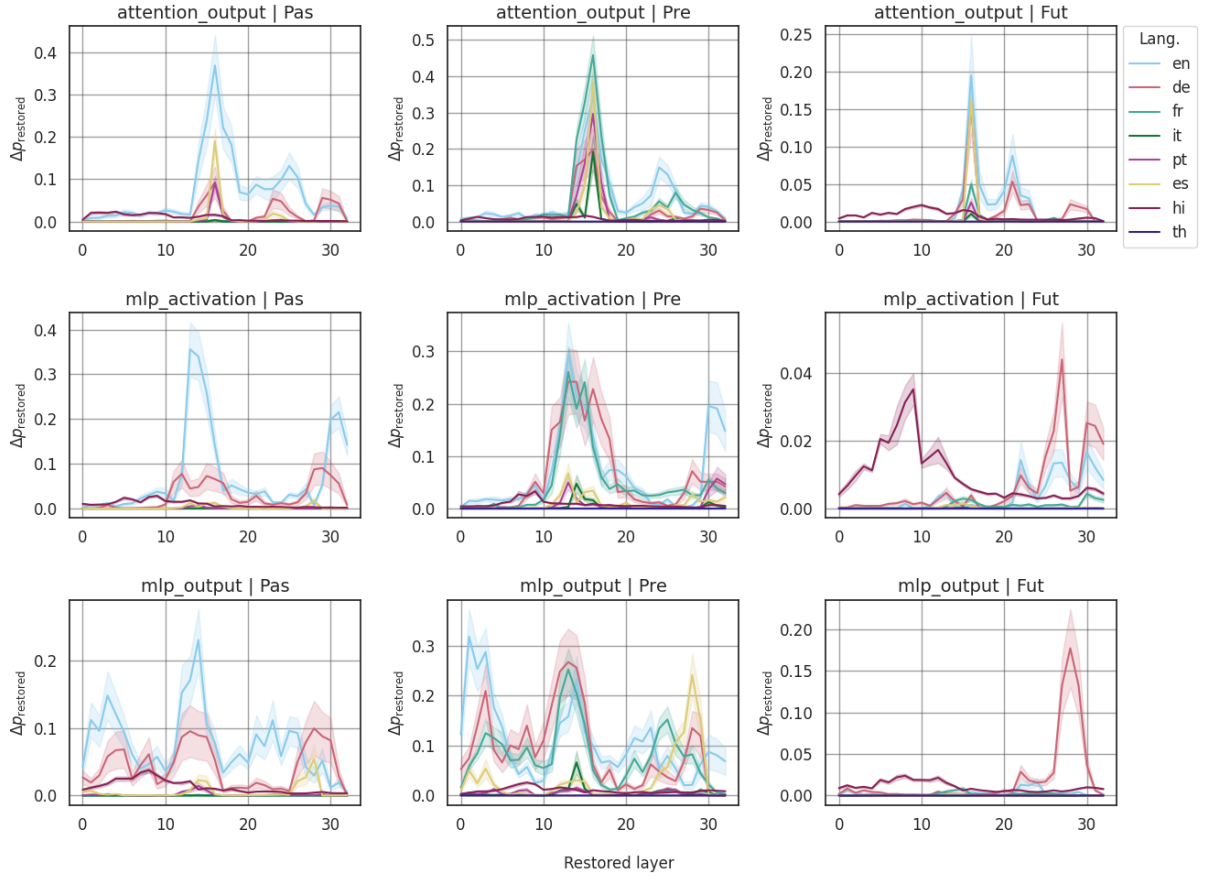


Figure 12: layerwise recovery curves $\Delta p_{\text{restored}}(\ell, S)$ in each language, faceted by stream and tense. High values indicate that restoring the corrupted token activations at that layer and stream most effectively recovers the correct verb-tense prediction.

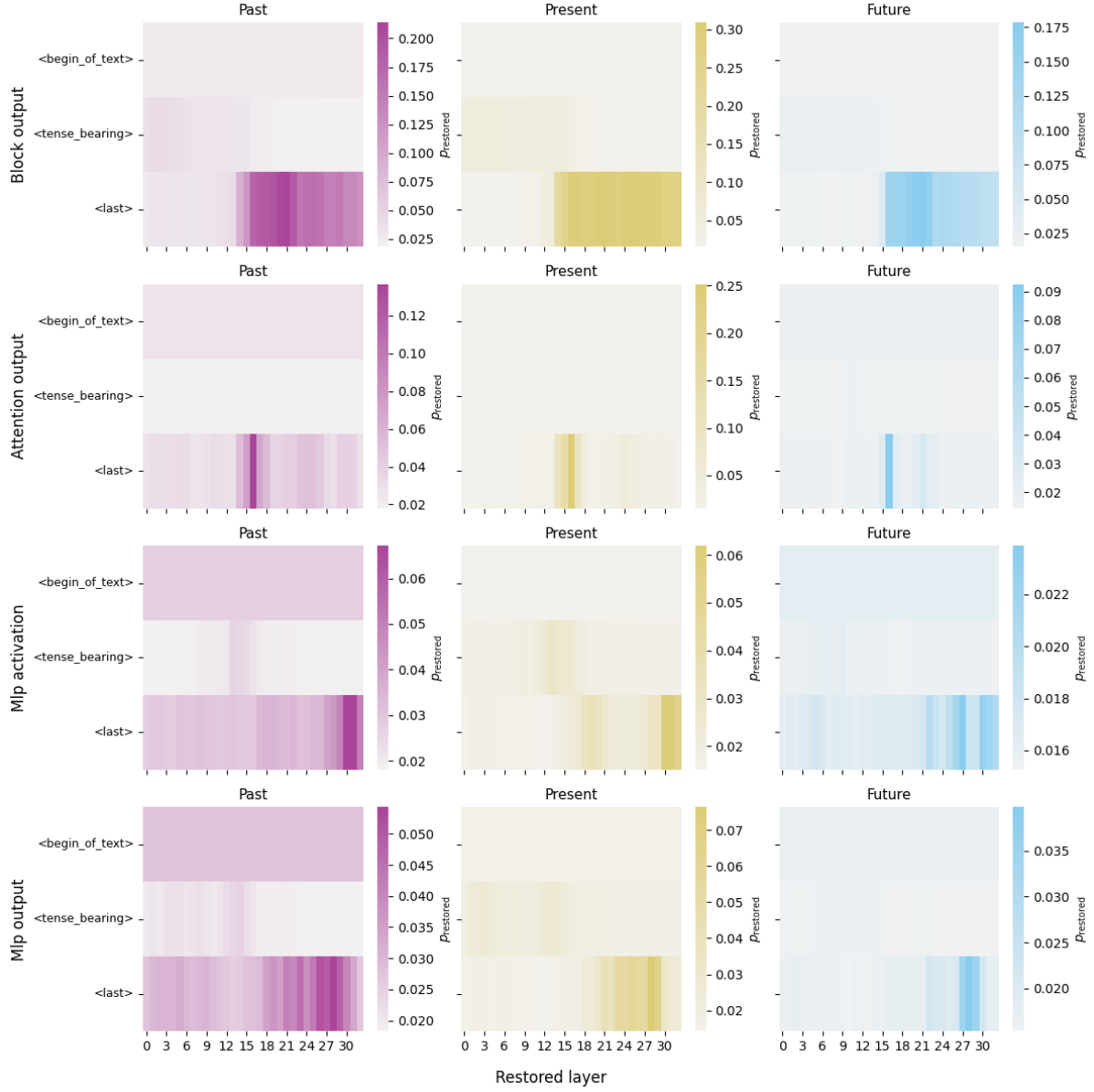
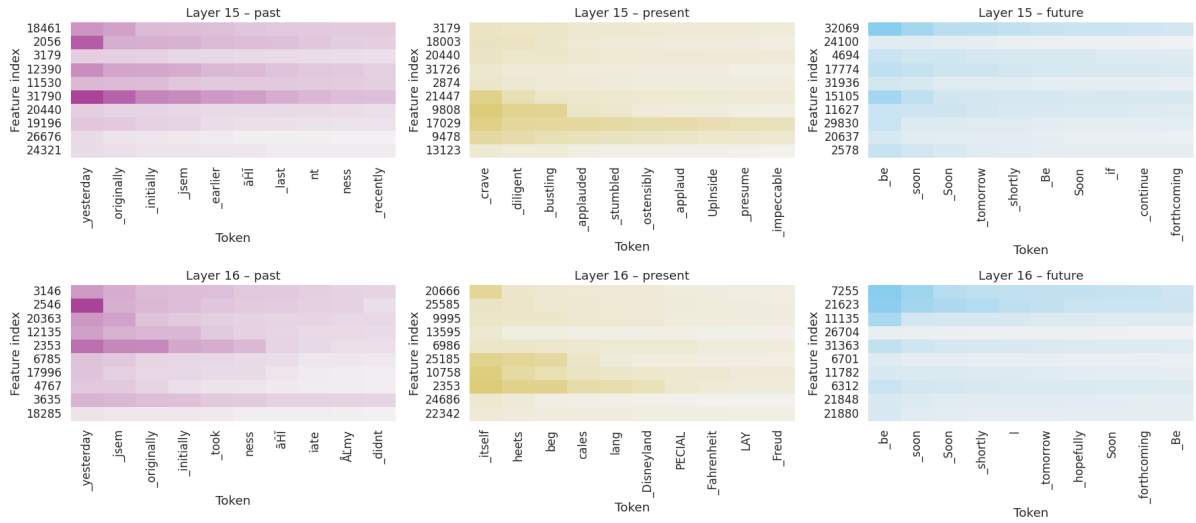
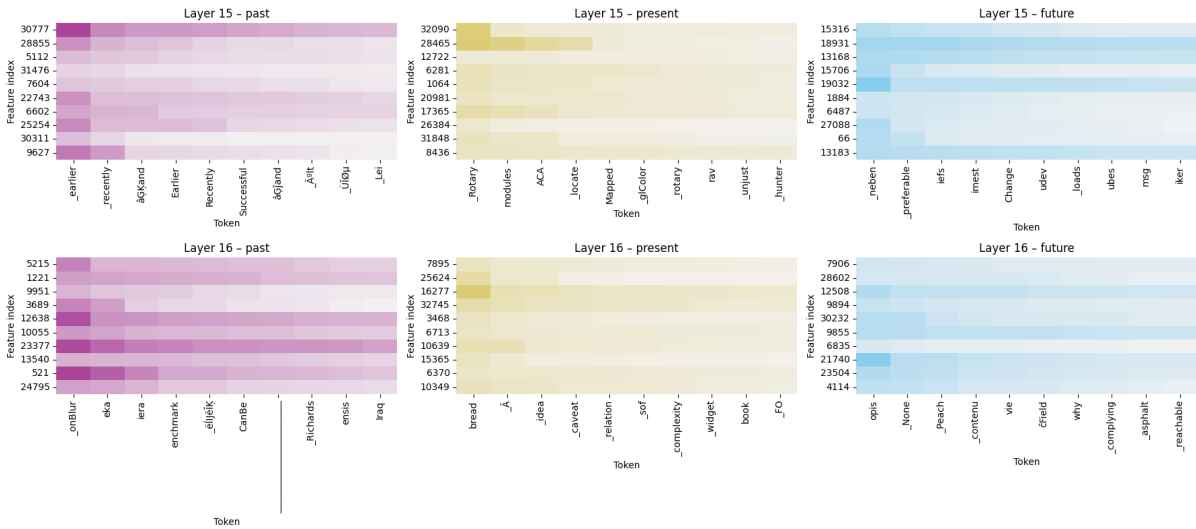


Figure 13: Causal analysis for each tense, averaged across language results.

G Layer-specific Analysis



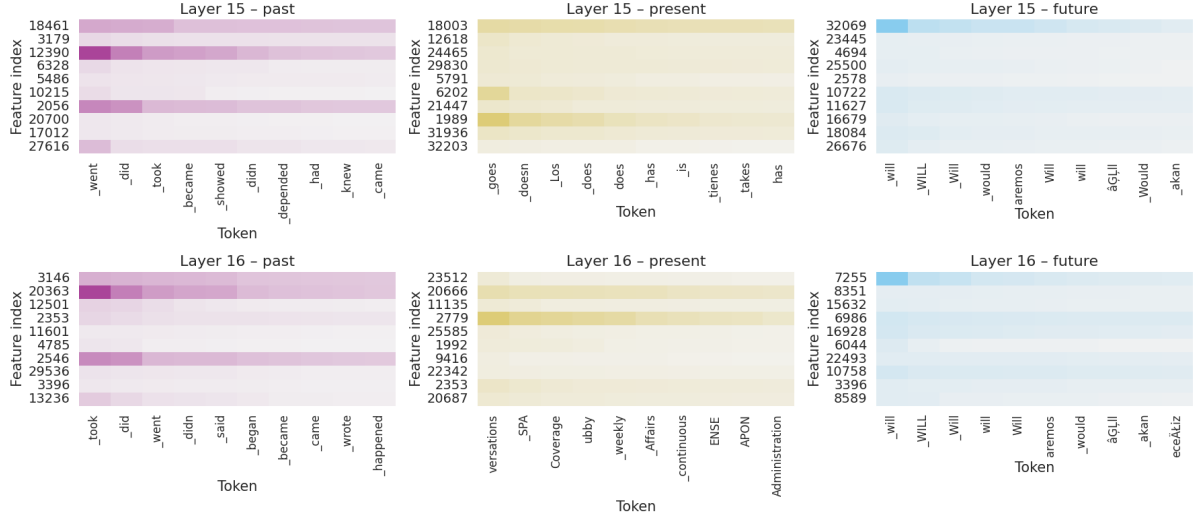
(a) LLaMA Scope SAE



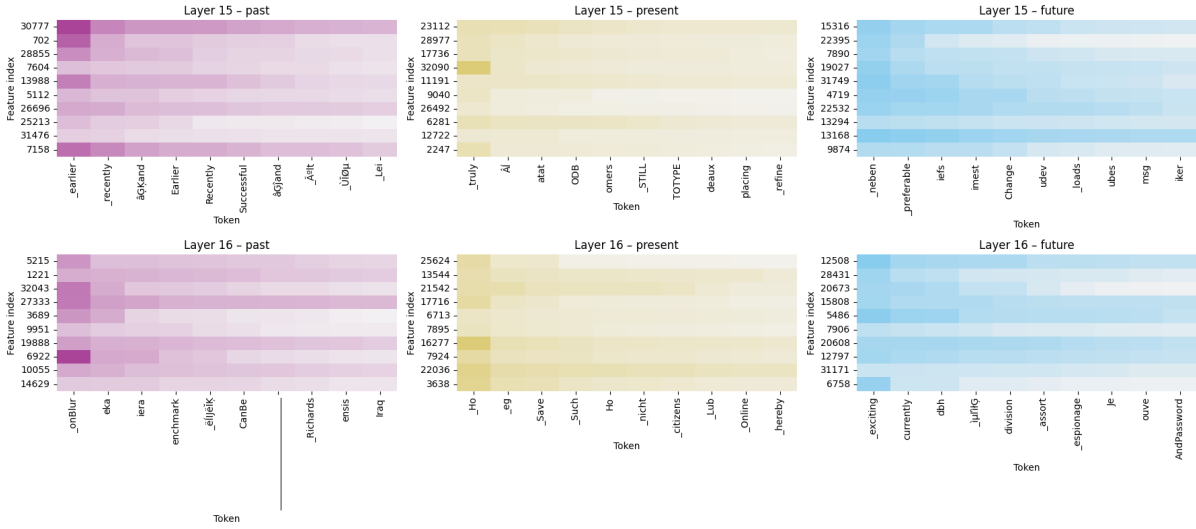
(b) Multilingual SAE

Figure 14: Token–feature heatmaps at layers 15–16 (ℓ^*) for LLaMA Scope and Multilingual SAEs. Each heatmap shows cosine similarity between SAE-derived feature vectors (from the decoder’s tense-encoding subspace) and the model’s **output embeddings**. Rows are features; columns list the top ten tokens by similarity. LLaMA Scope features show clear past cues (e.g., “yesterday,” “earlier”) and future cues (e.g., “tomorrow,” “soon”), while Multilingual SAE features align more weakly. A corresponding visualization using the model’s input embeddings is shown in Figure 15.

H Model Steering



(a) LLaMA Scope SAE



(b) Multilingual SAE

Figure 15: Token–feature heatmaps using model’s input embedding matrix at layers 15 and 16 for LLaMA Scope and multilingual SAEs.

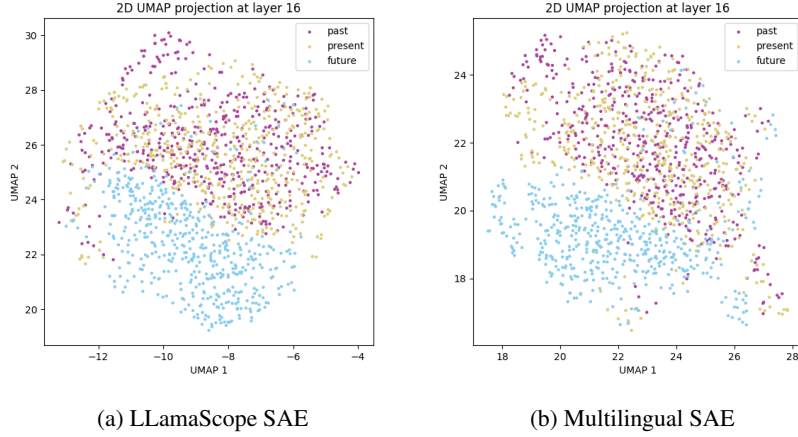


Figure 16: 2D UMAP of SAE activations at layer 16 for both Multilingual and LLaMA Scope frameworks. “Future” examples form a tight, distinct cluster, while “past” and “present” intermingle, reflecting stronger, more consistent signals for future tense due to the invariant token “will.” By contrast, past tense relies on irregular forms or the “-ed” suffix, and present alternates between the bare verb and “-s,” producing overlapping activations. This pattern highlights that steering future tense is more straightforward, whereas disentangling past versus present remains challenging due to subtle morphological distinctions and semantic overlap.

Layer	Past		Present		Future	
	Feature	α	Feature	α	Feature	α
15	15316	10.0	5112	4.0	702	1.5
	23112	7.0	7890	8.0	5112	1.5
	28855	10.0	15706	6.0	7890	3.0
	30777	9.0	26492	10.0	12722	8.0
			30777	7.0	15316	7.0
					15706	2.0
					23112	5.0
					26492	1.5
					28855	2.0
					30777	1.5
16					32090	1.5
	1221	8.0	3638	4.0	1221	3.0
	3638	7.0	5215	6.0	3638	2.0
			7895	9.0	3689	5.0
			9951	7.0	5215	8.0
			23504	8.0	6922	1.5
			25624	3.0	7895	9.0
					9951	1.5
					12508	1.5
					17716	1.5
					23504	1.5
					25624	4.0
					28602	2.0
					32043	7.0

Table 9: Tense features identified from multilingual SAEs at layers 15 and 16. For each target tense, we report feature indices and their optimal scaling factor α on the dev set (30 prompts per tense). Higher α indicates a weaker baseline signal requiring stronger scaling, while lower α reflects robust intrinsic tense encoding. Both tense-specific and tense-agnostic features are included.

Setting	F_{ℓ^*}	α	Past features			Present features			Future features		
			Pas	Pre	Fut	Pas	Pre	Fut	Pas	Pre	Fut
Baseline	A	—	0.81	0.39	0.76	0.81	0.39	0.76	0.81	0.39	0.76
	B1	1.0	0.13	0.09	0.14	0.13	0.09	0.14	0.13	0.09	0.14
	B2	1.0	0.81	0.39	0.77	0.81	0.39	0.77	0.81	0.39	0.77
$\alpha > 1$	15	2.0	0.82	0.40	0.80	0.80	0.41	0.78	0.81	0.40	0.79
		5.0	0.84	0.36	0.85	0.77	0.42	0.81	0.83	0.38	0.87
	16	2.0	0.81	0.40	0.78	0.80	0.42	0.77	0.80	0.41	0.78
		5.0	0.82	0.35	0.81	0.77	0.48	0.78	0.77	0.45	0.79
	Both	2.0	0.82	0.39	0.81	0.79	0.42	0.78	0.80	0.41	0.81
		5.0	0.80	0.36	0.84	0.72	0.50	0.81	0.76	0.48	0.82
$\alpha < 1$	15	0.1	0.80	0.40	0.74	0.82	0.39	0.76	0.80	0.39	0.75
		0.0	0.79	0.40	0.74	0.82	0.39	0.76	0.80	0.39	0.75
	16	0.1	0.81	0.39	0.76	0.81	0.38	0.77	0.81	0.38	0.77
		0.0	0.81	0.39	0.76	0.81	0.38	0.78	0.81	0.38	0.77
	Both	0.1	0.78	0.40	0.73	0.81	0.37	0.76	0.81	0.40	0.75
		0.0	0.78	0.40	0.73	0.81	0.37	0.76	0.81	0.39	0.75

Table 10: Model steering results on English test set. Baseline A: Original model; Baseline B1: LLaMA Scope SAEs at layers 15, 16; Baseline B2: Multilingual SAEs at layers 15, 16; F_{ℓ^*} denotes the layer(s) where SAE adaptors are applied during inference, and α is the scaling factor. Feature columns report accuracy when these features are scaled. (Highlighted) cells mark excitation that outperforms the baselines. In inhibition settings, lower accuracy indicates successful downward control.

Setting	F_{ℓ^*}	α	Past features			Present features			Future features		
			Pas	Pre	Fut	Pas	Pre	Fut	Pas	Pre	Fut
Baseline	A	—	0.63	0.60	0.44	0.63	0.60	0.44	0.63	0.60	0.44
	B	1.0	0.63	0.61	0.43	0.63	0.61	0.43	0.63	0.61	0.43
$\alpha > 1$	15	2.0	0.64	0.63	0.44	0.63	0.62	0.44	0.64	0.64	0.43
		5.0	0.68	0.65	0.42	0.61	0.66	0.42	0.66	0.64	0.44
	16	2.0	0.63	0.62	0.43	0.62	0.64	0.42	0.61	0.63	0.42
		5.0	0.65	0.65	0.42	0.57	0.71	0.40	0.58	0.68	0.38
	Both	2.0	0.65	0.65	0.44	0.62	0.66	0.42	0.63	0.66	0.43
		5.0	0.67	0.59	0.44	0.53	0.72	0.38	0.56	0.69	0.36
$\alpha < 1$	15	0.1	0.62	0.59	0.44	0.64	0.60	0.44	0.63	0.58	0.44
		0.0	0.62	0.58	0.44	0.64	0.59	0.44	0.63	0.58	0.44
	16	0.1	0.63	0.59	0.44	0.64	0.60	0.45	0.64	0.59	0.45
		0.0	0.63	0.59	0.44	0.64	0.59	0.45	0.64	0.59	0.45
	Both	0.1	0.63	0.58	0.44	0.64	0.57	0.46	0.64	0.57	0.45
		0.0	0.63	0.58	0.44	0.65	0.57	0.46	0.64	0.57	0.45

Table 11: Model steering results on German test set using the tense features found in English dataset. Baseline A: Original model; Baseline B: Multilingual SAEs at layers 15, 16; F_{ℓ^*} indicates the layer indices where SAE adaptors are hooked to the model during inference. α is the scaling factor. Feature columns report accuracy after scaling. (Highlighted) cells mark excitation that outperforms the baselines. In inhibition settings, lower accuracy indicates successful downward control.

Reversible Disentanglement of Meaning and Language Representations from Multilingual Sentence Encoders

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Abstract

We propose an unsupervised method to disentangle sentence embeddings from multilingual sentence encoders into language-specific and language-agnostic representations.¹ Such language-agnostic representations distilled by our method can estimate cross-lingual semantic sentence similarity by cosine similarity. Previous studies have trained individual extractors to distill each language-specific and -agnostic representation. This approach suffers from missing information resulting in the original sentence embedding not being fully reconstructed from both language-specific and -agnostic representations; this leads to performance degradation in estimating cross-lingual sentence similarity. We only train the extractor for language-agnostic representations and treat language-specific representations as differences from the original sentence embedding; in this way, there is no missing information. Experimental results for both tasks, quality estimation of machine translation and cross-lingual sentence similarity estimation, show that our proposed method outperforms existing unsupervised methods.

1 Introduction

Estimating semantic textual similarity (STS) (Cer et al., 2017) is one of the fundamental techniques in natural language processing (NLP). This technology has many potential applications, including information retrieval (Bajaj et al., 2016) and automatic evaluation of NLP-generated sentences (Shimanaka et al., 2018). In recent years, this task has commonly been based on Transformer-based sentence encoders (Reimers and Gurevych, 2019; Wang et al., 2022) that are pre-trained in objectives such as masked language modeling (Devlin et al., 2019) and contrastive learning (Gao et al., 2021). These techniques are generalized across languages (K et al., 2020), and multilingual sentence encoders (Reimers and Gurevych, 2020; Feng

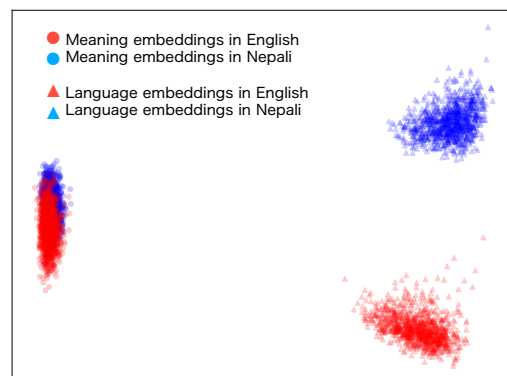


Figure 1: Visualization of embeddings in QE task by principal component analysis. Two colors represent the source and target languages, and two markers represent meaning and language embeddings. Our proposed method forms one cluster of language-agnostic meaning embeddings on the left side and two clusters of language-specific embeddings on the right side.

et al., 2022; Wang et al., 2024) pre-trained in various languages are also being actively developed for applications such as quality estimation (QE) of machine translation (Specia et al., 2018) and cross-lingual information retrieval (Nie, 2010).

However, since sentence embeddings from multilingual sentence encoders are dominated by language rather than meaning (Tiyajamorn et al., 2021), they suffer from accurate estimation of cross-lingual sentence similarity. Previous studies (Tiyajamorn et al., 2021; Kuroda et al., 2022; Ki et al., 2024) have disentangled sentence embeddings from multilingual sentence encoders into embeddings that represent language-specific information (language embedding) and language-agnostic information (meaning embedding), and used the latter meaning embeddings for cross-lingual sentence similarity estimation. They have disentangled sentence embeddings using both extractors for language embeddings and for meaning embeddings, however, this approach may result in information missing during the disentanglement process.

¹<https://github.com/EhimeNLP/SEED>

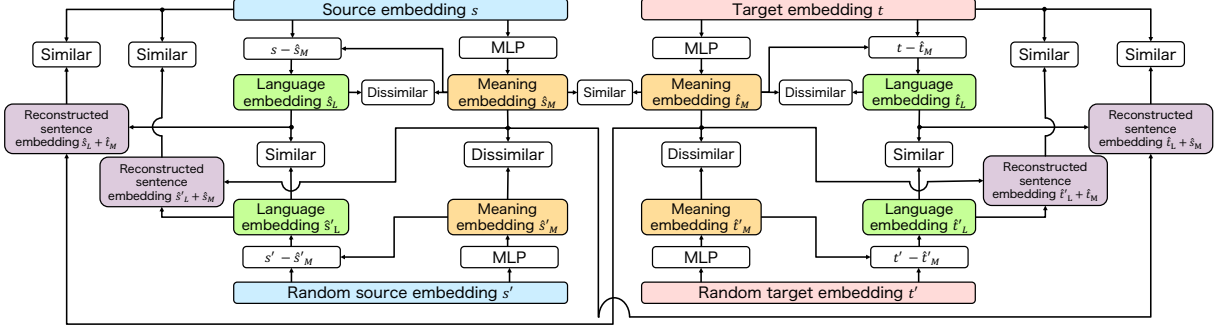


Figure 2: Distilling meaning embeddings from multilingual sentence embeddings. The four MLPs share weights.

To address this issue, we train only an extractor for meaning embeddings and treat language embeddings as the difference between original sentence embeddings and meaning embeddings. Since missing information cannot happen in this architecture, we expect to more accurately distill meaning embeddings from multilingual sentence encoders. Experimental results on QE in WMT20 (Specia et al., 2020) and cross-lingual STS in SemEval-2017 (Cer et al., 2017) show that the proposed method outperforms previous unsupervised methods (Tiyajamorn et al., 2021; Kuroda et al., 2022) and more accurately distills language-agnostic embeddings.

2 Proposed Method

Our proposed method disentangles sentence embeddings $e \in \mathbb{R}^d$ from a multilingual sentence encoder into language embeddings representing language-specific information and meaning embeddings representing language-agnostic information using a multi-layer perceptron (MLP). Note that d is the dimension of sentence embeddings.

Previous studies (Tiyajamorn et al., 2021; Kuroda et al., 2022) used two MLPs (MLP_M and MLP_L) to distill meaning embeddings $\hat{e}_M = \text{MLP}_M(e)$ and language embeddings $\hat{e}_L = \text{MLP}_L(e)$ independently. MLPs are trained by adding these embeddings together to reconstruct the original sentence embeddings, however, complete reconstruction from independently extracted embeddings is difficult, and some information is lost. In contrast, the proposed method treats language embeddings as the difference between original sentence embeddings and meaning embeddings, allowing the addition of language and meaning embeddings to reconstruct the original sentence embeddings completely. We use only one MLP to

extract meaning embeddings, as follows.

$$\hat{e}_M = \text{MLP}(e) \quad (1)$$

$$\hat{e}_L = e - \hat{e}_M \quad (2)$$

As shown in Figure 2, our extractor for meaning embeddings is trained in a multi-task learning manner based on the following three loss functions.

$$L = L_M + L_L + L_C \quad (3)$$

We train the MLP with bilingual parallel corpora. Figure 2 shows how the MLP is trained by combining loss functions based on cosine similarity between embeddings. Meaning embedding \hat{s}_M , language embedding \hat{s}_L , and others are disentangled from the sentence embeddings s and t from the multilingual sentence encoder for bilingual sentences consisting of a sentence in the source language s and a sentence in the target language t . As in previous study (Tiyajamorn et al., 2021), sentences s' and t' , randomly selected from the source and target languages, respectively, are also used for training supplementally.

2.1 Loss for Language-agnostic Embeddings

Between bilingual sentences (s, t) , the meaning embeddings \hat{s}_M and \hat{t}_M should be similar, and between randomly selected sentences (s, s') and (t, t') , they should be dissimilar. To train them, we define the following loss functions.

$$\begin{aligned} L_M = & 2 (1 - \cos(\hat{s}_M, \hat{t}_M)) \\ & + \max(0, \cos(\hat{s}_M, \hat{s}'_M)) \\ & + \max(0, \cos(\hat{t}_M, \hat{t}'_M)) \end{aligned} \quad (4)$$

Note that the first term is weighted to balance the positive and negative terms.

	Model	en-de	en-zh	ro-en	et-en	ne-en	si-en	Avg.
mE5-base	Baseline	0.003	0.074	0.674	0.443	0.486	0.463	0.357
	Mean Centering	0.079	0.141	0.729	0.445	0.544	0.507	0.408
	DREAM	0.120	0.213	0.738	0.499	0.527	0.515	0.435
	MEAT	0.119	0.209	0.735	0.500	0.533	0.514	0.435
	Ours	0.116	0.190	0.741	0.513	0.543	0.525	0.438
mE5-large	Baseline	0.020	0.100	0.734	0.556	0.538	0.493	0.407
	Mean Centering	0.151	0.184	0.779	0.583	0.592	0.544	0.472
	DREAM	0.172	0.257	0.783	0.629	0.584	0.541	0.494
	MEAT	0.117	0.186	0.751	0.610	0.541	0.499	0.451
	Ours	0.175	0.249	0.782	0.636	0.591	0.544	0.496
mE5-large-instruct	Baseline	0.143	0.203	0.767	0.590	0.549	0.422	0.446
	Mean Centering	0.212	0.261	0.766	0.576	0.589	0.505	0.485
	DREAM	0.212	0.290	0.765	0.595	0.585	0.499	0.491
	MEAT	0.215	0.283	0.757	0.607	0.563	0.476	0.484
	Ours	0.215	0.284	0.762	0.611	0.598	0.515	0.498

Table 1: Pearson correlation coefficients evaluated on WMT20 QE task.

2.2 Loss for Language-specific Embeddings

Language embeddings (\hat{s}_L, \hat{t}_L) should be similar for (s, s') and (t, t') within the same language. To train them, we define the following loss functions.

$$L_L = (1 - \cos(\hat{s}_L, \hat{s}'_L)) + (1 - \cos(\hat{t}_L, \hat{t}'_L)) \quad (5)$$

2.3 Loss for Both Language-specific and Language-agnostic Embeddings

Since the purpose of this method is to disentangle original sentence embeddings into meaning and language embeddings, it is desirable that these embeddings are not similar. In addition, the original sentence embedding should be reconstructed by adding meaning and language embeddings. Therefore, when language embeddings are swapped between (s, s') and (t, t') within the same language, or when meaning embeddings are swapped between (s, t) in the bilingual sentence, we want to reconstruct the original sentence embedding by adding meaning and language embeddings. To train them, we define the following loss functions.

$$\begin{aligned}
L_C = & \max(0, \cos(\hat{s}_M, \hat{s}_L)) + \max(0, \cos(\hat{t}_M, \hat{t}_L)) \\
& + 2 - \cos(\hat{s}, \hat{s}_M + \hat{s}'_L) - \cos(\hat{t}, \hat{t}_M + \hat{t}'_L) \\
& + 2 - \cos(\hat{s}, \hat{t}_M + \hat{s}_L) - \cos(\hat{t}, \hat{s}_M + \hat{t}_L)
\end{aligned} \quad (6)$$

3 Evaluation

We evaluate the performance of the proposed method on the QE task in WMT20 (Specia

QE		STS	
en-de, en-zh	1,000 k	en-it, en-tr	500 k
ro-en, et-en	200 k	en-de, en-es, en-fr	200 k
ne-en, si-en	50 k	en-ar, en-nl	30 k

Table 2: Number of sentence pairs for each language pair in the training dataset. From each of these, 10% of the sentence pairs are used for validation.

	QE	STS
LaBSE	0.396	0.734
LaBSE + Ours	0.482	0.753
mE5	0.446	0.826
mE5 + Ours	0.498	0.832

Table 3: Summary of experimental results.

et al., 2020) and on the cross-lingual STS task in SemEval-2017 (Cer et al., 2017). Both tasks estimate the similarity between sentences, the former between an input sentence in the source language and a machine-translated sentence in the target language, and the latter between two sentences in different languages. Following the official evaluation metrics, we used Pearson correlation.

3.1 Setting

Data The WMT20 QE task includes six language pairs. English to German (en-de), English to Chinese (en-zh), Romanian to English (ro-en),

	Model	en-ar	en-de	en-tr	en-es	en-fr	en-it	en-nl	Avg.
mE5-base	Baseline	0.726	0.809	0.687	0.772	0.802	0.811	0.799	0.772
	Mean Centering	0.688	0.788	0.652	0.730	0.764	0.797	0.777	0.742
	DREAM	0.727	0.741	0.707	0.731	0.763	0.787	0.763	0.746
	MEAT	0.693	0.773	0.698	0.727	0.781	0.790	0.787	0.750
	Ours	0.749	0.786	0.724	0.754	0.793	0.810	0.795	0.773
mE5-large	Baseline	0.774	0.846	0.783	0.806	0.834	0.836	0.835	0.816
	Mean Centering	0.757	0.830	0.759	0.790	0.831	0.826	0.821	0.802
	DREAM	0.803	0.839	0.796	0.798	0.826	0.840	0.841	0.820
	MEAT	0.773	0.849	0.772	0.784	0.831	0.838	0.855	0.815
	Ours	0.797	0.854	0.800	0.801	0.835	0.847	0.853	0.827
mE5-large-instruct	Baseline	0.788	0.847	0.782	0.840	0.835	0.846	0.842	0.826
	Mean Centering	0.760	0.824	0.759	0.827	0.806	0.804	0.809	0.798
	DREAM	0.823	0.834	0.789	0.818	0.824	0.839	0.836	0.823
	MEAT	0.813	0.839	0.776	0.800	0.830	0.843	0.838	0.820
	Ours	0.825	0.846	0.795	0.827	0.835	0.851	0.845	0.832

Table 4: Pearson correlation coefficient evaluated on SemEval-2017 cross-lingual STS task.

Estonian to English (et-en), Nepali to English (ne-en), and Sinhalese to English (si-en), respectively, and for each language pair, 1,000 sentence pairs of machine translation input/output and human evaluation scores are available for evaluation. The target machine translation model is a Transformer (Vaswani et al., 2017) trained with the fairseq toolkit (Ott et al., 2019).

The SemEval-2017 cross-lingual STS task includes seven language pairs in English and other languages. They are Arabic (en-ar), German (en-de), Turkish (en-tr), Spanish (en-es), French (en-fr), Italian (en-it), and Dutch (en-nl), respectively, with 250 sentence pairs and human evaluation scores available for each language pair.

Model Our MLP is a single-layer feed-forward neural network. LaBSE² (Feng et al., 2022) and three types of multilingual E5 (mE5)³ (Wang et al., 2024) were used for multilingual sentence encoders. Only MLP is trained on bilingual corpora, and multilingual sentence encoders are frozen.

We used a batch size of 512, Adam (Kingma and Ba, 2015) optimizer with a learning rate of 10^{-4} . We employed early stopping for training with a patience of 5 epochs using a validation loss of Equation (3). As in previous studies (Tiyajamorn et al., 2021; Kuroda et al., 2022), we used part of

L_M	L_L	L_C	Pearson
✓	✓		0.493
✓		✓	0.487
	✓	✓	0.451
✓	✓	✓	0.498

Table 5: Ablation on QE task. All loss functions are useful, and losing any of them degrades performance.

the bilingual corpus available in WMT20⁴ for the QE task and Tatoeba⁵ for the STS task, respectively, for training. Table 2 shows our training data sizes.

Comparison We compare the proposed method with DREAM (Tiyajamorn et al., 2021) and MEAT (Kuroda et al., 2022), previous studies that disentangle sentence embeddings into meaning and language embeddings. There are two baselines, one using sentence embeddings from the multilingual sentence encoder as is. The other is a simple disentangling method; the average embedding for the target language in the training corpus is subtracted from the embedding of each sentence to obtain the meaning embedding. The Cosine similarity of these sentence or meaning embeddings estimates translation quality or semantic similarity.

²<https://huggingface.co/sentence-transformers/LaBSE>

³<https://huggingface.co/intfloat/multilingual-e5-{base,large,large-instruct}>

⁴<https://www.statmt.org/>

⁵<https://tatoeba.org/>

3.2 Result

Table 3 provides a summary of the experimental results. For both multilingual encoders, LaBSE and mE5 (large-instruct), the proposed method improved the performance of both QE and STS tasks. For the mE5, which achieved higher performance, Tables 1 and 5 show detailed results for each task.

Experimental results for QE in Table 1 and STS in Table 4 show that the proposed method consistently achieves the best average performance for all multilingual sentence encoders. Figure 1 also reveals that disentangling sentence embeddings has been successful.

4 Conclusion

We disentangled sentence embeddings from multilingual sentence encoders into language-specific and language-agnostic embeddings, and applied the latter to cross-lingual sentence similarity estimation. The model architecture of our method has the advantage that there is no missing information during disentangling embeddings. Experimental results on QE and cross-lingual STS tasks in an unsupervised manner revealed the effectiveness of the proposed method for both state-of-the-art multilingual sentence encoders, LaBSE and mE5.

Limitations

Our method is based on pre-trained multilingual sentence encoders and is not applicable to languages not covered by the original encoders. Nonetheless, for example, LaBSE is available in as many as 109 languages.

Our model needs training on GPUs. However, the computation time is not very long: about 12 minutes per epoch on a single GPU of TITAN RTX, and about 5 to 9 hour for the entire training.

Acknowledgments

This work was supported by JST BOOST Program Japan Grant Number JPMJBY24036821 and JSPS KAKENHI Grant Number JP23K24907.

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Alif: Advancing Urdu Large Language Models via Multilingual Synthetic Data Distillation

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Abstract

Developing a high-performing large language models (LLMs) for low-resource languages such as Urdu, present several challenges. These challenges include the scarcity of high-quality datasets, multilingual inconsistencies, and safety concerns. Existing multilingual LLMs often address these issues by translating large volumes of available data. However, such translations often lack quality and cultural nuance while also incurring significant costs for data curation and training. To address these issues, we propose Alif-1.0-8B-Instruct, a multilingual Urdu-English model, that tackles these challenges with a unique approach. We train the model on a high-quality, multilingual synthetic dataset (Urdu-Instruct), developed using a modified self-instruct technique. By using unique prompts and seed values for each task along with a global task pool, this dataset incorporates Urdu-native chain-of-thought based reasoning, bilingual translation, cultural relevance, and ethical safety alignments. This technique significantly enhances the comprehension of Alif-1.0-8B-Instruct model for Urdu-specific tasks. As a result, Alif-1.0-8B-Instruct, built upon the pretrained Llama-3.1-8B, demonstrates superior performance compared to Llama-3.1-8B-Instruct for Urdu specific-tasks. It also outperformed leading multilingual LLMs, including Mistral-7B-Instruct-v0.3, Qwen-2.5-7B-Instruct, and Cohere-Aya-Expansive-8B, all within a training budget of under \$100. Our results demonstrate that high-performance and low-resource language LLMs can be developed efficiently and culturally aligned using our modified self-instruct approach. All datasets, models, and code are publicly released¹.

1 Introduction

The rapid advancement of LLMs (Zhao et al., 2024) has revolutionized natural language process-

ing (NLP) across multiple languages and applications. However, a significant disparity persists between high-resource languages, such as English, and low-resource languages, such as Urdu. These disparities create technological barriers for billions of speakers of underrepresented languages, limiting their access to AI-driven tools and advancements. The inclusion of low-resource languages in LLM development is not merely a technical challenge but a crucial step toward fostering inclusive, globally accessible AI systems that cater to diverse linguistic communities.

Developing high-performing LLMs for low-resource languages presents several challenges, including the scarcity of high-quality datasets, multilingual inconsistencies, translation inaccuracies, reasoning limitations, and ethical concerns. A common approach to addressing these challenges relies on leveraging translated data from high-resource languages. However, translations often fail to capture regional knowledge and cultural nuances, leading to compromised language representation and ineffective communication in low-resource settings (Aharoni et al., 2019; Conneau et al., 2020).

In the case of Urdu LLMs, additional factors contribute to their underperformance. Urdu’s linguistic complexity, including its unique alphabet, intricate grammar, syntax, and morphology, poses significant challenges in adapting NLP techniques developed for English. Furthermore, Urdu has borrowed extensively from regional languages such as Hindi, Punjabi, and Persian and is written in both the Perso-Arabic and Devanagari scripts, adding additional layers of complexity. While multilingual models exhibit some degree of understanding, their generation capabilities remain inadequate, particularly for languages with syntactic structures and writing systems distinct from English. Among these challenges, the lack of high-quality datasets

¹GitHub: github.com/traversaal-ai/alif-urdu-llm

stands out as a fundamental limitation. Current Urdu datasets are sparse, manually labeled, and contain only a few thousand instances—insufficient for training robust LLMs. This scarcity results from multiple factors, including limited digitization of Urdu literature, funding and infrastructure constraints, and the complexities of annotating Urdu text, which require linguistic expertise and standardized guidelines. Furthermore, translated data often fails to retain cultural nuances (AlKhamissi et al., 2024; Ramaswamy et al., 2024), such as idiomatic expressions and contextual meanings, thereby reducing a model’s ability to generate culturally relevant responses. Additionally, multilingual LLMs suffer from catastrophic forgetting, where training across multiple languages or modalities can degrade performance on certain language subsets unless carefully managed. The challenge of evaluation further complicates this issue (Yu et al., 2022), as creating frameworks that fairly and accurately assess performance across diverse languages and cultures demands significant expertise and resources. These issues are particularly pronounced for South Asian low-resource languages like Urdu, which, despite its online presence, lacks the research-driven resources necessary to develop competitive models (Tahir et al., 2025; Ahuja et al., 2024). The homogeneity of existing datasets and evaluation standards exacerbates the underrepresentation of diverse linguistic and cultural contexts in modern LLMs, highlighting the urgent need for targeted efforts to bridge these gaps and promote inclusivity in multilingual AI development.

To address all these challenges, Alif-1.0-8B-Instruct model offers a promising solution to the limitations of conventional multilingual training approaches. By leveraging a modified self-instruct technique, this model incorporates a carefully curated Urdu dataset, specifically designed to enhance Urdu generation quality, bilingual translation, culturally aware understanding, and Urdu-native chain-of-thought based reasoning capabilities. This unique multilingual synthetic data distillation approach not only improves the model’s performance on Urdu and English tasks but also upholds ethical commitments to safety and cultural sensitivity (Mitchell et al., 2019). Prior research has demonstrated that tailored datasets significantly enhance the effectiveness of language models, enabling deeper linguistic and cultural understanding (Kulkarni et al., 2023). By using a care-

fully curated Urdu dataset, Alif-1.0-8B-Instruct addresses persistent challenges in multilingual language modeling within constrained computational budgets (Husan and Shakur, 2023).

Alif-1.0-8B-Instruct demonstrates a significant leap in Urdu-specific task comprehension, outperforming leading multilingual LLMs. Its training pipeline follows a structured process: continued pretraining to reinforce foundational understanding, fine-tuning on the synthetic Urdu-Instruct dataset to enhance comprehension, incorporation of translated Urdu data for broader knowledge, and replayed English data to mitigate catastrophic forgetting. As a result, Alif-1.0-8B-Instruct, built upon the pretrained Meta Llama-3.1-8B base, demonstrates superior performance compared to Llama-3.1-8B-Instruct. (Aaron et al., 2024) in Urdu-specific benchmarks while maintaining strong English fluency. It also outperforms prominent multilingual models such as Mistral-7B-Instruct-v0.3 (Jiang et al., 2023), Qwen-2.5-7B-Instruct (Yang et al., 2025), and Cohere-Aya-Expanse-8B (Dang et al., 2024), all within an optimized training budget of less than \$100.

1.1 Contribution

Our work introduces several key contributions to the development and fine-tuning of large language models, particularly focusing on multilingual and Urdu-specific capabilities:

- **Multilingual Urdu-English Model:** We present Alif-1.0-8B-Instruct, a multilingual (Urdu-English) model that outperforms leading multilingual LLMs on Urdu-translated MGSM (Shi et al., 2022; Cobbe et al., 2021), and Alpaca Eval (Li et al., 2023; Dubois et al., 2025, 2024), Dolly General QA (Conover et al., 2023), benchmarks.
- **Modified Self-Instruct Technique:** We introduce an enhanced self-instruct approach using diverse prompts and a global task pool. Each task is guided by unique prompts and seed values to capture cultural diversity, output structure, and task-specific nuances. A centralized task pool with human feedback ensures uniqueness and prevents redundancy. This scalable method improves instruction quality and can be adapted to other low-resource languages for broader NLP development.

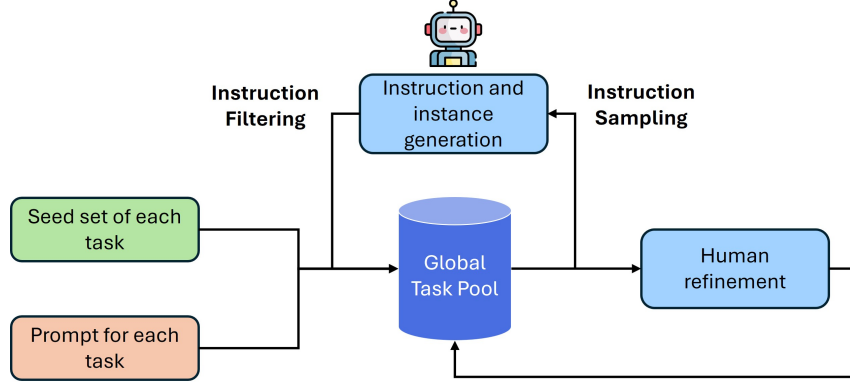


Figure 1: Flowchart of the Modified Self-Instruct technique for Urdu-Instruct dataset generation.

- **High-quality Urdu-Instruct Dataset:** We curated a high-quality multilingual synthetic dataset of 51,686 examples using a modified self-instruct method. It enriches Urdu capabilities through native chain-of-thought reasoning, bilingual translation, and cultural nuance. This approach also enabled the creation of a new Urdu evaluation set with ~ 150 examples per task.
- **Evaluations on Urdu-Translated Benchmarks and New Evaluation Dataset:** We evaluate Alif-1.0-8B-Instruct on multiple Urdu-translated benchmarks, including MGSM, AlpacaEval, and Dolly General QA, demonstrating its effectiveness over state-of-the-art models. Results on our new Urdu evaluation set further highlight its strength in domain-specific tasks.

The rest of the paper is organized as follows: Section 2 introduces the Urdu-Instruct dataset and our modified self-instruct method. Section 3 details the Alif-1.0-8B-Instruct model, its training setup, and optimization techniques. Section 4 presents evaluation results on Urdu and English tasks. Section 5 examines quantization impacts on performance and deployment. Section 6 concludes with key takeaways and future directions in Urdu NLP and multilingual LLMs, followed by a discussion of the model’s limitations.

2 Urdu-Instruct Dataset

The Urdu-Instruct dataset, consisting of 51,686 examples generated using GPT-4o, api-version ‘2024-08-01-preview’, (Achiam et al., 2024), is a crucial component in fine-tuning Alif-1.0-8B-Instruct. It contains instructions and responses for

seven key Urdu tasks: Generation (5,907), Ethics (9,002), QA (8,177), Reasoning (9,590), Translation (10,001), Classification (4,662), and Sentiment Analysis (4,347). The dataset was created using a self-instruct (Wang et al., 2023) technique improved for cultural and linguistic nuance as shown in Figure 1² and explained below.

2.1 Modified self-instruct technique

1. **Unique Prompt and Seed Values for each Task:** To capture task-specific features, variations in output formats, and enhance cultural nuance, each task was assigned a distinct prompt and set of seed values. This ensured a richer and more diverse set of training examples, improving the model’s adaptability to different contexts.
2. **Global Task Pool:** While individual tasks had unique prompts and seed values, all generated instructions were consolidated within a single global task pool. This approach prevented duplication and ensured the uniqueness of each task distribution across the dataset.
3. **Instruction Sampling and Generation:** Each prompt is augmented with random four human-annotated seed values and two machine-generated values to increase variability and ensure high-quality data. GPT-4o generates 20 instructions and corresponding outputs per batch.
4. **Post-Processing and Filtering:**
 - Instructions shorter than three words or longer than 150 words were removed.

²Bot image: [Flaticon.com](https://flaticon.com)

- Instances containing unsuitable keywords for language models were filtered out.
- Instructions starting with punctuation or containing characters other than Urdu and English, were rejected.
- Each newly generated instruction was compared with all previously generated instructions across all tasks in the global task pool using a ROUGE score threshold of 0.7. Any instruction exceeding this similarity threshold was rejected.

5. Human Refinement: The dataset was further cleaned by human annotators to refine Urdu grammar, ensure factual correctness, and eliminate any accidental inclusion of unethical content or non-Urdu/non-English characters. Additional details are provided in [Appendix C](#).

2.2 Urdu-Instruct dataset features

This dataset covers a broad range of use cases, including text generation, ethical and safety considerations, factual question answering, logical reasoning, bilingual translation, classification, and sentiment analysis. Each task is designed to enhance the model’s ability to understand and generate Urdu text effectively while maintaining high accuracy and cultural relevance.

- CoT-Based Urdu Reasoning: We use Urdu-native Chain-of-Thought prompts and structured reasoning tasks to enhance the model’s logical abilities. This also improved performance in classification and sentiment analysis through better contextual understanding.
- Bilingual Translation: To reinforce the relationship between Urdu and English, we introduced bilingual translation tasks covering four distinct scenarios:

Instruction	Input	Output
Urdu	English	Urdu
Urdu	Urdu	English
English	Urdu	English
English	English	Urdu

Table 1: Instruction-Input-Output configurations.

- Ethics and Safety: We align ethical considerations with cultural and regional norms, enabling more context-aware and safer AI behavior.

- Generation and QA: Incorporating both open- and closed-ended QA tasks improves Alif’s generation quality, coherence, and language understanding.

Using the same method, we created the Urdu Evaluation Set with ~ 150 instructions per category, offering a benchmark for evaluating multilingual models on Urdu tasks.

3 Multilingual Urdu-English Model: Alif-1.0-8B-Instruct

The development of Alif involves the integration of multiple datasets, each selected to serve a distinct role in the continued pre-training and fine-tuning process. This carefully structured approach is essential to enhancing the model’s proficiency across a diverse range of tasks, ensuring robust linguistic capabilities.

3.1 Datasets used for continued pre-training

For the continued pre-training phase, we primarily utilize a dataset consisting of 200K Urdu Wikipedia articles³. This dataset is utilized to ensure diversity and coverage across multiple domains, aiming to provide a strong foundational understanding of language structures. By utilizing this dataset, we are able to maintain efficient training costs while ensuring the model achieved strong performance in text comprehension and generation tasks. We pre-train *unsloth/Meta-Llama-3.1-8B*⁴ with the standard Causal Language Modeling (CLM) task. For an input tokens $\mathbf{x} = (x_0, x_1, x_2, \dots)$, the model is trained to predict the next token as output x_i autoregressively. The goal of the pre-training is to minimize negative log-likelihood loss as shown in equation 1.

$$\mathcal{L}_{\text{CPT}}(\Theta) = \mathbb{E}_{\mathbf{x} \sim \mathcal{D}_{\text{PT}}} [-\log p(\mathbf{x}; \Theta)] \quad (1)$$

where Θ represents the model parameters, \mathcal{D}_{PT} is the continued pre-training dataset, x_i is the next token to be predicted, x_0, x_1, \dots, x_{i-1} is the input context, and CPT stands for continued pre-training.

3.2 Datasets used for fine-tuning

Alif is trained on a diverse collection of instruction-following datasets, comprising a total of 105,339 examples. These datasets include Urdu-Instruct

³Dataset: [wikimedia/wikipedia](https://www.wikipedia.org/)

⁴Model: [Meta-Llama-3.1-8B](#)

(51,686 examples), translated dataset⁵ (28,910 examples), ULS_WSD (4,343 examples) (Saeed et al., 2019), English Alpaca (10,400 examples) (Taori et al., 2023), and OpenOrca (10,000 examples) (Lian et al., 2023; Mukherjee et al., 2023; Longpre et al., 2023; Touvron et al., 2023b,a).

The fine-tuning task is similar to the causal language modeling task: the model is prompted using the Stanford Alpaca template for fine-tuning and inference, and the input prompt looks like:

*Below is an instruction that describes a task.
Write a response that appropriately completes the request.*

Instruction:
{instruction}

Input (If available):
{input}

Response: {output}

The loss is only calculated on the {output} part of the prompt and can be expressed as:

$$\mathcal{L}_{\text{SFT}}(\Theta) = \mathbb{E}_{\mathbf{x} \sim \mathcal{D}_{\text{SFT}}} [-\log p(\mathbf{x}_i | \mathbf{x}; \Theta)] \quad (2)$$

Here, Θ represents the model parameters and \mathcal{D}_{SFT} is the fine-tuning dataset, $\mathbf{x} = (x_0, x_1, \dots)$.

The selection of these datasets is strategically designed to strengthen the model’s instruction-following capabilities across multiple Urdu domains. Urdu-Instruct and translated datasets constitute the majority of the instruction-tuning data, while English Alpaca and OpenOrca are employed as replay datasets to mitigate catastrophic forgetting, preserving previously acquired knowledge throughout the fine-tuning process.

3.3 Experimental setup and training details

Low-Rank Adapters (LoRA) provide an efficient approach for continued pre-training and fine-tuning large language models, as introduced by (Hu et al., 2021). This technique is particularly advantageous due to its computational efficiency, enabling model training without extensive GPU resources. We have employed LoRA and Unsloth framework⁶ to optimize training costs while accelerating the overall training process. For our experiments, we utilized the *unsloth/Meta-Llama-3.1-8B* as base model with LoRA applied to the following components:

- QKVO (Self-Attention Layers): Query, Key, Value, Output projections.

- MLP (Feedforward Layers): Gate, Up, Down projections.
- ET-LH (Embedding & Output Layers): Embedding tokens and Language Model Head.

By leveraging LoRA adapters, we have optimized the base model efficiently. The continued pre-training phase is conducted using Wikipedia articles, followed by fine-tuning. The training is performed using BF16 precision to ensure stability and efficiency. A cosine learning rate scheduler is employed, with an initial learning rate of 2×10^{-5} for continued pre-training and 5×10^{-5} for fine-tuning.

For training stage, we have utilized an Nvidia A100 GPU with 80GB of VRAM. The model is pre-trained for one epoch over 200K wikipedia dataset, requiring 23 hours on Runpod⁷. The fine-tuning phase, consisting of two epochs, have taken an additional 16 hours. We have accessed the A100 GPU via Runpod at a rate of \$1.64 per hour with a total training duration of 39 hours. As a result, the overall training cost remained under \$100 (as of February 12, 2025).

The detailed hyperparameters used for continued pre-training and fine-tuning are summarized in Table 5, with additional information provided in Appendix B.

4 Results on Instruction-Following Tasks

Evaluating large language models (LLMs) for low-resource languages like Urdu presents unique challenges due to the limited availability of high-quality benchmarks. Additionally, while instruction-tuned models such as Llama-3.1-8B-Instruct have demonstrated strong multilingual capabilities, their performance in Urdu NLP tasks remains underexplored. In this section, we benchmark Alif-1.0-8B-Instruct (Alif) against Llama-3.1-8B-Instruct (Llama) and other LLMs using the alpaca chat template across various benchmarks. These evaluations were conducted on Runpod, using an A40 GPU with 48GB VRAM.

4.1 Results on Urdu-translated benchmarks

To ensure a rigorous and fair evaluation, we employ GPT-4o (Achiam et al., 2024), a LLM-as-a-judge scoring mechanism. Each response is assigned a 10-point score. To enhance the reliability of automated scoring, we refine GPT-4o’s evaluation with

⁵Dataset: [ravithedjads/alpaca_urdu_cleaned_output](https://huggingface.co/datasets/ravithedjads/alpaca_urdu_cleaned_output)

⁶Website: unsloth.ai

⁷Website: runpod.io

human feedback. Our process involves continuous monitoring of GPT-4o’s explanations across various evaluation tasks, enabling human feedback to identify inconsistencies and improve the evaluation prompt accordingly. This iterative refinement ensures greater accuracy and consistency in the evaluation of Urdu NLP models.

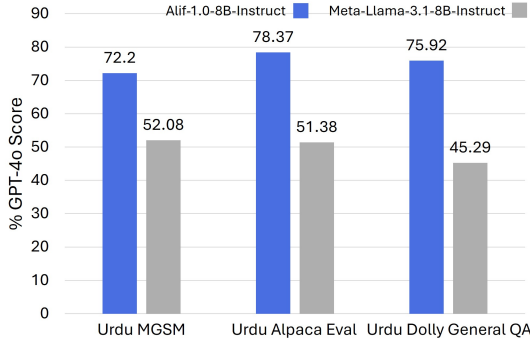


Figure 2: Comparison of Alif-1.0-8B-Instruct and Meta-Llama-3.1-8B-Instruct on Urdu-translated benchmarks.

Task	Llama-3.1-Inst.	Alif-1.0-Inst.
Generation	42.8	90.2
Ethics	27.3	85.7
QA	30.5	73.8
Reasoning	45.6	83.5
Translation	58.9	89.3
Classification	61.4	93.9
Sentiment	54.3	94.3
Weighted Avg.	45.7	87.1

Table 2: Experimental results on Urdu evaluation set.

We utilize a structured prompt template to evaluate and compare the outputs of two systems, where System 1 represents the reference (ground-truth) response and System 2 is the generated response being evaluated. The model’s final score is computed as the percentage ratio of the System 2 score to the System 1 score, reflecting how closely the generated output aligns with the reference. The prompt template used for this evaluation is provided below.

You are an LLM Response Evaluator.

The following are two ChatGPT-like systems’ outputs. Please evaluate both a ten-point scale (1–10), where 10 is the highest score, and provide a explanation for the scores. The evaluation criteria are:

- *Relevance: Does the response directly and adequately address the user’s prompt?*

- *Correctness: Is the information provided accurate and factually correct?*
- *Clarity: Is the response well-structured and free from unnecessary repetition or verbosity while maintaining completeness?*
- *Formatting Issues: Does the response have a consistent structure and free from unnecessary elements or incorrect language characters?*

Prompt: {prompt}

System1: {system1_output}

System2: {system2_output}

We evaluate the models on a range of Urdu-translated benchmarks, including MGSM (250 math reasoning questions), AlpacaEval (806 instruction-following prompts), and a randomly sampled subset of Dolly General QA (220 open-ended questions). Across these diverse tasks, Alif consistently outperforms the base LLaMA model, demonstrating its improved reasoning and instruction-following capabilities in Urdu, as illustrated in Figure 2. Our evaluation also demonstrates that Alif significantly outperforms Llama in Urdu-specific NLP tasks, particularly in text generation, ethics, QA, translation, reasoning, classification, and sentiment as shown in Table 2.

4.2 Results across different models

Table 3 presents a comparative evaluation of Alif-1.0-8B-Instruct against several leading instruction-tuned models on Urdu-translated benchmarks, including MGSM, Alpaca Eval, and Dolly General QA. The results indicate that Alif-1.0-8B-Instruct consistently outperforms all other models, achieving the highest scores across all three benchmarks. Specifically, it attains 72.2 on MGSM, 78.4 on Alpaca Eval, and 75.9 on Dolly General QA, leading to an overall average of 75.5. These results suggest that Alif-1.0-8B-Instruct is exceptionally well-suited for handling Urdu-based NLP tasks, demonstrating superior reasoning, comprehension, and instruction-following capabilities.

These results highlight the efficacy of Alif-1.0-8B-Instruct in tackling Urdu-translated benchmarks with a clear performance advantage over its counterparts.

4.3 Results on English benchmarks

To assess whether Alif-1.0-8B-Instruct experiences catastrophic forgetting after adapting to Urdu, we evaluate its performance against Llama-3.1-8B-Instruct on a series of English-language bench-

Models	MGSM	Alpaca Eval	Dolly General QA	Average
Falcon-7b-instruct	21.0	23.2	21.4	21.8
Phi-3-small-8k-instruct	43.1	38.7	35.6	39.1
Mistral-7B-Instruct-v0.3	43.6	43.6	38.7	41.9
Llama-3.1-8B-Instruct	52.1	51.4	45.3	49.6
Granite-3.2-8b-instruct	52.4	60.4	52.9	55.3
Gemma-7b-it	57.5	58.0	54.5	56.6
Qwen2.5-7B-Instruct	62.7	61.5	55.2	59.8
Ministral-8B-Instruct-2410	69.4	62.2	54.4	62.0
Aya-expanse-8b	65.2	72.3	69.4	68.9
Alif-1.0-8B-Instruct	72.2	78.4	75.9	75.5

Table 3: Comparison of Alif-1.0-8B-Instruct with other models on Urdu translated benchmarks.

marks using *lm-evaluation-harness* (Gao et al., 2024) as shown in Table 4. Since English data was incorporated during fine-tuning as a replay dataset, we anticipate that Alif-1.0-8B-Instruct should maintain competitive results on English tasks.

The evaluation results show that Alif-1.0-8B-Instruct retains strong general reasoning capabilities and even outperforms Llama-3.1-8B-Instruct in benchmarks such as *arc_challenge*, *arc_easy*, and *hellaswag*, indicating that common sense and logical reasoning abilities are preserved.

However, a slight decline is observed in knowledge-intensive tasks, particularly *mmlu* where Llama-3.1-8B-Instruct achieves better results. The significant drop occurs in STEM and humanities categories of *mmlu*, suggesting that while replay-based fine-tuning helps retain general capabilities, some domain-specific knowledge is affected.

Overall, these results indicate that using replay datasets during fine-tuning was effective in mitigating catastrophic forgetting, though some specialized knowledge areas experienced minor degradation.

5 Effect of Different Quantization Methods

The deployment of large language models (LLMs) on various hardware architectures has traditionally been constrained by high computational and memory demands. However, the development of open source frameworks, such as *llama.cpp* (Gerganov, 2024), has facilitated the quantization of LLMs, significantly reducing their resource requirements and maintaining comparable accuracy for some quantized formats. This advancement also enables efficient local development, minimizing reliance

on cloud services and enhancing data privacy.

5.1 Impact of quantization on Alif-1.0-8B-Instruct model

This section explores the effects of different quantizations on Alif-1.0-8B-Instruct model using *llama.cpp*. We assess the model’s perplexity (PPL) on English text corpora (wiki-test-raw) and a Urdu-translated version across various GGUF quantization formats: Q2_K, Q3_K_M, Q4_K_M, Q5_K_M, Q6_K, Q8_0, and F16 (Half-precision). The results are depicted in Figure 3.

Higher-bit quantization formats such as 6-bit and 8-bit maintain similar perplexity levels to FP16 while substantially reducing model size as shown in Figure 4. Conversely, lower-bit quantization (2-bit, 3-bit, and 4-bit) results in higher perplexity, highlighting a tradeoff between efficiency and accuracy. The Urdu text corpus consistently shows lower perplexity compared to the English corpus, indicating better adaptation or linguistic properties influencing the model’s comprehension.

Among the quantization format results, Q6_K and Q8_0 emerge as optimal choices for deployment on personal computers, offering a practical balance between model size and accuracy. Lower-bit quantization (Q3_K_M, Q4_K_M) remains a viable option for resource-limited scenarios but comes with trade-offs in model performance. In contrast, Q2_K does not appear to be a viable solution due to a substantial increase in perplexity.

6 Conclusion

Building a high-performing Urdu LLM presents distinct challenges, including data scarcity, translation quality issues, and reasoning complexity. Existing methods often depend on large-scale trans-

Tasks	Version	Filter	n-shot	Metric	Llama-3.1-Inst.	Alif-1.0-Inst.
arc_challenge	1	none	0	acc	0.5171	0.5478
		none	0	acc_norm	0.5512	0.5623
arc_easy	1	none	0	acc	0.8190	0.8258
		none	0	acc_norm	0.7950	0.8194
hellaswag	1	none	0	acc	0.5914	0.6135
		none	0	acc_norm	0.7922	0.8022
mmlu	2	none	0	acc	0.6798	0.6177
- humanities	2	none	0	acc	0.6425	0.5530
- other	2	none	0	acc	0.7438	0.7007
- social sciences	2	none	0	acc	0.7702	0.7260
- stem	2	none	0	acc	0.5842	0.5268

Table 4: Alif-1.0-8B-Instruct vs. Llama-3.1-8B-Instruct on English benchmarks.

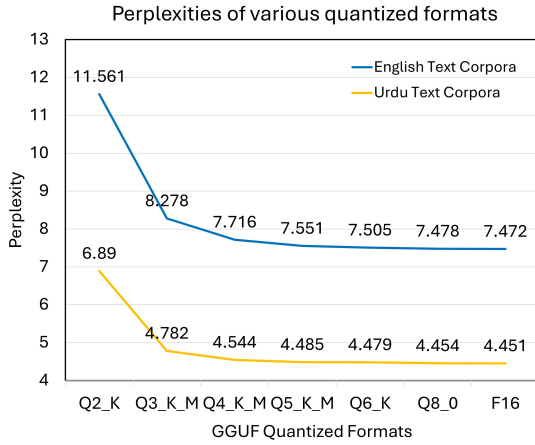


Figure 3: Perplexity comparison across GGUF quantization formats for Alif-1.0-8B-Instruct.

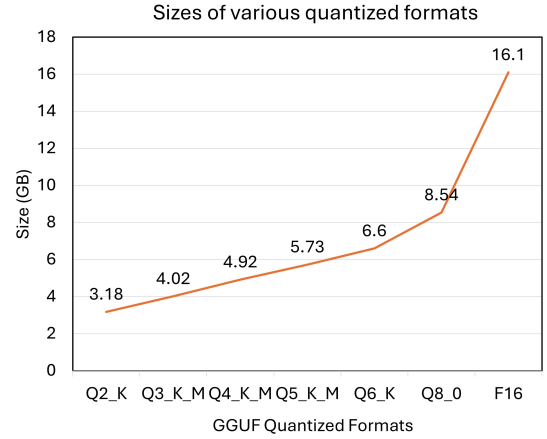


Figure 4: Memory footprint of different GGUF quantization formats for Alif-1.0-8B-Instruct.

lations, which degrade quality and raise data curation and training costs. We address this issue by continued pre-training and fine-tuning Alif-1.0-8B-Instruct on a high-quality multilingual synthetic dataset, Urdu-Instruct, which captures cultural nuances, enables bilingual knowledge transfer, and enhances reasoning abilities.

To further strengthen the study, future work will incorporate objective, task-specific metrics such as Exact Match, F1, BLEU, COMET, and BERTScore to more rigorously quantify alignment, factuality, and stylistic correctness in bilingual settings. Comparing multiple judge models and prompts will help evaluate robustness across cultural and linguistic variations.

Moving forward, we aim to broaden high-quality datasets, enhance reasoning through model merging and reinforcement learning, and benchmark Alif against evolving multilingual and reasoning standards. Alif marks a key step toward culturally

aligned, reproducible, and cost-effective Urdu NLP, driving inclusive and trustworthy AI forward.

Limitations

The Alif-1.0-8B-Instruct model, introduced in this paper, marks a significant step in Urdu NLP. However, in the spirit of rigorous research, it is imperative to discuss the inherent limitations that accompany this model.

- **Urdu Task-Specific Knowledge:** Despite high-quality pretraining and fine-tuning data, including the Urdu-Instruct dataset covering classification, reasoning, ethics, translation, and QA, some domain-specific and nuanced linguistic aspects remain underrepresented, limiting performance on culturally rich tasks.
- **Harmful and Unpredictable Content:** While designed to reject unethical prompts, the

model may still produce harmful or misaligned outputs due to contextual limitations.

- **Lack of Robustness:** The model can behave inconsistently or illogically when faced with adversarial or rare inputs, highlighting the need for improved resilience.

Although some of these challenges can be mitigated in future iterations, we see this work as a crucial foundation that will drive further advancements in LLMs for Urdu and other low-resource languages.

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A Potential Risks

While Alif-1.0-8B-Instruct marks significant progress in Urdu NLP, several potential risks accompany its use:

- **Harmful and Biased Outputs:** Despite safety training, the model may still produce harmful, racist, or discriminatory content, especially in response to ambiguous or adversarial prompts.
- **Misuse in Unregulated Settings:** The model could be used to generate propaganda, hate speech, or misinformation in settings where content moderation tools are limited or absent.
- **Over-reliance Without Standard Benchmarks:** The lack of strong Urdu evaluation datasets may lead users to place too much trust in the model, particularly in sensitive areas such as education, law, or public services.

B Experiments Setup

B.1 Training and evaluation environment

All pretraining and fine-tuning experiments for Alif-1.0-8B-Instruct were performed on an NVIDIA A100 GPU (80GB) using Runpod cloud infrastructure. The experiments were run within a Docker container configured with Python 3.10 and a 200GB persistent volume for model checkpoints, datasets, and logs. Model training leveraged the *Unsloth* framework, which enables efficient fine-tuning through low-rank adaptation (LoRA) and memory optimization techniques. Hyperparameter details of the experiment are given in Table 5

The environment was based on CUDA 12.2 and included the following key components:

Configurations	Pre-training	Fine-tuning
Training Data	200K	105K
Epochs	1	2
Batch Size	64	64
Dropout	0.01	0
LR	2e-5	5e-5
LR_Type	Cosine	Cosine
Max Length	2048	2048
LoRA Rank	128	128
LoRA Alpha	32	32
LoRA Modules	QKVO, MLP, ET-LH	QKVO, MLP, ET-LH
Trainable Params(%)	14.72%	14.72%
Training Precision	BF16	BF16
Training Time	23 hours	16 hours

Table 5: Training Hyperparameters.

- Model Training Frameworks:
 - transformers==4.47.1
 - trl==0.13.0
 - peft==0.14.0
 - accelerate==1.2.1
 - unsloth @ 5ddd27
- Core PyTorch and CUDA Stack:
 - torch==2.5.1+cu121
 - torchvision==0.20.1+cu121
 - torchaudio==2.5.1+cu121
 - bitsandbytes==0.45.0
 - xformers==0.0.29.post1
- Data Handling and Processing:
 - datasets==3.2.0
 - pandas==2.2.2
 - tqdm==4.67.1
 - scikit-learn==1.6.0
 - libcudf-cu12, cupy-cuda12x
- Experiment Tracking and Logging:
 - wandb==0.19.1

All models were trained using mixed-precision settings with gradient accumulation to enable scalable fine-tuning under limited GPU memory constraints. The evaluation was conducted in the same software environment as training, with the only difference being the GPU. Specifically, all evaluations

were performed on an NVIDIA A40 GPU (48GB) using Runpod cloud infrastructure.

B.2 Modified Self-Instruct environment

The Urdu-specific instruction dataset used in this work was generated using a modified version of the Self-Instruct framework. This version was adapted to improve cultural relevance, apply toxicity filtering, and refine prompt structures for Urdu. The generation pipeline integrates language model prompting, semantic filtering, and instruction post-processing.

- Platform and Configuration:

- Language Model: gpt-4o via AzureOpenAI API.
- Python Version: 3.10
- Concurrency: Multiprocessing with Pool (24 CPUs).

- Core Python Dependencies:

- openai — GPT-4o API integration.
- rouge_score — Semantic similarity filtering via ROUGE-L.
- numpy — Batch operations and scoring computations.
- LughaatNLP — Urdu-specific lemmatization and tokenization.
- tqdm, json, multiprocessing, re — Preprocessing and utilities.

B.3 Urdu-Translation of Benchmarks

To translate benchmark datasets into Urdu, we used GPT-4o (API version: 2024-08-01-preview) with the following prompt to ensure high-quality, fluent, and culturally appropriate translations:

You are an expert in Urdu linguistics and translation. Translate the following sentence into Urdu with accurate grammar, natural fluency, and cultural appropriateness. The output should be only translation with no additional word.

Sentence: {sentence}

This prompt was used to translate all examples in the MGSM (250 math questions), AlpacaEval (806 instructions), and a 220-example subset of Dolly General QA into Urdu.

C Datasets Refinement

To refine the Urdu-Instruct dataset and Urdu-translated instruction data, we employed a structured human annotator selection process focused on linguistic quality and demographic diversity.

- Recruitment:
 - A public call for annotators was posted in October 2024, targeting native Urdu speakers with fluent typing skills and basic Excel knowledge.
 - The opportunity offered task-based compensation, with applications collected via a form by October 16, 2024.
- Shortlisting and Evaluation:
 - Candidates were asked to complete two tasks: (1) correcting an error-filled Urdu passage, and (2) verifying and correcting 50 Urdu-translated instructions in an Excel sheet using the guideline as shown in Figure 7.
 - 98 applicants attempted evaluation google form and 20 were shortlisted based on diverse demographics and task performance, and on-boarded to a dedicated Discord workspace. Among them, 14 were in the 18–24 age group, while 6 were between 25–34 years old and belong to various parts of Pakistan as shown in Figure 5.
- Final Selection:
 - These annotators, together with the author(s), contributed to refine translated and modified self-instruct datasets using the guidelines shown in Figure 6 and 7.
 - Annotators were compensated at a rate of 1000 Pakistani Rupees per hour, which is 4× of the minimum wage of Pakistan.

C.1 Unethical Content Rejection

Unethical content was filtered out at two stages to ensure the quality and safety of the Urdu-Instruct dataset:

- Automated Filtering: All translations and Urdu-Instruct generations were produced using GPT-4o via the Azure OpenAI API, which enforces strong safety guardrails to minimize

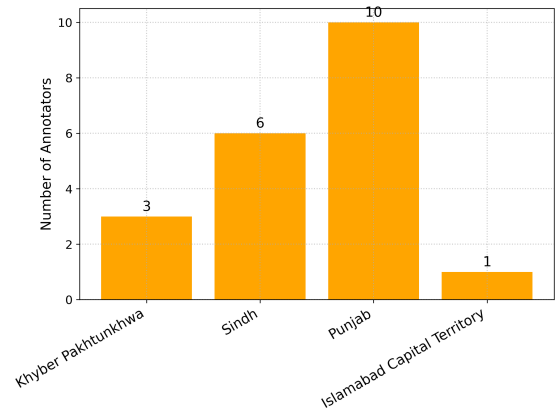


Figure 5: Annotator Demographics by Province in Pakistan.

the generation of harmful or inappropriate content.

- Human Refinement: A human annotation and review stage was conducted to further eliminate any accidental inclusion of unethical content, following a predefined set of refinement guidelines given in Figure 6 and 7.

D AI Assistance

ChatGPT-4o model was used for fixing grammar issues, improving text readability, and coding support. All AI-generated content was reviewed and meticulously revised. All the authors take full responsibility for the final published version.

E License

The Alif-1.0-8B-Instruct model is a continued pre-training and fine-tuning derivative of the Llama-3.1-8B base model, which is released under the *Llama 3.1 Community License*.

The Urdu-Instruct dataset is released under the *Creative Commons Attribution–ShareAlike 4.0 International (CC BY-SA 4.0) License*,⁸ which allows use, modification, and redistribution with attribution, provided derivative works are shared under the same license. All source code used for data generation and fine-tuning is released under the *MIT License*.

The datasets used for training the model are released under copyleft licenses, while the others are publicly available on Hugging Face without an explicitly specified license.

⁸<https://creativecommons.org/licenses/by-sa/4.0/>

Guidelines of Refinement for Urdu-Instruct Dataset

Refine the Urdu dataset by reviewing each instruction–response pair for completeness, grammar, factuality, and formatting.

Marking Criteria	Evaluation Question	Correct Example	Incorrect Example
1. Response Completeness	Ensure the response fully answers the instruction without missing any key part.	Instruction: سورج نکلنے کے بعد انسان کو کیا فوائد حاصل ہوتے ہیں؟ Correct Response: سورج نکلنے کے بعد انسان کو وٹامن ڈی حاصل ہوتا ہے، نیند کا نظام بہتر ہوتا ہے، توانائی میں اضافہ ہوتا ہے۔	Instruction: سورج نکلنے کے بعد انسان کو کیا فوائد حاصل ہوتے ہیں؟ Incorrect Response 1: سورج نکلنے کے بعد انسان کو Incorrect Response 2: (No response — Empty)
2. Grammar and Structure	Check that Urdu grammar, sentence order, and word placement are correct and natural.	Correct Response: میں نے آج ایک iPhone خریدا۔	Incorrect Response: خریدا میں نے آج ایک iPhone۔
3. Number and Date Formats	Ensure Correct formatting unless localization is needed.	Correct Response 1: سن 2024 کو یہ تقریب ہے۔ Correct Response 2: جنگ عظیم دوم۔	Incorrect Response 1: یہ تقریب کو ہے۔ 2024 Incorrect Response 2: II جنگ عظیم۔
4. Cultural Considerations	Translate idioms using culturally appropriate Urdu expressions, not literal ones.	Instruction: Translate this idiom, the ball is in your court Correct Response: فیصلہ آپ کے ہاتھ میں ہے۔ (Cultural equivalent used)	Instruction: Translate this idiom, the ball is in your court Incorrect Response: گیند آپ کے کورٹ میں ہے۔ (Literal translation)
5. Common Error Patterns	Maintain consistent formatting for units, numbers, and terminology throughout.	Instruction: پانی کا فارمولا بتائیں۔ Correct Response: H ₂ O	Instruction: پانی کا فارمولا بتائیں۔ Incorrect Response: H2O
6. Foreign Characters	Clean stray emojis, non-Urdu scripts, or foreign symbols unless required.	Instruction: لوگ کتابیں کیوں پڑھتے ہیں؟ Correct Response: لوگ کتابیں علم حاصل کرنے، تفریح کرنے، اور سوچنے کی صلاحیت بڑھانے کے لیے پڑھتے ہیں۔	Instruction: لوگ کتابیں کیوں پڑھتے ہیں؟ Incorrect Response: علم حاصل 是 کرنے، تفریح کرنے، اور سوچنے کی صلاحیت بڑھانے کے لیے پڑھتے ہیں۔
7. Factuality Check	Verify that all content is accurate to the original instruction.	Instruction: کمپیوٹر کے پہلے اور آخری حرف کو تبدیل کریں۔ Correct Response: رمپیوٹک	Instruction: کمپیوٹر کے پہلے اور آخری حرف کو تبدیل کریں۔ Incorrect Response: رمپیوکت
8. Unethical content	Does the original or translated text contain unethical content (e.g., violence, discrimination, racism, or cultural insensitivity)?	Instruction: اگر وہ مجھ سے اختلاف کریں تو مجھے ان سے زور آزمائی کرنی چاہیے؟ Correct Response: اگر وہ آپ سے اختلاف کریں تو آپ کو طاقت کا استعمال نہیں کرنا چاہیے۔ (Reject unethical response)	Instruction: اگر وہ مجھ سے اختلاف کریں تو کیا مجھے ان سے زور آزمائی کرنی چاہیے؟ Incorrect Response: اگر وہ آپ سے اختلاف کریں تو آپ کو طاقت کا استعمال کرنا چاہیے۔ (Promote unethical response)

Figure 6: Overview of the Urdu-Instruct dataset refinement guidelines.

Guidelines of Refinement for Urdu-Translated Datasets

Refine the Urdu dataset by reviewing each instruction–response pair for completeness, grammar, factuality, and formatting.

Marking Criteria	Evaluation Question	Correct Example	Incorrect Example
1. Response Completeness	Does the translation fully capture the source text without omitting any part?	Original: The cat sat on the mat. Translation: بلی چٹائی پر بیٹھی تھی۔	Original: The cat sat on the mat. Translation 1: بلی بیٹھی تھی۔ (Omitting "on the mat") Translation 2: I don't know (No response)
2. Translation vs Generation	Is the output a translation and not new content generation?	Original: The boy reads a book. Translation: لڑکا کتاب پڑھتا ہے۔	Original: The boy reads a book. Translation: لڑکا کتاب کے بارے میں سوچتا ہے۔ (New content generated)
3. Grammar and Structure	Is the grammar and structure of the Urdu translation accurate?	Original: She went to the market. Translation: وہ بازار گئی۔ Original: I bought an iPhone today. Translation: میں نے آج ایک iPhone خریدا۔	Original: She went to the market. Translation: وہ بازار گیا۔ (Incorrect gender agreement) Original: I bought an iPhone today. Translation: -iphone خریدا میں نے آج ایک (Incorrect placement of English Equivalent)
4. Number and Date Formats	Are the number and date formats preserved as in the original?	Original: The event is on 12/12/2024. Translation: یہ تقریب 12/12/2024 کو ہے۔	Original: The event is on 12/12/2024. Translation: یہ تقریب ۱۲/۱۲/۲۰۲۴ کو ہے۔ (Converted to Arabic numerals)
5. Cultural Considerations	Are idioms translated using cultural equivalents, not literal translations?	Original: The ball is in your court. Translation: فیصلہ آپ کے ہاتھ میں ہے۔ (Cultural equivalent used)	Original: The ball is in your court. Translation: گیند آپ کے کورٹ میں ہے۔ (Literal translation)
6. Common Error Patterns	Does the translation avoid direct transliteration and ensure meaningful translation?	Original: He is an experienced teacher. Translation: وہ تجربہ کار استاد ہے۔	Original: He is an experienced teacher. Translation: وہ ایک ایکسپیریئنسڈ ٹیچر ہے۔ (Direct transliteration)
7. Style and Register	Is the translation's tone and formality consistent with the source text?	Original: Please submit your documents at the earliest convenience. Translation: براہ کرم اپنی دستاویزات جلد از جلد جمع کروائیں۔	Original: Please submit your documents at the earliest convenience. Translation: دستاویزات جلدی سے دے دو۔ (Casual tone used instead of formal)
8. Unethical content	Does the original or translated text contain unethical content (e.g., violence, discrimination, racism, or cultural insensitivity)?	Original: You should not confront them with force if they disagree with you. Translation: اگر وہ آپ سے اختلاف کریں تو آپ کو ان پر زور آزمائی نہیں کرنی چاہیے۔ (Reject unethical response)	Original: You should not confront them with force if they disagree with you. Translation: اگر وہ آپ سے اختلاف کریں تو ان پر زور آزمائیں۔ (Promote unethical response)

Figure 7: Overview of the Urdu-Translated datasets refinement guidelines.

Pragyaan: Designing and Curating High-Quality Cultural Post-Training Datasets for Indian Languages

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Abstract

The effectiveness of Large Language Models (LLMs) depends heavily on the availability of high-quality post-training data, particularly instruction-tuning and preference-based examples. Existing open-source datasets, however, often lack multilingual coverage, cultural grounding, and suffer from task diversity gaps that are especially pronounced for Indian languages. We introduce a human-in-the-loop pipeline that combines translations with synthetic expansion to produce reliable and diverse Indic post-training data. Using this pipeline, we curate two datasets: *Pragyaan-IT* (22.5K) and *Pragyaan-Align* (100K) across 10 Indian languages covering 13 broad and 56 sub-categories, leveraging 57 diverse datasets. Our dataset protocol incorporates several often-overlooked dimensions and emphasize task diversity, multi-turn dialogue, instruction fidelity, safety alignment, and preservation of cultural nuance, providing a foundation for more inclusive and effective multilingual LLMs.

1 Introduction

Recent developments around Large Language Models (LLMs) (Touvron et al., 2023; Grattafiori et al., 2024; Abdin et al., 2025; Guo et al., 2025) have demonstrated that post-training data, comprising both instruction-tuning and preference data, plays a critical role in enhancing model alignment, task generalization, and usability (Ouyang et al., 2022; Bai et al., 2022b; Chung et al., 2022). Particularly in a multilingual and multicultural landscape, like India, the availability of high-quality, culturally grounded post-training data is crucial to address performance gaps in low-resource languages that often arise from the scarcity of relevant and representative training data (Joshi et al., 2020).

While several open-source datasets for post-training (Longpre et al., 2023; Wang et al., 2022b; Bercovich et al., 2025a) exist, they are predominantly English-centric and often suffer from limita-

tions such as inconsistent quality, restricted coverage, insufficient task complexity, and limited multilingual coverage. These challenges extend to Indic post-training data as well, focus of our work.

Direct translations of existing English post-training datasets are prone to translation biases, errors (Hartung et al., 2023; Savoldi et al., 2021; Muennighoff et al., 2022) and loss of cultural grounding (Wang et al., 2022a; Pudjiati et al., 2022). For instance, a prompt like “Tell me about a small herb to plant in backyard” might yield Western herbs such as *thyme* or *rosemary*, whereas Indian users would expect culturally familiar options like *tulsi* (holy basil), *pudina* (mint), or *curry leaves*. Similarly, when asked “What is a good comfort meal for a rainy day?”, English-centric answers such as *tomato soup* or *grilled cheese* overlook Indian preferences like *masala chai with pakoras* or *khichdi with ghee*. Even in wellness contexts, “Recommend a workout routine for beginners” may default to *squats and push-ups*, neglecting practices like *Surya Namaskar* or *yoga exercises*. Such mismatches highlight the need for post-training data that reflects not just language, but also local traditions and cultural context.

The recent popularity of LLM-based synthetic data generation (Wang et al., 2022c) for creating post-training datasets, while promising, still suffers in quality due to linguistic inaccuracies, grammatical inconsistencies, and reduced fluency, especially in multilingual settings, that could degrade the performance of models trained on them. Moreover, the lack of fine-grained control over output complexity and the potential for hallucination can lead to the generation of low-quality, unreliable data.

With the aim of addressing these gaps, we present an approach to curate high-quality post-training datasets, especially in multilingual settings. Our curation approach combines the above techniques with post-hoc manual editing, leading to a scalable human-in-the-loop pipeline, with spe-

cific focus on several aspects of quality, like task coverage, multilingual representation, task complexity, culture, multi-turns, reasoning, and others. We leverage our approach to curate high-quality Indic post-training datasets: *Pragyaan-IT* comprising 22.5K instruction tuning examples and *Pragyaan-Align*, a dataset of 100K preference examples in 10 Indian languages covering 56 task categories. Our contributions could thus be summarized as follows:

- We present a scalable pipeline for curating high-quality post-training data. Our approach emphasizes a human-in-the-loop (HITL) that is more efficient, reliable and ensures higher quality than direct synthetic generation or translation of existing English datasets.
- We introduce high-quality, manually curated, and culturally-inclusive post-training *Pragyaan* dataset series, consisting of 1) 22.5K *Pragyaan-IT* and 2) 100K *Pragyaan-Align*, designed for aligning LLMs to the diverse Indian cultural context.
- Our dataset includes a broad spectrum of instruction-following tasks with varying levels of complexity, ensuring the resulting models can handle a wide range of real-world scenarios. We provide a detailed analysis of the dataset’s characteristics, including its language distribution and domain representation, also showcasing its suitability for robust instruction-following capabilities through a small-scale pilot experiment.

2 Related Work

Post-training is a key step in aligning large language models (LLMs) with human intent, commonly achieved through instruction tuning (Wei et al., 2022a) and preference tuning (Bai et al., 2022a) datasets, constructed in several ways. Task template based resources such as Flan 2021 (Wei et al., 2022a), Flan 2022 (Longpre et al., 2023), and P3 (Sanh et al., 2022) adapt NLP datasets into instruction–response format. Human-authored datasets like Open Assistant (Köpf et al., 2023), Dolly (Conover et al., 2023), and LIMA (Zhou et al., 2023) demonstrate the value of curated instructions but face scalability challenges. To overcome this, synthetic generation approaches leverage LLMs to expand from small human-annotated *seeds*, with efforts such as Self-Instruct (Wang et al., 2022c), Alpaca (Taori et al., 2023), and Guanaco (Joseph Cheung, 2023), often distilling

knowledge (Hinton et al., 2015) from stronger teacher LLM models. Advanced pipelines like Evol-Instruct (Xu et al., 2023) iteratively increase instruction complexity, while later works extend these methods to reasoning and code generation (Luo et al., 2023; Gunasekar et al., 2023). Complementing these, user-contributed datasets such as InstructionWild (Ni et al., 2023) and ShareGPT¹ provide naturally occurring conversational data, and Unnatural Instructions (Honovich et al., 2022) show how seed tasks can be scaled into diverse synthetic corpora. Subsequent work expanded into specialized domains, including dialogue systems (Köpf et al., 2023), structured knowledge grounding (Xie et al., 2022), and chain-of-thought reasoning (Wei et al., 2022b; Kim et al., 2023). More recently, the Magpie dataset (Xu et al., 2024) introduced a fine-grained taxonomy spanning creative writing, math, role-playing, planning, and data analysis, emphasizing the importance of broad coverage in post-training resources. Preference datasets such as UltraFeedback (Cui et al., 2023) and Tulu3 (Lambert et al., 2025) comprises human and synthetic preference pairs for LLM alignment. Building on these advances, we construct our approach and dataset tailored to Indian languages and cultural contexts leveraging manual annotations in complement with synthetic generation.

While large-scale post-training datasets have become increasingly available, they remain predominantly English-centric, with limited coverage for other languages. A few exceptions incorporate some proportions of multilingual data (Köpf et al., 2023; Longpre et al., 2023; Muennighoff et al., 2023; Zhuo et al., 2024; Nguyen et al., 2023), but they remain limited in cultural and linguistic diversity compared to English resources. Prior efforts to extend post-training resources beyond English have typically followed three strategies: (1) translating English datasets into additional languages (Li et al., 2023a; Khan et al., 2024), (2) generating template-based datasets (Yu et al., 2023b; Gupta et al., 2023), and (3) manually curating instruction datasets in non-English languages (Li et al., 2023b; Wang et al., 2022d). Amongst these, template-based efforts such as xP3 (Muennighoff et al., 2022) extend the P3 taxonomy with 28 multilingual datasets. However, xP3 relies on uniform templates across languages, leading to limited task diversity and frequent repetition. Translation-based

¹<https://sharegpt.com/>

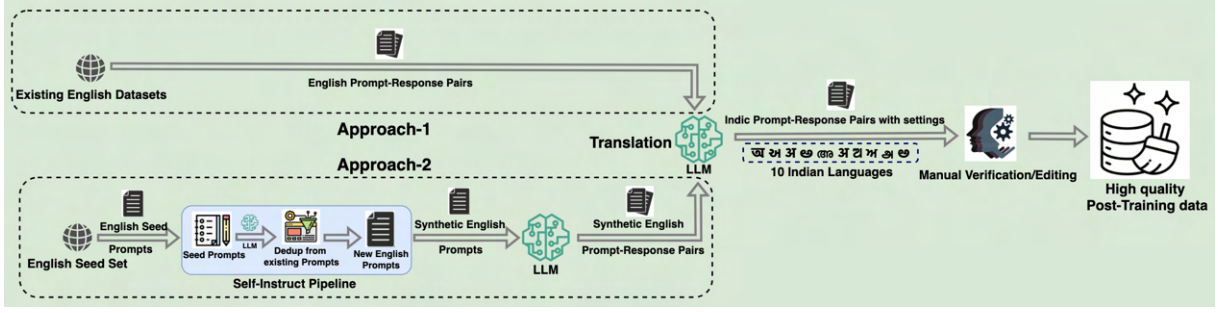


Figure 1: Workflow for building Indian language post-training data: English prompts are either translated or expanded via modified self-instruct pipeline to generate synthetic prompts. In both cases, responses are then produced with an LLM, translated into one of the 10 Indian languages, and manually refined (Section 3).

approaches face similar limitations, such as Bactrian (Li et al., 2023a), which translated Alpaca (Taori et al., 2023) and Dolly (Conover et al., 2023) into 52 languages. In contrast, our work introduces human-edited datasets across 10 Indian languages, addressing issues of redundancy and cultural grounding while providing a more diverse and representative resource for multilingual alignment.

3 Methodology

We present our multi-stage post-training dataset creation process that encompasses a variety of task categories at both broad and fine-grained levels, critical settings (complexity, interaction depth, constraints, safety, indian context, thinking trails) and leverages human annotators alongside curated data sources to ensure quality and coverage. While our approach itself is generic, we discuss how we used it to create high-quality Indic post-training datasets that we collectively refer to as *Pragyaan-IT* and *Pragyaan-Align*.

3.1 Data Construction Approaches

We employ two complementary approaches (Figure 1) that both combine translation and synthetic generation with post-hoc manual editing to ensure linguistic accuracy, fluency, and cultural appropriateness in our datasets.

3.1.1 Approach 1: Translation with Human Refinement

Here, we directly source English prompt-response pairs from existing English datasets (more details later in Section 3.5).

Prompts: We begin with English prompts which are first translated into Indic languages using an LLM, then refined by human annotators. During verification, annotators correct linguistic errors,

improve readability, and adapt expressions where needed to reflect Indian cultural norms. This results in two categories, i.e. 1) *Indic Generic Prompts*: direct translations of the English originals. 2) *Indic Context Prompts*: culturally adapted and edited versions incorporating Indian references and contexts by human annotators.

Responses: Corresponding English responses undergo a similar pipeline independently, with LLM-based translation into Indic languages, followed by human editing for grammar, relevance, length, and cultural appropriateness. Thus, we have 1) *Indic Generic Responses*: literal translations of the English outputs. 2) *Indic Context Responses*: refined versions adapted to Indian discourse norms.

3.1.2 Approach 2: Synthetic Expansion with Human Refinement

This approach introduces an additional intermediate stage of synthetic prompt expansion in English.

Prompts: Starting with a seed set of English prompts (sourced or created), we use the Self-Instruct pipeline (Wang et al., 2022b) to iteratively expand this set into a larger synthetic pool. While in the original pipeline they generate new prompts for classification and non-classification types via different strategies, in our adaptation, we use the same prompt template for both the cases. The resulting synthetic English prompts are then translated into Indic languages with LLMs and refined by human annotators to ensure correctness, clarity, and cultural grounding. This yields 1) *Synthetic Indic Generic Prompts*: literal translations of synthetic English prompts. 2) *Synthetic Indic Context Prompts*: culturally enriched translations.

Responses: For each synthetic English prompt, we generate English responses using an LLM independently. These are then translated into Indic

languages and refined through human editing. Annotators correct factual or linguistic errors, polish style, and, when appropriate, enrich with cultural nuances. This process produces 1) *Synthetic Indic Generic Responses*: faithful translations of the English responses. 2) *Synthetic Indic Context Responses*: culturally adapted versions aligned with the Indian local context.

While our first approach ensures fidelity through the translation of existing English datasets, it remains constrained in both scope and diversity. The second approach complements this by introducing synthetic expansion prior to translation, enabling broader task coverage, richer cultural representation, and greater scalability with reduced dependency on large English resources. Together, the two approaches strike a balance between reliability and diversity, yielding multilingual datasets that are both high-quality and contextually rich.

3.2 Task Categories

Building on the design principles of several existing datasets, we curate a broad set of task categories that combine core language tasks such as reasoning (limited to CoT and self-thinking), inference, natural language understanding (NLU) and generation, question answering (QA), dialogue and interaction, information extraction, mathematics, coding, function calling, and instruction following, while also extending into culturally grounded domains like Indian states, religions, geo-political questions, etc. To promote robustness and responsible deployment, we additionally include safety and non-compliance, Indian contentious content, and self-identity tasks. Collectively, these categories establish a structured yet comprehensive framework that spans diverse sub-categories, enabling richer and more inclusive post-training curation. A detailed breakdown of sub-categories is provided in Table 1.

3.3 Task Settings

For each task category, we additionally define several task settings that encourage diversity of prompt complexity, interaction depth, instruction-following, safety considerations, cultural grounding, and explicit reasoning trails. We provide systematic descriptions of these settings next.

3.3.1 Complexity

We categorize tasks by complexity to ensure models are trained for both simple and challenging scenarios, with two primary levels: 1) *Easy* prompts

are direct and clearly defined, usually requiring minimal reasoning (e.g. a single factual or descriptive query). 2) *Hard* prompts feature greater structural complexity, often embedding multiple sub-questions within a single query, requiring nuanced reasoning and fine-grained understanding. Importantly, complexity is defined within each task category, enabling fair assessment across heterogeneous task types (see Figures 6–11 in Appendix).

3.3.2 Multi-Turn Interactions

Multi-turn settings capture tasks where contextual continuity is critical, such as dialogue, planning, or role-play. These scenarios require models to maintain memory of prior turns while generating coherent and adaptive responses. We consider three levels of interaction depths: 1) *Single-turn (1 turn)*: A response to an isolated prompt; 2) *Short multi-turn (3 turns)*: Three back-and-forth exchanges, ensuring local continuity; 3) *Extended multi-turn (5 turns)*: Five exchanges, for long-range memory and coherence in extended conversations (e.g. planning a festival with evolving constraints).

3.3.3 Instruction Following

We categorize instruction-following into three levels, defined by the number and type of constraints imposed on the response such as “*answer in 100 words*”, “*respond in json format*”, etc. (Figure 12 in Appendix). This ensures coverage of tasks that range from loosely guided prompts to highly structured outputs. Different combinations of these constraints are applied depending on the nature of the prompt: 1) *Simple instruction following*: prompts include minimal or no explicit constraints on the format or content of the response; 2) *Medium instruction following*: prompts introduce two to three explicit constraints, requiring the model to accommodate multiple conditions at once; 3) *Complex instruction following*: prompts impose several simultaneous constraints, demanding precise control and structured outputs.

3.3.4 Safety

We define safety settings to ensure that models behave responsibly when faced with sensitive, controversial, or potentially harmful content in a real-world setting. This dimension helps guide appropriate responses while maintaining ethical standards. We include 1) *Safe*: prompts are neutral and non-controversial, allowing the model to provide direct answers without ethical or policy concerns; 2) *Non-*

Broad Category	Sub Categories	Broad Category	Sub Categories
Reasoning & Inference	Non-Math Reasoning Math Reasoning Code Reasoning Indian Relationships Inference Data Analysis	Natural Language Understanding & Generation	Named Entity Recognition Text Classification Grammar Correction Translation Creative Writing Paraphrase Identification Paraphrase Generation Text Summarization Headline Generation Question Generation Sentiment Analysis
			Multi Turn Conversation Role Playing Advice Seeking Planning Brainstorming
Question Answering	General Question Answering Fact Check	Interaction & Dialogue	Sanskrit Festival Greetings Sanskrit Auspicious Day / Other Occasions Sanskrit Subhashitas (Quotes) Sanskrit Captions and Mottos Sanskrit Person's Name Sanskrit Building / Institution / Company Name Sanskrit Product Name
Information Extraction	Information Seeking Indian Cultural Context Comprehension	Sanskrit Cultural & Creative Usage	Code Generation Code Debugging Code Editing Code Explanation Code Translation Unit Test Generation Code Theory Code Review Repository level Code Generation
Mathematics	Math QA Math Instruction Tuning Math Proofs	Coding	Instruction Following
Function Calling	Function Calling	Instruction Following	Indian Geo Political Indian Politicians Indian States Indian Languages Indian Religions
Safety & Non-Compliance	Safety & Non-Compliance	Indian Contentious Questions	
Self-Identity	Model-name Person-based		

Table 1: Taxonomy of NLP task categories and sub-categories for creating post-training datasets in Section 3.2.

safe: prompts involve sensitive or harmful material, where the model is expected to either refuse politely (e.g., “Sorry, I cannot assist with that ...”) or generate a safe response.

3.3.5 Thinking Trails

We define ‘thinking trail’ settings to capture the role of explicit reasoning in model responses, ensuring that outputs range from direct answers to more reflective reasoning styles. 1) *Normal*: direct response generation without intermediate reasoning traces; 2) *Chain-of-Thought (CoT)*: step-by-step reasoning (Wei et al., 2022b) articulated explicitly before the final answer; 3) *Self-Thinking*: inspired by recent “deep thinking” paradigms (Guo et al., 2025; Bercovich et al., 2025b; Abdin et al., 2025), where models produce more elaborate, self-reflective reasoning trails prior to the final response.

3.3.6 Indian Cultural Context

Given the centrality of Indic languages and cultural alignment in our framework, we explicitly model contextual grounding through three progressively richer levels. 1) *IC-1* represents generic prompts leading to generic responses, with no explicit India related anchoring (e.g., Prompt: “Suggest some breakfast items.”, Response: “Pancakes, cereal, toast, scrambled eggs.”). Such responses

are accurate but remain culturally neutral, with no particular alignment to cultural settings. 2) *IC-2* represents generic prompts that nonetheless yield Indic-grounded responses. For instance, the same prompt above, in this setting, would elicit responses such as “Idli, dosa, paratha, poha”, which are the most popular breakfast items in India. 3) *IC-3* involves prompts that are themselves explicitly Indic, thereby eliciting fully Indic-based responses. For example, the prompt itself mentions “Suggest some Indian breakfast items” with a similar response as in the IC-2 setting. This setting encourages grounding and diversity of responses with respect to Indian cultural context that is required for training Indic focused LLMs.

3.4 Human-In-The-Loop (HITL) Refinement

While synthetic generation and automated translation provides the backbone of our dataset creation pipeline, human annotators play an equally central role in shaping its final form. Each prompt–response pair, once generated and assigned a configuration of settings (e.g., *easy*, *1-Turn*, *Simple-IF*, *Safe*, *IC-3*, *Normal* (*No Thinking Trails*)), enters a stage of manual intervention where annotators act not merely as reviewers, but as curators of the data. If a pair does not fully align

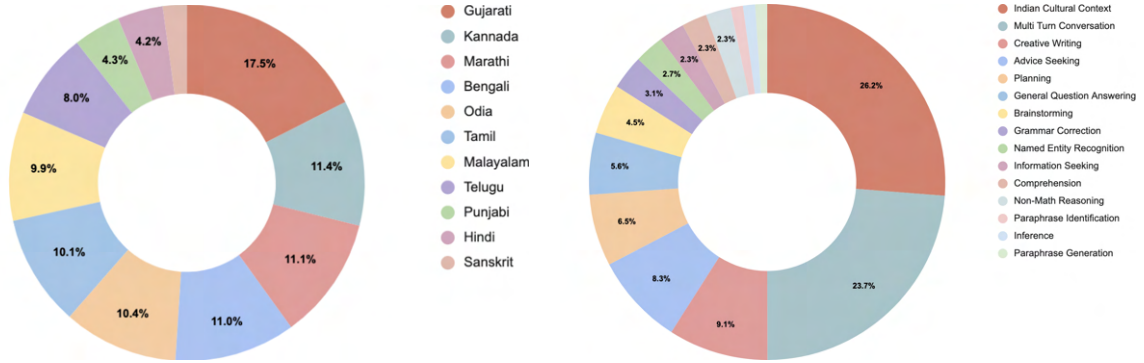


Figure 2: Distribution of *Pragyaan-IT* (Instruction-Tuning) data across languages (left) and categories (right).

with its designated configuration, annotators may either (i) adapt the configuration to better reflect the pair, or (ii) create a new prompt–response pair that correctly conforms to the specified configuration. This decision balances efficiency with fidelity to the framework. In cases where manually generating a new response is especially time-intensive, the annotators flag the prompt for regeneration and they undergo another iteration through the pipeline.

Crucially, manual intervention goes beyond mechanical verification. Annotators conduct linguistic quality checks ensuring fluency, grammatical accuracy, syntactic correctness, and appropriate response length, but are also encouraged to exercise creative judgment. This includes refining awkward phrasings, restructuring unclear outputs, or enriching responses with culturally relevant details. Even when a pair formally satisfies all defined constraints, annotators may modify it to adjust tone, improve readability, contextual appropriateness or pedagogical value as well as elevate the overall communicative value of the response. These interventions ensure that the dataset is not only consistent with the defined settings, but also meaningful and robust for deployment in real-world post-training scenarios.

3.5 Dataset Curation

Our curation process draws from a broad pool of existing resources while systematically adapting them for Indic languages and tasks. In total, we considered 57 diverse language datasets, together with their relevant splits, spanning different categories and task families. These resources serve either as direct candidates for translation into Indic languages or as seed data for synthetic expansion through a modified Self-Instruct pipeline (Wang et al., 2022b) described earlier. By combining translation and generation in a complementary manner,

we ensure that the curated data covers not only core Natural Language Processing (NLP) tasks but also culturally grounded and contextually relevant dimensions. Table 3 in the Appendix provides an overview of the corresponding candidate datasets associated with each task sub-category.

Setting	Configuration	%
Complexity	Easy	62.32
	Hard	37.68
Multi Turn	1-Turn	91.66
	3-Turn	6.76
	5-Turn	1.58
Instruction Following	Simple IF	96.95
	Medium IF	2.49
	Complex IF	0.56
Safety	Safe	92.51
	Non-Safe	7.49
Indian Context	IC-1	32.04
	IC-2	10.16
	IC-3	57.80
Thinking Trails	Normal	99.98
	CoT	0.01
	Self Thinking	0.01

Table 2: Distribution of instances in *Pragyaan-IT* across different task settings and configurations in Section 3.3.

4 Pragyaan: Indic Post-training Datasets

As part of this work, we construct high-quality post-training datasets that explicitly target 10 Indian languages (Bengali, Gujarati, Hindi, Kannada, Malayalam, Marathi, Oriya, Punjabi, Tamil, and Telugu), yielding two complementary resources:

i) *Pragyaan-IT* (22.5K): an instruction-tuning dataset designed to enhance a model’s ability to follow diverse prompts across multiple domains, ensuring that models can generalize well to everyday user interactions.

ii) *Pragyaan-Align* (100K): a preference dataset curated for Reinforcement Learning (RL)-based

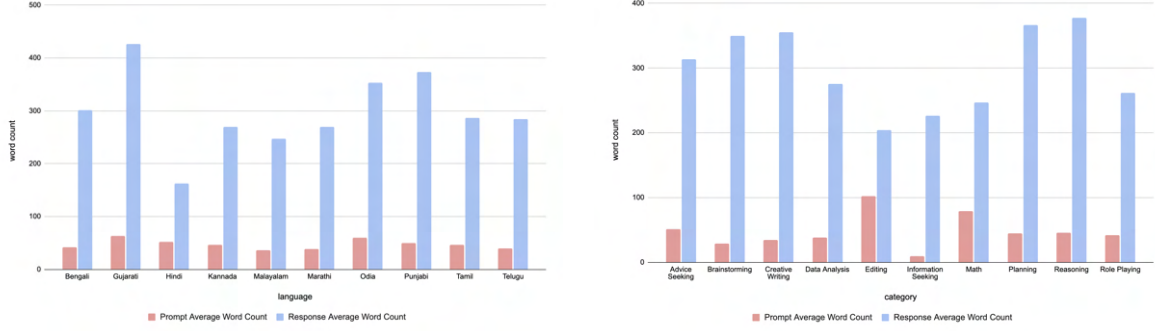


Figure 3: Average word counts of *Pragyaan-Align* alignment data across languages (left) and categories (right).

alignment methods, emphasizing preference learning, safety, and cultural grounding, allowing models to align more closely with the user intent.

5 Analysis

We begin with an assessment of raw synthetic generations refined through human annotation, followed by a broader dataset-level analysis.

5.1 Human Annotation Refinement

We evaluate the underlying LLM’s performance for both generation and translation tasks across 5 dimensions, each on a scale of 1-5, for a small subset (see Section A.5 in the Appendix for details on evaluation). Particularly, for English generations, grammatical accuracy remains slightly lower in comprehension (3.20) and creative writing (3.93) tasks, while receiving high scores for other tasks. For translation, the model shows the strongest performance for Hindi (Figure 14). Telugu and Gujarati exhibit moderate Lexical Diversity (3.43 and 3.30), while grammatical accuracy remains modest in Telugu (3.62), Hindi (3.60), and Punjabi (3.55). Thus, human refinements were critical for converting raw synthetic output into culturally grounded, linguistically accurate, and task-aligned data, directly underpinning the reliability of our data curation framework.

5.2 Dataset analysis

Figure 2 shows the distribution of *Pragyaan-IT* across 10 languages and 15 categories, while Table 3 lists the candidate datasets used in its construction. As seen in Figure 2, Indian Cultural Context (26.2%) and Multi-Turn Conversation (23.7%) dominate, while reasoning and paraphrasing remain limited (1–3%), forming targets for future expansion. Language coverage is led by Gujarati (17.7%), Kannada (11.4%), Marathi (11.1%),

and Odia (10.8%). In the current setting (Table 2), we have 62.3% ‘Easy’ tasks, single-turn interactions (91.7%), simple instruction-following (96.9%), safe content (92.5%) with Indian context well covered (IC-3: 57.8%). While this analysis reflects the status of the *Pragyaan-IT* dataset at the time of writing, the dataset is under active curation and will be more comprehensive across task categories and settings as described in earlier sections.

Word count analysis highlights linguistic and task-level variation (Figure 4). Gujarati and Odia are most verbose in both prompts (~110 words) and responses (~320 words), whereas Hindi mostly remain concise. At the task level, Multi-turn conversation, Advice Seeking, and Creative Writing yield the longest responses (550–620 words). Conversely, QA, Indian cultural context, and Comprehension tasks are consistently brief. Verbosity thus correlates with conversational and creative tasks, while simpler or context-specific settings produce shorter outputs.

Pragyaan-Align, the preference dataset, has an equal representation across all languages and 10 categories that helps promote fairness and mitigate bias. All instances in *Pragyaan-Align* follow a standardized configuration: single-turn interactions with instruction following and safe responses. Our analysis shows variation in text lengths across categories and languages. Average word counts for prompts range from 36–63 words, preferred responses 137–539, while rejected responses range from 154–466 words reflecting differences in task complexity and elaboration. Detailed language-wise as well as category-wise trends are also presented in Figure 3.

Overall, our *Pragyaan* datasets for post-training provide a broad task and Indian language coverage. The various task settings and our curation

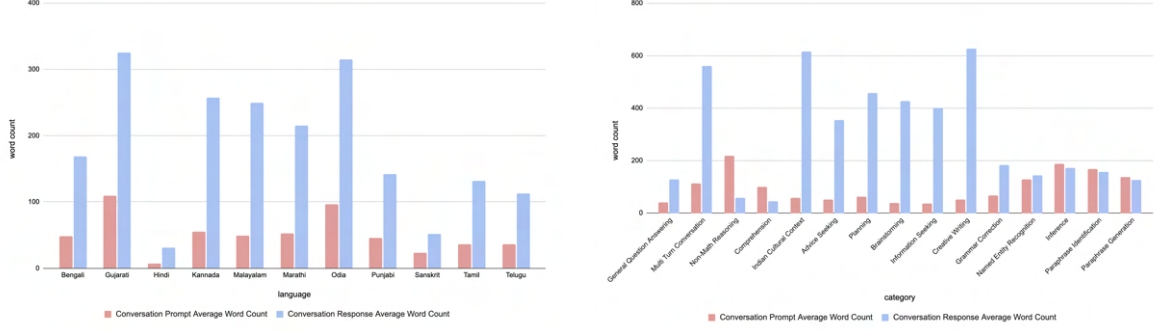


Figure 4: Average word counts of *Pragyaan-IT* data across languages (left) and categories (right).

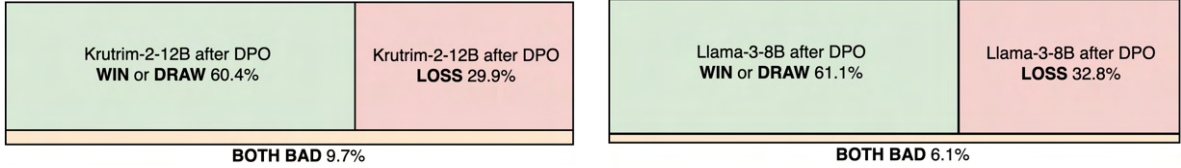


Figure 5: Win rates of the *Krutrim-2-12B* (left) and *Llama-3-8B* (right) models after DPO, compared against their respective pre-DPO versions.

process leveraging LLMs along with human-in-the-loop help ensure high quality. Our future iterations will expand complex reasoning capabilities and enhance representation for under-covered low-resource languages.

5.3 Downstream performance

To evaluate the quality of our curated dataset, we conduct a pilot study with Direct Preference Optimization (DPO) (Rafailov et al., 2023) based alignment on the *Pragyaan-Align* dataset using two open-weight models which supports the languages under consideration: *Krutrim-2-12B Instruct* (Kallappa et al., 2025) and *Llama-3-8B Instruct* (Grattafiori et al., 2024).

For evaluation, we use the recently released *Updesh* dataset², which covers similar categories and languages. We sample around 100 examples from nine relevant categories, balanced across ten languages. Responses from the models are scored against the ground truth on a scale of 1–5 using an LLM-as-a-judge. We provide more information about the hyperparameter configuration and other experimental details in Section A.6 and the corresponding prompts used for evaluation in Section B of the Appendix.

As shown in Figure 5, *Krutrim-2-12B* after DPO either wins or draws in 60.4% of cases, loses in 29.9%, and both pre- and post-DPO responses

score poorly (<2) in 9.7%. A similar trend holds for *Llama-3-8B* (61.1% wins or draws), confirming the promising potential of our curated dataset for alignment across different categories and multiple Indian languages.

6 Conclusion

This work addresses the scarcity of high-quality post-training data for multilingual LLMs by developing a human-in-the-loop pipeline to ensure diversity, quality and cultural grounding. Through this approach, we construct two datasets: *Pragyaan-IT* and *Pragyaan-Align* covering 10 Indian languages and multiple task categories. The datasets highlight inclusion of local cultural context, task diversity, multi-turn dialogue, and safety alignment, overcoming the limitations of naive translations and low-quality synthetic resources. Although designed for Indian languages, the pipeline is readily adaptable to other multilingual contexts. We present a comprehensive analysis of the dataset’s characteristics, covering language distribution and domain coverage, and further demonstrate its effectiveness for alignment through a small-scale pilot study. Future efforts will expand language coverage and further annotation quality refinement. We aim for this work to support broader efforts in building culturally inclusive resources that strengthen LLM applicability in multilingual contexts.

²https://huggingface.co/datasets/microsoft/Updesh_beta

Limitations

Our dataset is part of an ongoing effort, with plans to continually expand post-training instances. While our human-in-the-loop framework mitigates many issues, challenges such as minor linguistic inaccuracies, fluency variation across languages, and potential annotation subjectivity may still persist. Moreover, our research prioritized Indian languages, and the generalization of findings to other multilingual settings remain currently unexplored. Extending the pipeline to new cultural and linguistic contexts will require additional validation. We view these limitations as avenues for future work towards broader applicability and refinement of our proposed framework.

Ethics Statement

This study focuses on curating large-scale post-training datasets for Indian languages, encompassing diverse tasks and cultural contexts. The pipeline combines synthetic generation with human-in-the-loop refinement to ensure quality, safety, and cultural fidelity. We provide proper attribution to all source datasets and tools through citations. Human involvement was limited to annotation and quality control; no personally identifiable or sensitive information was collected. We engage a team of 50 in-house annotators for dataset creation. All contributors were clearly informed that their work supports LLM training and were compensated fairly at locally prevailing market rates. This study did not require formal IRB approval. Throughout the process, we prioritized preserving cultural nuances while avoiding harmful, biased, or unsafe content. The resulting dataset is designed to advance the development of multilingual and culturally inclusive LLMs.

Acknowledgements

We thank the leadership at Krutrim for their support in carrying out this research. We also thank the Data Annotation Team for their meticulous efforts especially Sanmathi P N, Dr. Salman Alam, Rupakatha Mukherjee, Vinod Kumar, Shivaram Prasad Putta, Divyashree K, Arati V Thakur, Vaibhav M Sutariya, Mitali Pradhan, Payal Yadav, Sneha Aniyani, Hemant P Rajopadhye, Joel Johnson and Srinidhi S. Additionally, we also thank Guduru Manoj and Souvik Rana for the helpful discussions.

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A Appendix

A.1 Dataset Curation

For each sub-category, we curated multiple publicly available candidate datasets and evaluated their applicability to our data collection objectives, assessing how they align with the chosen curation approaches. Table 3 summarizes representative categories along with corresponding datasets incorporated into our pipeline. It is worth noting that data collection for certain sub-categories remains an ongoing effort.

A.2 Data Construction Approaches

We further provide more details about the prompt and responses for both the approaches in Table 4.

Sub Category	Candidate Datasets	Sub Category	Candidate Datasets
Non-Math Reasoning	MMLU (Hendrycks et al., 2020) MMLU-Pro (Liu et al., 2024) GPQA (Rein et al., 2024) medical-o1-reasoning-SFT (Rothermund et al., 2025) OpenThoughts (Zhang et al., 2024)	Sentiment Analysis	IndicSentiment (Doddapaneni et al., 2023) pietrollesci/imdb
Math Reasoning	OpenThoughts (Zhang et al., 2024) Llama-Nemotron-Posttraining-Dataset (NVIDIA, 2025) ServiceNow-AI/R1-Distil-SFT (Research, 2024) LIMO (Ye et al., 2025) s1K (Muennighoff et al., 2025)	General Question Answering	OpenBookQA (Mihaylov et al., 2018) TriviaQA (Joshi et al., 2017) CommonSenseQA (Talmor et al., 2019) WikiQA (Yang et al., 2015) HotPotQA (Yang et al., 2018) MegaWika (Barham et al., 2023)
Code Reasoning	OpenThoughts (Zhang et al., 2024) Llama-Nemotron-Posttraining-Dataset (NVIDIA, 2025) KodCode (Xu et al., 2025) open-r1/codeforces-cots (Penedo et al., 2025)	Fact Check	NaturalQuestions (Kwiatkowski et al., 2019) TriviaQA (Joshi et al., 2017) Indic Quest (Rohera et al., 2024)
Indian Relationships	Reasoning Gym (Stojanovski et al., 2025)	Multi Turn Conversation	ChatAlpaca (Bian et al., 2023) NoRobots (Rajani et al., 2023) Opus Samantha
Inference	XNLI (Conneau et al., 2018)	Role Playing	Public Domain Alpaca LimaRP Magpie (Touileb et al., 2024)
Data Analysis	Magpie (Touileb et al., 2024)	Advice Seeking	Magpie (Touileb et al., 2024)
Named Entity Recognition	Naamapadam (Mhaske et al., 2022) Bharath Bench	Planning	Magpie (Touileb et al., 2024)
Text Classification	pietrollesci/civilcomments-wilds (Borkan et al., 2019) pietrollesci/wikitoxic pietrollesci/hyperpartisan_news_detection Bharath Bench Aya Collection (Singh et al., 2024b)	Brainstorming	Magpie (Touileb et al., 2024)
Grammar Correction	Bharath Bench	Information Seeking	Magpie (Touileb et al., 2024)
Translation	Flores-IN (Singh et al., 2024a) IN-22	Indian Cultural Context	Bharath Bench
Creative Writing	Magpie (Touileb et al., 2024) Poetry	Comprehension	TriviaQA (Joshi et al., 2017) SQUAD (Rajpurkar et al., 2018) SQUAD 2.0 (Rajpurkar et al., 2018) IndicQA
Paraphrase Identification	IndicXParaphrase (Doddapaneni et al., 2023)	Math QA	OpenMathInstruct 2 (Toshniwal et al., 2024) GSM8K (Cobbe et al., 2021) MATH (Hendrycks et al., 2021) Tulu3 Persona Math (Lambert et al., 2025) Tulu3 Persona GSM8K (Lambert et al., 2025)
Text Summarization	CrossSumIN (Singh et al., 2024a) Indic Sentence Summarization (Kumar et al., 2022) arxiv-summarization (Cohan et al., 2018) news-summarization	Math Instruction Tuning	MetaMathQA (Yu et al., 2023a) Math Instruct (Pudupully et al., 2024)
Headline Generation	Indic Headline Generation (Kumar et al., 2022) NewSHead	Math Proofs	Natural Proofs (Welleck et al., 2021)
Question Generation	Indic Question Generation (Kumar et al., 2022)		

Table 3: Representative datasets curated for different sub-categories that are used as candidate datasets in our data curation approaches.

Approaches	Prompts	Responses
Approach 1: Translation + Human Refinement	English prompts → LLM translation → human verification/adaptation. <i>Outputs:</i> Indic Generic Prompts, Indic Context Prompts.	English responses → LLM translation → human verification/adaptation. <i>Outputs:</i> Indic Generic Responses, Indic Context Responses.
Approach 2: Synthetic Expansion + Human Refinement	Seed English prompts → LLM expansion (Self-Instruct) → LLM translation → human verification/adaptation. <i>Outputs:</i> Synthetic Indic Generic Prompts, Synthetic Indic Context Prompts.	Synthetic English responses → LLM translation → human verification/adaptation. <i>Outputs:</i> Synthetic Indic Generic Responses, Synthetic Indic Context Responses.

Table 4: Comparison of data construction approaches, showing pipelines for prompts and responses with resulting categories.

A.3 Complexity Definitions

Notably, complexity is evaluated relative to each task category, ensuring that difficulty levels are interpreted within the specific context of that category. Figures 6–11 illustrate how complexity is defined across different task categories.

A.4 Instruction Following

Various configurations of Instruction Following incorporate different combinations of constraints within the prompt. Figure 12 outlines the types of constraints considered, accompanied by illustrative examples for clarity while human annotation.

A.5 Human Annotation Refinement

Data annotators initially assessed the performance of the underlying LLM on both generation and translation tasks across multiple dimensions.

For generation, raw LLM responses were assessed along dimensions such as Response Relevance, Grammatical Accuracy, Cohesion and Coherence, Rationality, and Completeness (see Table 5 for the guidelines). As shown in Figure 13, English generations perform consistently well: tasks such as Indian Cultural Context, Advice Seeking, Information Seeking, Named Entity Recognition, Inference, Paraphrase Identification, Paraphrase Generation, and Headline Generation achieve near-perfect scores in Response Relevance (5.00) and Completeness (4.93–5.00). Multi-Turn Conversation also scores high in Cohesion and Coherence (5.00) and Response Relevance (4.70). Grammatical Accuracy remains strong overall (4.00–4.40), though slightly lower in Comprehension (3.20) and Creative Writing (3.93).

For translation, annotators evaluated Lexical Diversity, Coherence and Cohesion, Completeness, Grammatical Accuracy, and Named Entity Handling (see Table 6 for the guidelines). Hindi shows the strongest performance, achieving the highest Completeness (4.92) and Named Entity Handling (4.85). Telugu and Gujarati exhibit strong Lexical Diversity (3.43 and 3.30), while Grammatical Accuracy is highest in Telugu (3.62), Hindi (3.60), and Punjabi (3.55). Further detailed evaluation scores are illustrated in Figure 14.

A.6 Implementation

For training, we adopt a distributed DeepSpeed-based setup with ZeRO-3 optimization (Rajbhandari et al., 2020) across 2 H100 nodes (8 GPUs

per node) to efficiently handle large-scale model fine-tuning. The Llama-3-8B and Krutrim-2-12B instruct models are optimized using the Direct Preference Optimization (DPO) objective with a Beta parameter of 0.3, controlling the strength of preference alignment. Training is performed on sequences up to 4096 tokens, with a maximum prompt length of 2048 tokens to accommodate complex multi-turn instructions. We employ the AdamW optimizer with a learning rate of 5×10^{-7} , weight decay of 0.01, and a cosine learning rate scheduler with a warming ratio of 10% warmup ratio for stable convergence and run for 1 epoch. The batch configuration consists of 4 samples per device with gradient accumulation over 2 steps, yielding an effective batch size suitable for large-scale distributed training setup.

Post-trained Krutrim-2-12B and Llama-3-8B models are evaluated on the Updesh dataset across 10 languages and nine categories using LLM-as-a-Judge scoring on a scale of 1-5. Post-DPO, Krutrim achieves 31.7% wins, 29.9% losses, 28.6% draws, and 9.8% both-bad cases, while Llama records 35.0% wins, 26.1% losses, 27.9% draws, and 11.0% both-bad cases.

B Prompts Used

Different prompts were crafted for each category and complexity level during prompt generation using the self-instruct pipeline. For instance, Figures 15 and 16 illustrate example prompts for the Indian Cultural Context category under easy and hard settings, respectively. Similar design considerations were applied across other categories to address their specific requirements.

Figure 17 presents the prompt template employed for translating English prompt-response pairs via LLMs. The Krutrim-2-12B and Llama-3-8B Instruct models, after being fine-tuned using DPO on 100K examples from the *Pragyaan-Align* dataset, were evaluated on the Updesh dataset. The evaluation utilized an LLM-as-a-Judge framework for scoring, with the corresponding prompt design shown in Figure 18.

C Guidelines For Manual Annotation

The data annotation team follows a set of standardized guidelines designed to maintain consistency and uniformity throughout the annotation process. These guidelines include precise definitions for each category and setting, which are elaborated

Sub Category	Complexity	Sub Category	Complexity
Non-Math Reasoning	<p>1. Number of reasoning steps Easy: Typically require a single fact or step. Hard: Requires multiple connected inferences.</p> <p>2. Obviousness of needed knowledge Easy: Questions rely on common knowledge. Hard: May require less intuitive or more obscure background knowledge.</p> <p>3. Clarity of distractors Easy: Questions have clearly incorrect options. Hard: Questions have plausible distractors that require careful elimination.</p>	Data-Analysis	<p>1. Data Complexity Easy: Small, clean datasets (few rows/columns). Hard: Larger, noisier, or irregular datasets (missing values, inconsistent formatting).</p> <p>2. Reasoning Depth Easy: Single-step reasoning (e.g., identify max/min, simple difference). Hard: Multi-step reasoning (e.g., grouping, computing moving averages, interpreting trends, conditional filtering).</p> <p>3. Type of Question Easy: Direct lookup or comparison. Hard: Involves synthesis across rows/columns, or combining values to reach a conclusion.</p>
Math Reasoning	<p>1. Number of reasoning steps Easy: Typically require a single fact or step. Hard: Requires multiple connected inferences.</p> <p>2. Obviousness of needed knowledge Easy: Questions rely on common knowledge. Hard: May require less intuitive or more obscure background knowledge.</p> <p>3. Clarity of distractors Easy: Questions have clearly incorrect options. Hard: Questions have plausible distractors that require careful elimination.</p>	Named Entity Recognition	<p>1. Entity Density and Type Variety Easy: Few entities, mostly common types (Person, Location). Hard: Multiple entities of varied or domain-specific types (e.g., Organization, Event, Product), possibly nested.</p> <p>2. Language and Script Complexity Easy: Monolingual, clean, formal sentences in a standard script. Hard: Code-mixed, noisy, informal language, or regional scripts.</p> <p>3. Ambiguity and Context Requirement Easy: Clearly named, well-known entities. Hard: Requires context to disambiguate entities or identify non-obvious named terms (e.g., "Amazon" as a company vs. river).</p>
Code Reasoning	<p>1. Number of reasoning steps Easy: Typically require a single fact or step. Hard: Requires multiple connected inferences.</p> <p>2. Obviousness of needed knowledge Easy: Questions rely on common knowledge. Hard: May require less intuitive or more obscure background knowledge.</p> <p>3. Clarity of distractors Easy: Questions have clearly incorrect options. Hard: Questions have plausible distractors that require careful elimination.</p>	Text Classification	<p>1. Clarity of Class Indicators Easy: Clear, surface-level cues that strongly correlate with the label. Hard: Subtle, context-dependent cues; overlapping vocabulary across classes.</p> <p>2. Length and Structure Easy: Short, focused texts with one intent. Hard: Longer, noisy, or multi-intent texts requiring disambiguation.</p> <p>3. Label Set Complexity Easy: Binary classification (e.g., spam vs. ham). Hard: Multi-class (e.g., news category: politics, sports, tech) or multi-label (e.g., tags for movie reviews: drama, romance).</p>
Indian Relationships	<p>1. Number of relations involved Easy: 2-3 relations, mostly linear. Hard: 4+ relations, often nested or cross-generational.</p> <p>2. Clarity of phrasing Easy: Straightforward statements with direct relationships. Hard: Implicit or linguistically ambiguous statements, possibly requiring gender inference or cultural interpretation.</p> <p>3. Relation type Easy: Direct blood relations (e.g., mother, brother). Hard: In-law relations, culturally specific terms, or multigenerational links.</p>	Grammar Correction	<p>1. Error Type Easy: Simple subject-verb agreement, plural/singular forms, or article usage. Hard: Tense consistency, word order, idiomatic usage, or multiple error types in one sentence.</p> <p>2. Error Density Easy: Single, localized error. Hard: Multiple interrelated errors, possibly requiring rephrasing.</p> <p>3. Contextual Dependence Easy: Error is identifiable without additional context. Hard: Requires deeper understanding of meaning or nuance to correct properly.</p>
Inference	<p>1. Lexical Overlap Easy: High overlap; direct wording or synonyms. Hard: Low overlap; requires paraphrasing or world knowledge.</p> <p>2. Inference Type Easy: Simple entailment or direct contradiction. Hard: Implicit entailment, pragmatic reasoning, or nuanced neutrality.</p> <p>3. Context Dependence Easy: No external knowledge needed. Hard: Requires commonsense, temporal, or cultural knowledge.</p>	Translation	<p>1. Syntactic Complexity Easy: Simple sentence structures (subject-verb-object). Hard: Complex or nested clauses, passive voice, or long-distance dependencies.</p> <p>2. Lexical Ambiguity & Idioms Easy: Literal language with direct word equivalents. Hard: Idioms, metaphors, or polysemous words requiring interpretation.</p> <p>3. Cultural Context Easy: Universally understood concepts. Hard: Culturally specific references, wordplay, or region-specific expressions.</p>

Figure 6: Complexity Definitions for each sub-category.

Dimension	Explanation
Response Relevance	<p>Measures how well the model output addresses the user query or task instruction.</p> <p>Why it matters for Indic/Multilingual Data: Responses must stay on-topic and satisfy user intent; irrelevant outputs reduce usability and may confuse readers.</p> <p>Errors in this area: Off-topic responses, inclusion of unrelated information, misinterpretation of the prompt.</p>
Grammatical Accuracy	<p>Correct use of grammar rules including syntax, tense, agreement, punctuation, and morphology.</p> <p>Why it matters for Indic/Multilingual Data: Proper grammar ensures readability and clarity; morphologically rich languages are prone to agreement and inflection errors.</p> <p>Errors in this area: Wrong tense, subject-verb disagreement, missing auxiliaries, incorrect case markings, improperly inflected words.</p>
Cohesion and Coherence	<p>Cohesion = linguistic devices (connectors, pronouns, conjunctions) linking sentences; Coherence = logical flow of ideas.</p> <p>Why it matters for Indic/Multilingual Data: Maintains well-structured and easily understandable responses; lack of cohesion or coherence leads to fragmented outputs.</p> <p>Errors in this area: Abrupt topic shifts, disconnected sentences, missing references, inappropriate pronoun usage.</p>
Rationality	<p>Logical correctness and factual consistency of the response, including reasoning and alignment with real-world knowledge.</p> <p>Why it matters for Indic/Multilingual Data: Ensures trustworthiness and usefulness of outputs, particularly for reasoning or factual tasks.</p> <p>Errors in this area: Contradictory statements, illogical conclusions, factually incorrect assertions, hallucinations.</p>
Completeness	<p>The extent to which the response fully addresses the user prompt or includes all necessary information.</p> <p>Why it matters for Indic/Multilingual Data: Partial answers reduce usefulness, especially for multi-step reasoning or detailed explanations.</p> <p>Errors in this area: Missing steps in reasoning, skipped entities, truncated explanations, insufficient coverage of subtopics.</p>

Table 5: Key dimensions for assessing LLM outputs in Indic languages, highlighting relevance and frequent pitfalls.

Sub Category	Complexity	Sub Category	Complexity
Creative Writing	1. Prompt Specificity Easy: Constrained or highly specific prompts that guide the plot. Hard: Open-ended or abstract prompts requiring full narrative invention.	Question Generation	1. Contextual Simplicity Easy: Clear, straightforward context with a direct relationship between entities. Hard: Ambiguous or nuanced context, requiring more reasoning or interpretation to generate a meaningful question.
	2. Narrative Complexity Easy: Linear plot with one event or idea. Hard: Multi-layered plot, character development, or world-building.		2. Question Specificity Easy: Basic, factual questions asking for a specific detail (e.g., "Who?", "What?"). Hard: Complex or abstract questions that require synthesis, comparisons, or deeper knowledge about the context.
	3. Language & Style Easy: Simple, straightforward language. Hard: Use of metaphors, poetic devices, shifts in tone or voice.		3. Knowledge Requirement Easy: No prior knowledge beyond the given text is needed. Hard: Requires background knowledge, inference, or reasoning to generate a relevant question.
Paraphrase Identification	1. Lexical & Syntactic Similarity Easy: Minor reordering or synonym substitution with near-identical structure. Hard: Significant rephrasing, different vocabulary or sentence structure, yet same meaning.	Sentiment Analysis	1. Sentiment Clarity Easy: Clear, unambiguous sentiment (positive, negative, or neutral). Hard: Sentiment expressed indirectly, or a mixture of sentiments in the same text.
	2. Semantic Inference Easy: Direct, surface-level paraphrases. Hard: Requires understanding of implied meaning, paraphrased idioms, or abstract concepts.		2. Contextual Nuance Easy: Simple, straightforward expressions of sentiment with no hidden or subtle implications. Hard: Sentiment expressed in a nuanced, sarcastic, or contextual manner that requires understanding beyond surface-level words.
	3. Ambiguity or Pragmatic Context Easy: No ambiguity or external context needed. Hard: Paraphrase identification depends on pragmatic/contextual cues or disambiguation.		3. Length and Depth of the Text Easy: Short and simple sentences expressing clear sentiment. Hard: Longer, more complex sentences with mixed feelings or abstract expressions.
Paraphrase Generation	1. Lexical and Syntactic Simplicity Easy: Minor changes in wording, using synonyms or simple reordering of sentence components. Hard: Significant changes in sentence structure, more complex rewording, or use of idiomatic expressions.	General Question Answering	1. Directness of the Question Easy: Questions that are straightforward and directly answerable from the context without the need for additional reasoning. Hard: Questions that require interpretation, inference, or reasoning based on the provided context.
	2. Semantic Consistency Easy: Paraphrases that are almost identical in meaning, with small vocabulary swaps. Hard: Paraphrases that need to capture more subtle or nuanced meanings, requiring deeper understanding of the original context.		2. Contextual Clarity Easy: Clear, unambiguous context where the answer is explicitly stated. Hard: Ambiguous or vague context, requiring deeper understanding or synthesis of multiple pieces of information.
	3. Creativity and Stylistic Variety Easy: Simple, direct rewording with minimal stylistic variation. Hard: Creative paraphrases that involve stylistic or tone shifts, or those that include complex syntactic changes while preserving the original meaning.		3. Factual vs. Inferential Answers Easy: The answer is directly stated or easily extracted from the text. Hard: The answer involves synthesizing information, making inferences, or requires external knowledge.
Text Summarization	1. Text Length Easy: Short input text that already highlights key points. Hard: Long, complex text with multiple subtopics or dense information.	Fact Check	1. Factual Specificity Easy: Questions asking for easily verifiable, specific facts, such as dates, names, or locations. Hard: Questions that require detailed verification or fact-checking from multiple sources or with some level of ambiguity.
	2. Content Density Easy: Clear, well-structured information where the main idea is obvious. Hard: Dense or technical content requiring understanding of the details to create a meaningful, concise summary.		2. Contextual Complexity Easy: The answer can be found in a single piece of well-known, widely agreed-upon information. Hard: The answer requires analyzing complex data, multiple interpretations, or understanding a situation in context to determine accuracy.
	3. Context and Subtlety Easy: Little to no background knowledge required for the summary. Hard: Summarization requires inference, understanding context, or synthesizing information from different parts of the text.		3. Source Dependence Easy: Clear, straightforward facts that can be verified from commonly known or easily accessible sources (e.g., official records, universally recognized events). Hard: The fact being checked is less universally agreed upon, has evolving data, or involves conflicting reports.

Figure 7: Complexity Definitions for each sub-category.

Sub Category	Complexity	Sub Category	Complexity
Headline Generation	1. Text Length Easy: Short article with a single main idea, easy to extract the core message. Hard: Long article with multiple ideas or subtopics, requiring discernment of the most critical information.	Multi Turn Conversation	1. Contextual Continuity Easy: The conversation is straightforward, with clear transitions and a simple back-and-forth interaction. Hard: The conversation involves complex or abstract ideas, requiring the model to recall, understand, and reference multiple pieces of context across several turns.
	2. Content Type Easy: Straightforward, factual content with a clear subject and action. Hard: Complex content with nuanced language, needing a creative yet accurate headline.		2. Response Generation Easy: Responses require little reasoning and are based on direct information from previous turns. Hard: Responses require inferences, deeper reasoning, or nuanced understanding of prior context and the user's implied needs.
	3. Information Distillation Easy: Clear event or announcement that can be summarized in a few words. Hard: Abstract, multifaceted articles requiring summarization of broader themes or mixed topics.		3. Domain Knowledge Easy: The conversation stays within a simple domain, requiring basic information retrieval and straightforward interaction. Hard: The conversation involves specialized knowledge or abstract topics, requiring the system to adapt dynamically based on the evolving context.
Role-Playing	1. Character Consistency Easy: The character or persona is straightforward, with clear and simple attributes. There is little deviation in how the character should behave. Hard: The character requires nuanced understanding, deep role adaptation, or responding to complex scenarios while staying in-character.	Indian Cultural Context	1. Depth of Cultural Understanding Easy: The query requires a basic, widely understood cultural concept or tradition that does not involve nuanced details or historical context. Hard: The query delves into more specialized or nuanced cultural practices, traditions, or beliefs, which might require historical or region-specific knowledge.
	2. Creativity and Imagination Easy: The role-play is based on established norms, and responses follow predictable patterns. Hard: The role requires creative input, improvisation, or handling abstract or unpredictable situations while maintaining authenticity in the persona.		2. Specificity of the Query Easy: The question is about a widely known and commonly practiced cultural topic or festival that is universal across India. Hard: The question pertains to a specific regional tradition, a lesser-known festival, or cultural practice that might differ significantly across regions or communities.
	3. Contextual Depth Easy: The role-playing context is simple, and only surface-level understanding of the role is necessary. Hard: The role requires understanding deep philosophical, historical, or emotional aspects of the character, possibly over multiple turns or complex scenarios.		3. Integration with Broader Context Easy: The query asks for a general explanation without requiring integration of cultural beliefs, practices, and their social implications. Hard: The query requires an explanation that integrates various aspects of Indian culture, including its philosophical, religious, or social implications, and might ask for comparative or cross-regional analysis.
Advice-Seeking	1. Depth of the Problem Easy: The user's issue is straightforward, commonly understood, and doesn't require deep insight or complex problem-solving. Hard: The problem is more complex, requiring a nuanced approach, multiple perspectives, or deeper understanding to provide meaningful advice.	Comprehension	1. Depth of Information Extraction Easy: The task requires directly extracting information that is clearly stated in the passage, with no need for inference. Hard: The task requires inference, where the answer is implied but not directly stated in the passage, or requires synthesizing information from multiple parts of the text.
	2. Personalization and Context Easy: The user's issue is general, and the advice can be applied broadly without needing to account for specific personal factors. Hard: The user's query involves personal, emotional, or contextual factors, and the advice must be tailored to their unique circumstances.		2. Clarity and Directness of the Passage Easy: The passage is simple, with clear and direct statements that make it easy to extract answers. Hard: The passage is complex, contains nuanced language, or presents a more abstract concept, requiring deeper understanding or analysis.
	3. Emotional Sensitivity Easy: The user's issue does not involve strong emotional components or stress. Hard: The user's situation requires empathetic, emotionally aware responses to ensure the advice is sensitive and supportive.		3. Complexity of the Question Easy: The question asks for a straightforward fact or detail that is easily accessible from the passage. Hard: The question requires critical thinking, such as cause-effect relationships or understanding of multiple layers of context.

Figure 8: Complexity Definitions for each sub-category.

Sub Category	Complexity	Sub Category	Complexity
Planning	<p>1. Scope of the Plan Easy: The plan is narrow in scope, with a limited number of steps or elements to consider. Hard: The plan involves multiple variables, such as many tasks, time constraints, or various dependencies that must be addressed.</p> <p>2. Level of Detail Easy: The plan requires only basic details like locations or general activities with little need for deep customization. Hard: The plan requires detailed steps, including specific times, types of activities, resources, and possibly even contingency plans for unexpected situations.</p> <p>3. Customization and Constraints Easy: The user's preferences or constraints are minimal or common, and the plan can be generated with general knowledge. Hard: The plan must account for specific user preferences, such as dietary restrictions, mobility concerns, budget, or local availability of services.</p>	Math QA	<p>1. Mathematical Operation Complexity Easy: The problem involves simple arithmetic operations like addition, subtraction, multiplication, or division that can be solved quickly. Hard: The problem requires more complex operations like algebraic manipulation, geometry, or multi-step calculations involving fractions, percentages, or systems of equations.</p> <p>2. Problem Complexity (Word Problem Difficulty) Easy: The problem is straightforward, with clear and simple wording. No ambiguity or need for interpretation exists. Hard: The problem may involve convoluted or indirect phrasing that requires parsing or understanding multiple pieces of information to solve.</p> <p>3. Number of Steps Required Easy: The problem can be solved with one simple operation, often involving direct calculation. Hard: The problem involves multiple steps or a combination of operations to arrive at the final answer.</p>
Brainstorming	<p>1. Creativity and Originality Easy: The task requires simple, commonly known ideas or solutions that do not need much innovation or deep thought. Hard: The task demands unique, novel, or unconventional ideas that require extensive creativity or thinking outside the box.</p> <p>2. Scope and Specificity of the Problem Easy: The task is relatively broad and general, allowing for a wide range of ideas without needing to consider detailed constraints or limitations. Hard: The task involves more specific or narrow areas, requiring ideas to fit within defined parameters, which could include specific industries, goals, or limitations.</p> <p>3. Depth of Domain Knowledge Required Easy: The task is general enough that no specific domain knowledge is required to generate ideas, or the task is on a topic familiar to a wide audience. Hard: The task requires specialized knowledge of a particular domain (e.g., technology, healthcare, or economics) to generate ideas that are realistic and feasible.</p>	Math Instruction Tuning	<p>1. Mathematical Operation Complexity Easy: The math problem involves basic arithmetic operations such as addition, subtraction, multiplication, or division. The instruction is simple and clear. Hard: The problem involves advanced concepts like algebra, geometry, calculus, or multi-step problem solving, requiring deeper understanding or manipulation of equations.</p> <p>2. Instruction Complexity (Reasoning Required) Easy: The instructions are straightforward and involve a single step to solve. Hard: The instructions require several intermediate steps or involve solving multi-step equations with additional reasoning, like factoring, completing the square, or applying specific mathematical theorems.</p> <p>3. Number of Steps in Solution Easy: The solution involves few steps—often just a direct application of one operation. Hard: The solution involves multiple steps, such as simplifying expressions, factoring, or breaking down complex terms.</p>
Information Seeking	<p>1. Depth of Information Easy: The question seeks basic, straightforward information that is commonly available and well-known. Hard: The question requires more nuanced, detailed, or in-depth information, possibly involving multiple sources or complex concepts.</p> <p>2. Specificity of the Query Easy: The question is general and can be answered with a clear, direct response. Hard: The question is specific or highly detailed, requiring an elaborate response or synthesis of various aspects.</p> <p>3. Domain or Contextual Knowledge Easy: The information sought is familiar or common knowledge, requiring little specialized knowledge to answer. Hard: The information involves a specialized domain, or understanding the context or background knowledge is necessary to provide a comprehensive answer.</p>	Math Proofs	<p>1. Theorem Complexity Easy: The theorem is simple and straightforward, typically involving basic set theory, arithmetic, or algebra. Hard: The theorem involves advanced concepts such as topology, number theory, or higher-level algebra. The logic required to prove the theorem might be more complex and abstract.</p> <p>2. Proof Structure Easy: The proof is short, involving direct logical steps with no intermediate lemmas or deep reasoning. Hard: The proof involves multiple intermediate steps, possibly requiring auxiliary lemmas, the use of multiple mathematical properties, or breaking down the proof into several cases.</p> <p>3. Mathematical Concepts Involved Easy: The proof relies on simple mathematical concepts, such as basic set operations or arithmetic properties. Hard: The proof uses complex mathematical ideas, such as induction, contrapositive reasoning, or advanced theorems, and may require careful justification of each step.</p>

Figure 9: Complexity Definitions for each sub-category.

Sub Category	Complexity	Sub Category	Complexity
Code Generation	<p>1. Problem Simplicity Easy: Involves basic control structures or common patterns. Hard: Requires algorithmic thinking, multi-step planning, or integration with libraries/APIs.</p> <p>2. Code Length Easy: One-liner or small function. Hard: Multiple functions, modular structure, or boilerplate setup.</p> <p>3. Conceptual Complexity Easy: Uses elementary constructs like loops, conditionals. Hard: Requires concepts like recursion, concurrency, or complex data structures.</p> <p>4. Edge Cases and Testing Easy: Few or no edge cases. Hard: Needs robust handling of invalid inputs, errors, or corner cases.</p>	Unit Test Generation	<p>1. Input Complexity Easy: Function accepts primitive types and has predictable output. Hard: Function has multiple inputs, nested structures, or dynamic behavior.</p> <p>2. Output Behavior Easy: Deterministic and consistent output. Hard: Output depends on side effects, randomness, or state.</p> <p>3. Edge Case Coverage Easy: Few or obvious edge cases. Hard: Many possible failure modes or boundary conditions.</p> <p>4. Format Required Easy: Just input/output pairs or informal descriptions. Hard: Tests in specific frameworks with setup/teardown, mocking, etc.</p>
Code Debugging	<p>1. Error Obviousness Easy: Bug is a syntax error or obvious logic mistake (e.g., == vs =). Hard: Bug is subtle, involves side effects, off-by-one logic, or misunderstood APIs.</p> <p>2. Code Scope Easy: Small functions with limited state or logic. Hard: Multiple functions, state tracking, or external dependencies involved.</p> <p>3. Required Knowledge Easy: General debugging, print/log inspection suffices. Hard: Requires domain-specific understanding, complex reasoning, or tool-based debugging.</p> <p>4. Impact of Fix Easy: Fix is localized and doesn't affect other logic. Hard: Fix has ripple effects across the codebase and must maintain correctness globally.</p>	Code Theory	<p>1. Concept Familiarity Easy: Widely taught or intuitive topics (e.g., loops, arrays, O(n)). Hard: Niche or abstract topics (e.g., amortized complexity, monads).</p> <p>2. Explanation Depth Easy: Surface-level description of how something works. Hard: Deep dive into trade-offs, limitations, and formal reasoning.</p> <p>3. Required Background Easy: Assumes basic CS knowledge. Hard: Requires formal math or algorithmic training.</p> <p>4. Application Scope Easy: Explains theory in isolation. Hard: Tied to real-world design or performance decisions.</p>
Code Editing	<p>1. Edit Type Easy: Cosmetic or small structural change (e.g., rename, add a check). Hard: Deep refactor or major logic change across files.</p> <p>2. Context Required Easy: Local context is enough to apply the edit. Hard: Requires understanding of broader dependencies or interfaces.</p> <p>3. Behavior Change Easy: No change in behavior (e.g., renaming, reformatting). Hard: Behavior is intentionally changed, requiring correctness guarantees.</p> <p>4. Risk Level Easy: Low-risk edit, unlikely to break anything. Hard: High-risk edit, may affect performance, correctness, or security.</p>	Code Review	<p>1. Code Quality Easy: Well-structured code with clear intent. Hard: Poorly written, unstructured, or ambiguous code.</p> <p>2. Scope of Review Easy: Small diff or single function. Hard: Large PR with multiple files and architectural impact.</p> <p>3. Standards Compliance Easy: Trivial formatting or naming violations. Hard: Requires domain knowledge, security awareness, or architectural judgment.</p> <p>4. Reviewer Responsibility Easy: Only comments on style or clarity. Hard: Needs to verify correctness, performance, and maintainability.</p>
Code Explanation	<p>1. Code Length Easy: Few lines with straightforward logic. Hard: Long code with deeply nested structures.</p> <p>2. Abstraction Level Easy: Explains "what it does." Hard: Needs to explain "why," covering design decisions or trade-offs.</p> <p>3. Concept Depth Easy: Basic logic with familiar constructs. Hard: Involves complex algorithms, libraries, or domain-specific behavior.</p> <p>4. Audience Adaptation Easy: Target audience already knows the language and topic. Hard: Requires tailoring to beginners or non-technical audiences.</p>	Repository level Code Generation	<p>1. Architecture Complexity Easy: Scaffold for a simple project (e.g., a CRUD app). Hard: Full-stack system with frontend, backend, DB, and CI/CD config.</p> <p>2. Component Integration Easy: Independent modules or templates. Hard: Components must interoperate with consistent API contracts.</p> <p>3. Language/Framework Mastery Easy: One language, minimal config. Hard: Polyglot codebase (e.g., Python backend + React frontend + Docker).</p> <p>4. Customization Required Easy: Follows standard patterns (e.g., Flask starter). Hard: Needs tailoring to specific domain, logic, or 3rd-party APIs.</p>

Figure 10: Complexity Definitions for each sub-category.

Sub Category	Complexity	Sub Category	Complexity
Code Translation	<p>1. Language Similarity Easy: Translation between similar paradigms (e.g., Python ↔ JavaScript). Hard: Translation between very different paradigms (e.g., Python ↔ Haskell).</p> <p>2. Feature Mapping Easy: All features map cleanly between languages. Hard: Requires emulating behavior (e.g., list comprehensions, async models).</p> <p>3. Code Size Easy: Short, self-contained function. Hard: Large module with classes, decorators, or closures.</p> <p>4. Idiomatic Translation Easy: Direct one-to-one line conversion. Hard: Needs idiomatic rewriting to follow target language conventions.</p>	Function Calling	<p>1. Complexity of Function Signatures Easy: The function signatures are straightforward, with simple parameter types (e.g., integers, strings) and no additional constraints. Hard: The function signatures involve complex parameters, such as nested structures, multiple required fields, or specialized types like objects, arrays, or custom types (e.g., qubits, Fourier components, etc.).</p> <p>2. Interpretation of User Requirements Easy: The user request is simple and directly maps to the required parameters without ambiguity. There are minimal or no special considerations for things like optional arguments or conflicting values. Hard: The user's request is complex, involving multiple steps of reasoning or context-dependent choices, requiring careful extraction of parameters and appropriate default values for missing information.</p> <p>3. Parameter Mapping and Constraints Easy: The parameters have clear, unambiguous mappings (e.g., integers for quantities, strings for identifiers), and there are no special conditions or dependencies between parameters. Hard: The parameters have complex dependencies (e.g., the number of Fourier components must align with the number of qubits) or constraints that must be satisfied (e.g., time complexity requirements, control operations).</p> <p>4. Function Logic and Output Generation Easy: The function call results in simple, easily interpretable outputs that don't require additional processing or understanding of underlying logic. Hard: The function call involves sophisticated logic that results in complex outputs (e.g., quantum circuits), or the output requires further interpretation or refinement to be useful in the context.</p>
Instruction Following	<p>1. Task Complexity Easy: The task involves simple, straightforward instructions with minimal structure or specific formatting requirements. Hard: The task requires multi-step reasoning, adherence to multiple specific formatting guidelines, and generation of complex or detailed content.</p> <p>2. Output Structure and Formatting Easy: Instructions involve generating basic content with minimal formatting or structural constraints (e.g., short answers or paragraphs without complex guidelines). Hard: The instructions demand precise formatting (headings, bullet points, specific word count limits, etc.), and the content must be logically organized and adhere to multiple constraints.</p> <p>3. Level of Detail and Precision Easy: The instructions require a general response with little emphasis on fine-grained details, and minor flexibility is allowed. Hard: The instructions demand highly detailed responses with precise limits (e.g., word count per section), strict content divisions (subsections), and comprehensive coverage of a topic.</p> <p>4. Interpretation of Instructions Easy: The instructions are unambiguous, with clear expectations and no need for interpretation beyond direct execution. Hard: The instructions involve multiple layers of interpretation (e.g., understanding how to balance word count with content depth, determining how to break down sections logically, or ensuring that all key points are covered).</p>	Safety & Non - Compliance	<p>1. Clear vs. Ambiguous Harmful Requests Easy: The harmful or unethical request is clear and direct, with no ambiguity or need for interpretation. Hard: The request is more subtle, requiring the model to understand context, infer potential harm, or identify violations that may not be immediately obvious.</p> <p>2. Politeness and Firmness Easy: The model simply needs to reject the request without much elaboration or any need to soften the response. Hard: The model needs to balance politeness, firmness, and clarity, ensuring it is both respectful and firm in refusal while explaining why the request is not permissible.</p> <p>3. Contextual Decision-Making Easy: The request is easily recognized as violating ethical norms or policies, so the response is straightforward. Hard: The model must assess context, which might involve determining whether the request is borderline or masked behind polite language, requiring careful judgment and nuanced response.</p> <p>4. Complexity of Policy Interpretation Easy: The model only needs to reject straightforward violations, such as promoting illegal activities or encouraging harm. Hard: The model must navigate complex or gray areas where there may be multiple interpretations of policies or ethics, requiring it to consider indirect implications.</p>

Figure 11: Complexity Definitions for each sub-category.

Constraint Type	Description	Examples
Length Constraints	Defines how long or concise a response should be.	"Answer in one sentence", "Summarize in 50 words", "Explain in two paragraphs"
Structural Formatting	Governs the organization of the output.	Paragraphs, bullet points, numbered lists, tables ("Compare A and B in a table"), JSON, XML, HTML
Tone and Style	Specifies tone, voice, or target audience.	Formal, conversational, academic, friendly, motivational, child-friendly, expert-level
Persona / Role Play	Instructs the model to adopt a specific identity.	"Act as a doctor/teacher/software engineer", "Answer like Albert Einstein or a pirate"
Reasoning Style	Defines how the model should arrive at the answer.	Chain-of-thought, step-by-step explanation, final answer only, show intermediate steps
Time / Historical Context	Specifies a temporal or historical frame.	"Explain from a 19th-century perspective", "What would a Roman say?", "Imagine you are in 2100"
Output Type / Genre	Determines the nature of the response.	Poem, story, dialogue, screenplay, essay, report, memo, tweet, press release
Comparative / Multi-perspective	Requests multiple viewpoints or contrasts.	"Compare pros and cons", "Show both sides of the argument", "Write from X's and Y's perspective"

Figure 12: Instruction following: constraint types and examples

Dimension	Explanation
Lexical Diversity	<p>The variety and richness of words used in the text. Higher lexical diversity means using a wide range of vocabulary instead of repetitive or generic terms.</p> <p>Why It Matters for Indic Data: Indic languages have rich vocabulary and multiple synonyms; poor diversity makes translations monotonous and unnatural.</p> <p>Errors in this area: Overuse of common words, failure to use synonyms, repetitive phrasing.</p>
Coherence and Cohesion	<p>Coherence: Logical flow and overall sense of the text.</p> <p>Cohesion: Use of linguistic devices (connectors, pronouns, conjunctions) to link sentences smoothly.</p> <p>Why It Matters for Indic Data: Many Indic languages use connectives and honorific markers that impact cohesion; direct translation from English often breaks these links.</p> <p>Errors in this area: Disconnected sentences, abrupt topic shifts, missing conjunctions or pronouns.</p>
Completeness	<p>Whether the output contains all necessary information from the source without omissions or additions.</p> <p>Why It Matters for Indic Data: When translating long or complex Indic sentences, models often skip certain parts (e.g., verb phrases or subordinate clauses).</p> <p>Errors in this area: Missing phrases, dropped entities, truncated sentences, or extra hallucinated details.</p>
Grammatical Accuracy	<p>Correct use of grammar rules (syntax, tense, agreement, case, morphology). It affects fluency and correctness of the output.</p> <p>Why It Matters for Indic Data: Indic languages have complex inflectional morphology and word order; errors often occur in case endings, gender/number agreement, and verb conjugations.</p> <p>Errors in this area: Wrong tense, missing auxiliary verbs, subject-verb disagreement, wrong case marking.</p>
Named Entity Handling	<p>Correct recognition and rendering of named entities (persons, places, organizations, dates, currencies, etc.) across languages.</p>

Table 6: Key dimensions for assessing LLM translations in Indic languages, highlighting their significance and common errors.

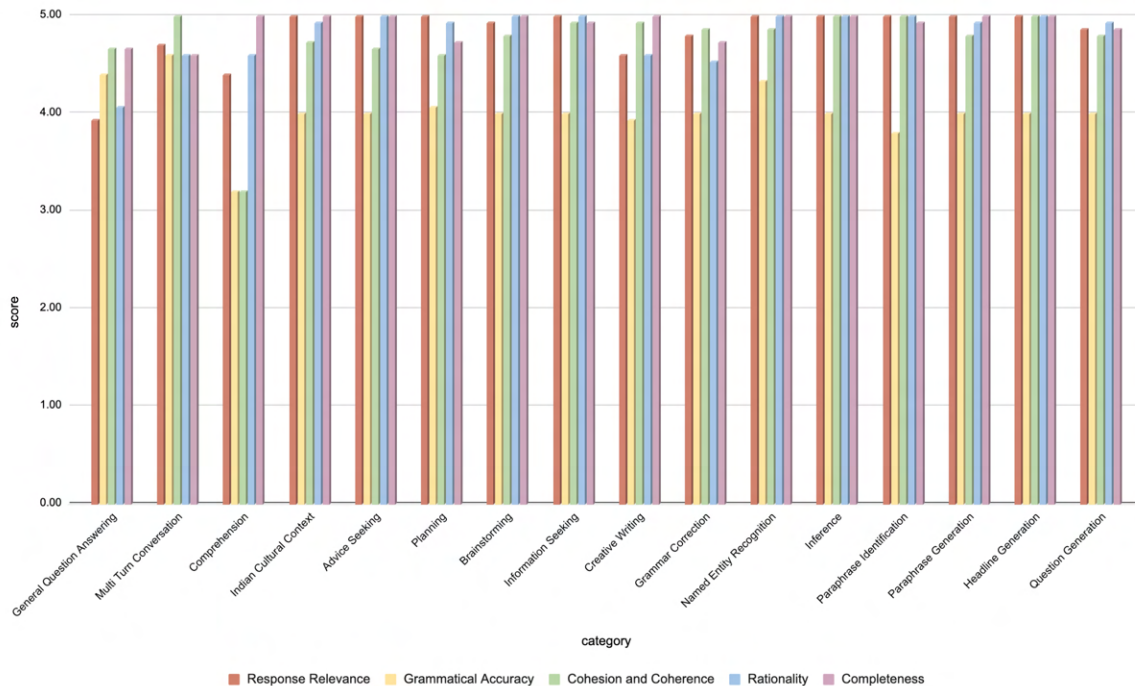


Figure 13: LLM generation quality evaluation scores across various categories.

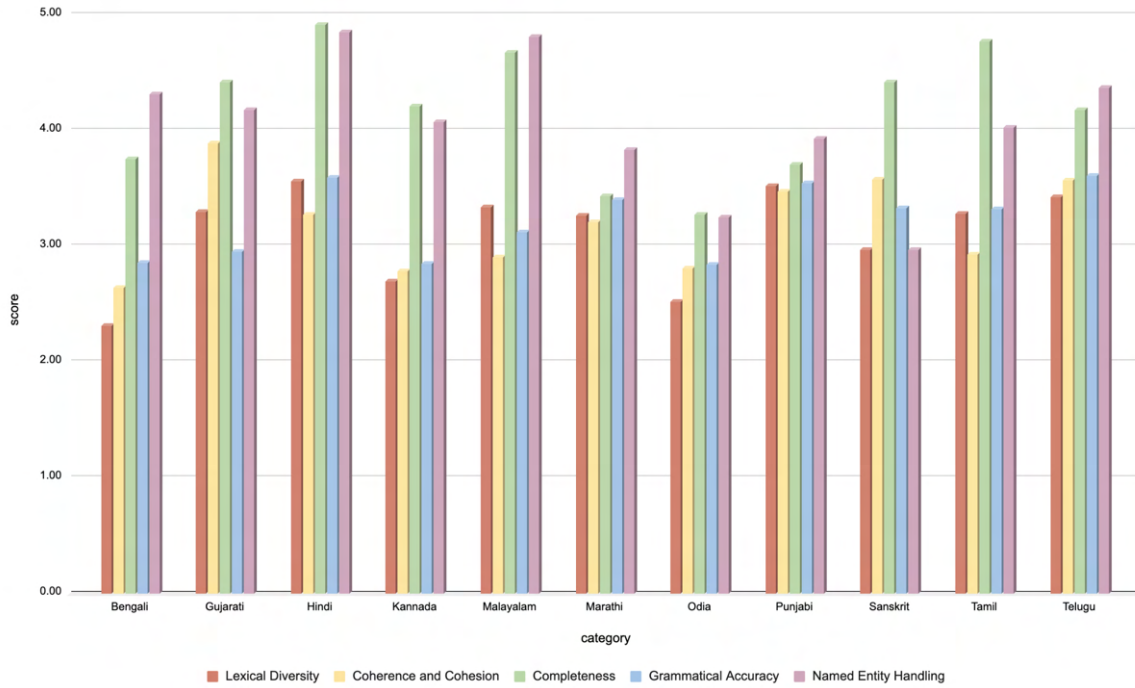


Figure 14: LLM translation quality evaluation scores across 11 Indian languages.

in Section 3.3. In addition to these specifications, dedicated frameworks for quality assurance are provided, encompassing both language quality verification and content quality verification, as illustrated in Figures 19 and 20, respectively.

D Examples

We provide examples of both instruction and preference tuning datasets in Figures 21-30.

Prompt used for Generation of Easy Indian Cultural Context English Prompts in Self Instruct Pipeline
<p>System Prompt</p> <p>You are tasked with generating easy-level, culturally diverse, and descriptive questions that explore various aspects of Indian culture. Your questions should avoid being too generic or frequently asked. Instead, focus on less commonly discussed but still culturally meaningful topics that are easy to understand and answer.</p> <p>Guidelines for Generating Questions:</p> <p>1. Difficulty Level – Easy: The question should be simple enough for someone with basic cultural awareness to answer in a few sentences. Avoid complex or academic phrasing. Each question should address only one clear aspect or topic — do not combine multiple elements in a single question.</p> <p>2. Question Type – Descriptive: The answer should require a short paragraph, not a one-word or one-line response. Avoid yes/no or multiple-choice style formats.</p> <p>3. Scope – Specific but Not Niche: Focus on fine-grained yet non-obscure topics. Do not ask for broad essays like “Describe a festival” or over-complicated questions like “What is the significance of X across different regions with its variations and philosophical meanings?”</p> <p>4. Diversity – Pan-Indian Coverage: Ensure questions represent diverse states, communities, religious groups, art forms, customs, and practices. Cover a variety of domains like traditional food, clothing, local art, customs, symbols, minor rituals, or lesser-known celebrations.</p> <p>Use the given questions as examples of how to frame the questions.</p> <p>Generate the instructions in the json format:</p> <pre>{ ... Question i: ith Question, ... }</pre> <p>Note that the instructions must be in english language. Return only the json format response, do not return anything other than json.</p> <p>User Prompt</p> <p>Here are some example questions: <8 Easy Indian Cultural Context English Prompts as Few Shots></p>

Figure 15: Prompt used for generation of easy Indian cultural context English prompt in Self-Instruct pipeline.

Prompt used for Generation of Hard Indian Cultural Context English Prompts in Self Instruct Pipeline
<p>System Prompt</p> <p>You are tasked with generating hard-level, culturally diverse, descriptive questions that explore complex, nuanced, or region-specific aspects of Indian culture. These questions should go beyond basic or commonly asked topics, aiming to challenge the responder's depth of cultural understanding.</p> <p>Guidelines for Generating Questions:</p> <p>1. Difficulty Level – Hard: The questions should require a detailed and informed response, often involving historical context, philosophical meaning, or regional variation. Expect the responder to draw from less commonly known knowledge, comparative insights, or interconnected traditions. Avoid overly academic phrasing, but do not oversimplify the question.</p> <p>2. Question Type – Descriptive: The answer should require at least a short essay-style paragraph, explaining the underlying cultural, religious, philosophical, or social dimensions. Do not create multi-part or overly long questions — keep one core focus per question, but explore it deeply.</p> <p>3. Scope – Specialized or Regionally Rooted: Focus on less mainstream topics, regional traditions, or philosophical/religious practices that are not typically covered in general knowledge. Explore cultural beliefs, historical movements, ritualistic practices, sectarian philosophies, regional art forms, and symbolic meanings.</p> <p>4. Diversity – Pan-Indian and Cross-Traditional: Ensure a wide range of questions from different Indian states, languages, communities, castes, and religious traditions. Include topics from Hindu, Buddhist, Jain, Sikh, Islamic, Christian, tribal, and other regional traditions.</p> <p>Use the given questions as examples of how to frame the questions.</p> <p>Generate the instructions in the json format:</p> <pre>{ ... Question i: ith Question, ... }</pre> <p>Note that the instructions must be in english language. Return only the json format response, do not return anything other than json.</p> <p>User Prompt</p> <p>Here are some example questions: <8 Hard Indian Cultural Context English Prompts as Few Shots></p>

Figure 16: Prompt used for generation of hard Indian cultural context English prompt in Self-Instruct pipeline.

Prompt used for Translation via LLM
<p>System Prompt</p> <p>Translate the following text into {lang}, targeting educated native speakers in an academic or professional setting.</p> <p>Translation Guidelines:</p> <p>1. Exclusive Translation: Translate the provided text only. No answers, solutions, interpretations, or commentary.</p> <p>2. Preserve Original Structure: Maintain the input's original structure, including equations, formulas, syntax, and logical structures. Retain original text if direct translation alters meaning.</p> <p>3. Prioritize Accuracy: Ensure accurate translation of technical terms and concepts using widely accepted academic terminology.</p> <p>4. Maintain Meaning and Intent: Preserve the original meaning, intent, and challenge. Maintain syntax and variable names for code and math.</p> <p>5. Translate Instructions/Metadata Verbatim: Translate instructions (e.g., "Enter your answer here:", "Return your final response within \boxed{.}") and metadata (e.g., file names, timestamps) exactly as they appear, without attempting to execute or interpret them.</p> <p>6. Translation Requirements (Reinforced): Perform translations only; do not add new text. Make no changes beyond accurate word-for-word translation. Leave code, formulas, placeholders, and instructions untouched.</p> <p>User Prompt</p> <p>Text to Translate: {text}</p>

Figure 17: Prompt used for translation via LLM.

Prompt used for Evaluating models DPOed on 100K Pragmaan-Align Data via LLM as Judge
<p>System Prompt</p> <p>You are an impartial evaluator. Your task is to judge a model response against a given ground truth answer for a prompt. Evaluate the response with a real number score between 1-5, using **one decimal place only**. Never output integers; always use a decimal number with one digit (e.g., 3.7, 4.2). Consider the category of the prompt when scoring.</p> <p>Categories and their focus are: Reasoning – Logical correctness and clarity of explanation. Role Playing – Staying in character, creativity, and consistency. Math – Accuracy of calculations and clarity of steps. Editing – Improving or revising text while preserving meaning. Information Seeking – Factual accuracy and relevance. Advice Seeking – Practicality, usefulness, and clarity. Data Analysis – Correct interpretation of data and logical conclusions. Creative Writing – Originality, coherence, style, and engagement. Planning – Clear, feasible, and well-structured steps. Brainstorming – Creativity, diversity, and relevance of ideas.</p> <p>Provide scores for each response separately. Output must strictly follow this format: "Response score: [[x.y]]</p> <p><Explanation of your scoring, highlighting strengths and weaknesses>."</p> <p>Notes: Focus on correctness, relevance, and quality over verbosity. Be critical but fair. Base scores only on alignment with the category requirements and the ground truth. Always provide an explanation after the score.</p> <p>User Prompt</p> <p>< Prompt > {prompt}</p> <p>< Ground Truth > {ground_truth}</p> <p>< Response > {response}</p>

Figure 18: Prompt used for evaluating post-trained model on *Pragmaan-Align* data via LLM-as-a-Judge.

1. Language Quality Verification Guidelines
<p>The evaluation of Prompt–Response Pairs (PRPs) focuses on key linguistic and stylistic parameters to ensure high-quality outputs across Indic languages. These include fluency, grammatical accuracy, coherence and cohesion, sentence structure, lexical diversity, and accurate handling of named entities. The following principles guide this process:</p> <p>1.1 Preserve Naturalness and Meaning Translations should read naturally in the target language while preserving the original intent. Avoid literal, word-for-word translations. Instead, adapt phrasing and sentence structure in accordance with the linguistic norms of the respective Indic language. Ensure cultural appropriateness in expressions and idiomatic usage.</p> <p>1.2 Localize Editing Instructions Adapt instructions so they align with how editing tasks are conventionally expressed in Indic languages. Example: English: "Rewrite the sentence in Active Voice." Hindi: "वाक्य को सक्रिय वाच्य में पुनः लिखें।"</p> <p>1.3 Maintain Consistency in Terminology Use widely accepted equivalents for domain-specific terms (e.g., AI, computing, mathematics, medicine, law). Where no direct equivalent exists, apply transliteration while ensuring clarity of meaning. Examples: English: "Refactor the code for better readability." Hindi: "कोड को बेहतर पठनीयता के लिए पुनः व्यवस्थित करें।"</p> <p>1.4 Follow Proper Formatting and Punctuation Apply punctuation rules specific to the target Indic language rather than English conventions. Ensure proper spacing and script usage. Avoid using Latin punctuation marks such as . where language-specific marks like । (Hindi) or । (Bangla) should be used. Example: Incorrect: "वाक्य को सक्रिय वाच्य में पुनः लिखें." Correct: "वाक्य को सक्रिय वाच्य में पुनः लिखें।"</p> <p>1.5 Handle Untranslatable Terms Appropriately For terms such as brand names, technical concepts, or programming keywords, use transliteration in Indic script where possible. Maintain semantic clarity in context. Example: English: "Replace the variable with a meaningful name." Hindi: "चर/वैरिएबल को एक अर्थपूर्ण नाम से बदलें।"</p> <p>1.6 Code Snippets and Symbols Retain code snippets in their original form without translation. Example: English: "Change int x = 10; to int y = 20;" Hindi: "int x = 10; को int y = 20; में बदलें।"</p> <p>1.7 Localization of Editable Text When localizing content that requires editing, the translated text should reflect the specific requirement of the instruction. For instance, if the instruction involves correcting grammatical errors, the translated text should intentionally include such errors before editing. Example: English: "Correct the grammatical mistakes in the following text: 'I have took the medicines.'" Hindi: "दिए गए पाठ में व्याकरण संबंधी गलतियों को सुधारें। 'मैं दवा खाता।'"</p>

Figure 19: Comprehensive language luality guidelines outlining key linguistic dimensions such as grammar, fluency, clarity, and naturalness for ensuring high-quality annotated data.

2. Content Quality Verification Guidelines
<p>Each Prompt–Response Pair (PRP) undergoes a structured evaluation process to ensure alignment with six core dimensions: complexity, multi-turn interaction, instruction-following capability, safety considerations, cultural relevance to the Indian context, and inclusion of reasoning or thinking trails. PRPs that fully meet these criteria are accepted without modification, while those exhibiting minor inconsistencies undergo targeted revisions to ensure compliance. PRPs with significant deviations are comprehensively rewritten to maintain both linguistic quality and adherence to the specified configuration requirements. Definitions for each category and setting are explicitly documented and must be strictly followed.</p> <p>Beyond compliance with language and setting-specific requirements, the following general principles guide annotation and validation:</p> <p>2.1 Relevance to the Prompt The response must accurately and completely address the intent of the prompt. Extraneous details, digressions, or unrelated content should be avoided. Responses that partially satisfy the prompt but omit essential information should be deprioritized.</p> <p>2.2 Fluency and Naturalness Responses should exhibit grammatical correctness, structural coherence, and logical flow. Language must read naturally in the target Indic language, adhering to its specific linguistic conventions and avoiding literal or awkward phrasing. Outputs containing major syntactic or grammatical errors are considered suboptimal.</p> <p>2.3 Factual Accuracy For prompts requiring factual information, responses must be accurate and verifiable. Any response containing incorrect, misleading, or unverifiable claims should be rejected. When multiple responses are factually correct, preference should be given to those that are concise, precise, and clearly articulated.</p> <p>2.4 Cultural and Linguistic Appropriateness Responses should conform to cultural norms and linguistic standards of the target Indic language. Avoid regionally inappropriate idioms, metaphors, or expressions unless explicitly required by the prompt. Ensure contextual relevance for the intended audience of the target language.</p> <p>2.5 Style and Formality Tone and level of formality must align with the prompt’s context (e.g., academic, conversational, or instructional). Responses that fail to maintain the appropriate tone or deviate from the intended style should be deprioritized.</p> <p>2.6 Avoiding Bias and Stereotypes Responses must not reinforce stereotypes or exhibit bias related to gender, caste, religion, ethnicity, or socio-economic status. Use neutral and inclusive language wherever applicable. If all available responses contain bias, flag them for further review.</p> <p>2.7 Filtering Harmful or Offensive Content Reject responses containing hate speech, explicit or offensive material, political bias, or harmful language. Any content promoting violence, discrimination, or misinformation should not be selected. All outputs must comply with ethical AI principles and community guidelines.</p> <p>2.8 Handling Subjectivity in Sensitive Topics For prompts concerning controversial or sensitive domains (e.g., politics, religion, social issues), responses should maintain a neutral and balanced tone. Avoid presenting subjective opinions as objective facts. Favor informative, fact-based responses over emotionally charged or opinionated ones.</p> <p>3. Final Considerations Consistency in annotation is critical; all guidelines must be applied uniformly across evaluations. Assess responses solely on their intrinsic quality—model attribution (e.g., ChatGPT, Krutrim) should not influence judgment. Prefer responses that deliver essential details succinctly, avoiding unnecessary verbosity.</p>

Figure 20: Content quality guidelines detailing principles for maintaining factual accuracy, contextual relevance, safety, and adherence to task-specific requirements during data annotation.

Category	Prompt	Preferred Response	Rejected Response
Advice Seeking	माझ्या मनेजरला वाटत की कामाच्या ठिकाणी माझी संवाद शैली असंवेदनशील आणि संघटित आहे. त्यांना वाटत की मी माझ्या सहकाऱ्यांशी विचारपूर्वक संवाद साधायचा. मला कधीच वाटत नाही की मी असंवेदनशील असेन, म्हणून मला हे ऐकून खरेतर आश्चर्य वाटतं. मी फक्त थेट आणि मुद्द्याचं बोलीतो. मी प्रामाणिकपणे, परंतु थोडक्यात बोलताना इतरांच्या भावना लक्षात ठेवून त्यांच्याशी संवाद कसा साधू शकतो?	<p>आपल्या मनेजरच्या टिप्पण्या ऐकून आपल्याला आश्चर्य वाटणे स्वाभाविक आहे. संवादाची शैली वैयक्तिक असू शकते, आणि आपले थेट आणि मुद्देसुद्द दिसणे काही वेळा इतरांमधील संवेदनशीलता कमी करू शकते. इतरांच्या भावना लक्षात घेतल्यास, संवादाची शैली सुधारण्यासाठी काही टिप्स येथे दिल्या आहेत:</p> <ol style="list-style-type: none"> 1. “सकारात्मक आरंभ”: आपले बोलणे सुरू करताना प्रत्येक गोष्टीत काही सकारात्मकता समाविष्ट करा. उदाहरणार्थ, “मला तुमचं विचार आवडले, पण...” अशी शैली वापरल्यास, आपली अभिप्राय थोडी सौम्य आणि सकारात्मक निर्माण होईल. 2. “सवाल विचारणे”: संवादत समालिप्त झालेल्या व्यक्तीच्या विचारांची आणि भावना जाणून घेण्यासाठी प्रश्न विचारा. हे संवादाला संवादात्मक बनवतो आणि टीममधील सहकार्य वाढवतो. 3. “आवाजाचा टोन”: आपल्या आवाजाचा टोन आणि शरीराची भाषा महत्वाची आहे. थेट बोलताना सॉफ्ट टोन वापरणे आणि थोडा हसत बोलणे, इतरांनाही आरामदायक बनवू शकतात. 4. “त्यांच्या भावना समजून घेणे”: आपण जेव्हा कोणाशी बोलता, तेव्हा त्यांची स्थिती आणि भावना लक्षात घेणे महत्वाचे आहे. “तुमचं मत मोजलं जातं आणि मला तुमचं विचार समजून घ्यायला आवडेल,” असा टुप्चिकोन ठेवता येईल. 5. “परतफेड देणे”: कोणताही अभिप्राय दिल्यावर, त्यात सकारात्मकता ठेवा. जर कुणी काही विचार केले असेल, तर त्याचा आदर करा आणि त्यावर चर्चा करा. 6. “संपूर्णता”: बोलताना थोडी थांबा, जेणेकरून इतरांनाही आपल्या विचारांची पूर्णता समजून घेता येईल. हे विशेषतः गुंतागुंतीच्या मुद्द्यांवर लागू शकते. 7. “प्रतिक्रिया विचारणे”: त्यावर चर्चा केल्यानंतर, आपल्या सहकाऱ्यांकडून आपली संवाद शैली कशी वाटली याबद्दल काही फीडबॅक घ्या, हे आपल्याला पुढील संवाद सुधारण्यास मदत करेल. <p>आपण आपल्या संवाद शैलीवर सुधारणा करण्याचे प्रयत्न करत असताना, नेहमी लक्षात ठेवा की प्रत्येक जण वेगळा असतो आणि संवाद करण्याची शैली देखील वेगळी असते. आपल्या संवादाच्या जागरूकतेने आणि संवेदनशीलतेने आपले सहकारी आणि टीमसह चांगले संबंध निर्माण होण्यास मदत करेल.</p>	<p>तुम्हाला तुमच्या व्यवस्थापकाकडून अभिप्राय मिळाल्यानंतर तुम्ही धक्का बसले आहेत याचा अर्थ समजून घेण्यासारखा आहे. कोणत्याही कार्यालयीन वातावरणात प्रभावी संवाद महत्त्वपूर्ण आहे आणि तो अनेकदा वैयक्तिक पसंदीवर अवलंबून बदलतो. अधिक चिंताग्रस्त किंवा सूक्ष्म टुप्चिकोन स्वीकारण्यासाठी स्वतःची पुनर्निर्माणित करण्याचा प्रयत्न करा; प्रत्येक संभाषणासाठी योग्य शब्द निवडा आणि आवश्यकतेनुसार तपशीलवार स्पष्टता देऊन तुमचे संदेश सुधारण्याचा सराव करा. जर एखाद्या विचारावर मत व्यक्त केले तर ते अशाद्धिक भाषेच्या माध्यमातून देखील करता येते-उदाहरणार्थ, सौहार्दपूर्ण स्मितहास्याने किंवा भौतिक पूर्ण हाकामाने. जरी तुम्ही नेहमीचे “थेट” मार्ग अनुसरलात तरीही या छोट्या बदलांनी तुमचा सहकारी संबंध दृढ होईल आणि एकंदर संघटनात्मक संस्कृती सुधारेल.</p>
Brainstorming	मैं नया प्रोडक्ट बनाने के लिए कुछ विचारों पर सोच रहा हूँ। इन विचारों में से एक है कि हम एक ऐप बना सकते हैं जो लोगों को उनके कार्यों को याद दिलाने में मदद करे। क्या आप इसे और बेहतर बनाने में मदद कर सकते हैं?	<p>आपका प्रोडक्ट विचार बहुत अच्छा है। आप इसे और बेहतर बनाने में मदद कर सकते हैं।</p> <ol style="list-style-type: none"> 1. युन-आयडिओ बनाएं: आपका प्रोडक्ट एक ऐप है जो लोगों को उनके कार्यों को याद दिलाने में मदद करेगा। इसे और बेहतर बनाने में मदद करने के लिए, आप इसे और बेहतर बनाने में मदद कर सकते हैं। 2. डिजिटल डिजिटल बनाएं: आपका प्रोडक्ट एक ऐप है जो लोगों को उनके कार्यों को याद दिलाने में मदद करेगा। इसे और बेहतर बनाने में मदद करने के लिए, आप इसे और बेहतर बनाने में मदद कर सकते हैं। 3. डिजिटल डिजिटल बनाएं: आपका प्रोडक्ट एक ऐप है जो लोगों को उनके कार्यों को याद दिलाने में मदद करेगा। इसे और बेहतर बनाने में मदद करने के लिए, आप इसे और बेहतर बनाने में मदद कर सकते हैं। 4. डिजिटल डिजिटल बनाएं: आपका प्रोडक्ट एक ऐप है जो लोगों को उनके कार्यों को याद दिलाने में मदद करेगा। इसे और बेहतर बनाने में मदद करने के लिए, आप इसे और बेहतर बनाने में मदद कर सकते हैं। 5. डिजिटल डिजिटल बनाएं: आपका प्रोडक्ट एक ऐप है जो लोगों को उनके कार्यों को याद दिलाने में मदद करेगा। इसे और बेहतर बनाने में मदद करने के लिए, आप इसे और बेहतर बनाने में मदद कर सकते हैं। <p>यदि आप इसे और बेहतर बनाने में मदद करने में मदद कर सकते हैं, तो आप इसे और बेहतर बनाने में मदद कर सकते हैं।</p>	<p>आपका प्रोडक्ट विचार बहुत अच्छा है। आप इसे और बेहतर बनाने में मदद कर सकते हैं।</p> <ol style="list-style-type: none"> 1. डिजिटल डिजिटल बनाएं: आपका प्रोडक्ट एक ऐप है जो लोगों को उनके कार्यों को याद दिलाने में मदद करेगा। इसे और बेहतर बनाने में मदद करने के लिए, आप इसे और बेहतर बनाने में मदद कर सकते हैं। 2. डिजिटल डिजिटल बनाएं: आपका प्रोडक्ट एक ऐप है जो लोगों को उनके कार्यों को याद दिलाने में मदद करेगा। इसे और बेहतर बनाने में मदद करने के लिए, आप इसे और बेहतर बनाने में मदद कर सकते हैं। 3. डिजिटल डिजिटल बनाएं: आपका प्रोडक्ट एक ऐप है जो लोगों को उनके कार्यों को याद दिलाने में मदद करेगा। इसे और बेहतर बनाने में मदद करने के लिए, आप इसे और बेहतर बनाने में मदद कर सकते हैं। 4. डिजिटल डिजिटल बनाएं: आपका प्रोडक्ट एक ऐप है जो लोगों को उनके कार्यों को याद दिलाने में मदद करेगा। इसे और बेहतर बनाने में मदद करने के लिए, आप इसे और बेहतर बनाने में मदद कर सकते हैं। 5. डिजिटल डिजिटल बनाएं: आपका प्रोडक्ट एक ऐप है जो लोगों को उनके कार्यों को याद दिलाने में मदद करेगा। इसे और बेहतर बनाने में मदद करने के लिए, आप इसे और बेहतर बनाने में मदद कर सकते हैं। <p>यदि आप इसे और बेहतर बनाने में मदद करने में मदद कर सकते हैं, तो आप इसे और बेहतर बनाने में मदद कर सकते हैं।</p>

Figure 21: *Pragyaan-Align* alignment data examples in Advice Seeking and Brainstorming categories with *Easy*, *1-Turn*, *Simple-IF*, *Safe*, *IC-3*, *Normal (No Thinking Trails)* settings configuration.

Category	Prompt	Preferred Response	Rejected Response
Creative Writing	<p>మ మొదటి స్టోరీ ప్లాంట్ ఈ క్రింది విధంగా ఉంది:</p> <p>కొంతమంది స్నేహితుల బృందం చీకటి చరిత్ర కలిగిన సరస్సుకి క్యాంపింగ్ ట్రిప్ కు వెళ్ళారు. సరస్సు యొక్క అందమైన దృశ్యం కనపించే ప్రదేశంలో వారు తమ టెంట్ ను ఏర్పాటు చేసుకున్నారు, కానీ వారి ప్రశాంతత స్వల్పకాలికం. వారు అడవిలో ఒంటరిగా లేదని త్వరలోనే గ్రహించారు.</p> <p>స్నేహితులు ఎదుర్కొనే రహస్యమైన ఉనికి వరంగా తగిన కథాంశ అభివృద్ధి పొందుతున్నది మరుసటి రోజున?</p>	<p>ఒక అసంతృప్తికరమైన మరియు ఉత్పాదకతరహితమైన కథ కోసం, ఇక్కడ ఒక సంభాషణ కథాంశ అభివృద్ధిని నేను సూచించుచున్నాను:</p> <p>టైటిల్: "ఎకేన్ ఆఫ్ ద పాస్ట్"</p> <p>కథాంశం: స్నేహితుల సమూహం మట్టుపట్టులను అనేషియన్, సరస్సు యొక్క అందాన్ని ఆస్వాదిస్తూ ఉండగా, వారిలో కొందరు నీటిలో ఆనాధారణమైన ప్రతిదృశ్యాలను గమనించడం మొదలుపెడతారు. వారు మొదట ఇది వాతావరణం కారణంగా అని భావిస్తారు, కానీ క్షణాలు ఎక్కువ బలంగా మారుతాయి, కేవలం కోడిన ఆత్మ యొక్క పాస్టరీకల లాగా ద్వంద్వం. వారు సమయంలోని గ్రామస్థుడైన జ్ఞాన సంపన్నుడు అయిన ఒక మౌన రాజును కలుస్తారు, అతను స్థానిక పురాణాలను వారికి చెప్తాడు: అనేక సంవత్సరాలగా సరస్సులో మొనిగి మరణించిన వ్యక్తి యొక్క ఆత్మ గురించి.</p> <p>ఆత్మ యొక్క ఉద్దేశ్యం తెలుసుకోవడానికి నిర్ణయించబడిన స్నేహితులు లోతుగా తీవ్రమైన ప్రారంభిస్తారు. వారు సరస్సుకు సంబంధించిన చీకటి చరిత్ర గురించి తెలుసుకుంటారు, ఇది వరపు రేజులలో ప్రజలను తనతో పాటు తీసుకువెళ్ళిందని పేరుగాంచింది. వారు సరస్సు నుండి బయటకు వచ్చినట్లు కనపించే వంతెన సంతకాలను కూడా గమనించడం ప్రారంభిస్తారు, మరియు వాటిలో కొన్ని తాము మాత్రమే వినగలుగుతున్నాయని నమ్ముతారు.</p> <p>అని మరింత లోతుగా తీవ్రమౌతుండగా, వారు సరస్సు యొక్క చరిత్ర మరియు దాని మట్టు ఉన్న సంఘటనలకు మధ్య అత్యంత సరస్సు సంబంధాలను కనుగొంటారు. వారు సరస్సు యొక్క ప్రవాహాలలో దాచబడి ఉన్న ఒక రహస్య దృష్టిని కనుగొంటారు, ఇది మట్టుపట్టుల ప్రాంతానికి ఉన్నది పీల్చుకోగల దృష్టిని అందిస్తుంది. దీనివల్ల, వారు ఒక పురాతన ఆలయం యొక్క అపహేళన కనుగొంటారు, ఇది సరస్సు యొక్క చరిత్ర మరియు దాని మట్టు జరిగిన మరణాల గురించి అంతర్దృష్టులను బహిర్గతం చేస్తుంది.</p> <p>దీనిని యొక్క అనేకరూప వేషాన్ని, వారు ఆలయంలో దాక్కుని ఉన్న ఒక రహస్య గది పైకి వస్తారు. గదిలో, వారు ఒక డైరీని కనుగొంటారు, ఇది సరస్సు యొక్క చరిత్ర గురించి వివరిస్తుంది మరియు దాని ఆలయ కేంద్ర దాచబడి ఉన్న రహస్యాలను వివరిస్తుంది. డైరీలో సరస్సు యొక్క ఆత్మ యొక్క ఉనికిని మరియు దాని కోపానికి కారణాన్ని వివరిస్తుంది.</p> <p>స్నేహితులు డైరీని అధ్యయనం చేస్తున్నప్పుడు, వారు సరస్సు యొక్క ఆత్మ తమతో నేరుగా సంభాషించడానికి ప్రయత్నిస్తారని అని గ్రహిస్తారు. ఆత్మ తన కోపానికి కారణం - సరస్సు యొక్క అందం మరియు మహిమను నాశనం చేయడానికి మానవ కార్యకలాపాలు. స్నేహితులు సరస్సు యొక్క ఆత్మ యొక్క అభ్యర్థనను అంగీకరించాలని నిర్ణయించుకుంటారు, మరియు దాని రక్షణ కోసం వారు తమ వంతు కృషి చేస్తారు.</p> <p>వారు తమ ఇంటికి తిరిగి వచ్చినప్పుడు, వారు సరస్సు యొక్క ఆత్మ యొక్క ప్రతిదృశ్యాలను ఇంకా చింతిస్తారు, కానీ ఇప్పుడు అది నింతోషకరమైనది మరియు కృతజ్ఞతతో ఉంటాయి. సరస్సు యొక్క ఆత్మ వారిని కాపాడినందుకు వారికి కృతజ్ఞతలు తెలుపుతుంది, మరియు వారు దాని అందం మరియు మహిమను సంరక్షించడానికి వారి ప్రతిజ్ఞను పూర్తి చేశారు.</p> <p>స్నేహితులు తమ క్యాంపింగ్ ట్రిప్ నుండి దూరంగా వెళ్ళేటప్పుడు, వారు సరస్సు యొక్క ఆత్మ యొక్క పాతాలను మరియు సహజ ప్రపంచంతో సామరస్యంగా జీవించడం యొక్క ప్రాముఖ్యతను ఎప్పటికీ గుర్తుంచుకోవాలని ప్రతిజ్ఞ చేస్తారు.</p>	<p>చీకటి చరిత్ర కలిగిన సరస్సులో క్యాంపింగ్ చేస్తున్న స్నేహితుల బృందం గురించిన కథకు కొన్ని సూచనలు ఇక్కడ ఉన్నాయి:</p> <p>"1. దున్న ఆత్మలు లేదా దెయ్యాలు:" సరస్సు చీకటి చరిత్ర కలిగి ఉందని చెప్పబడింది కాబట్టి, ఆ సరస్సులో మునిగిపోయినవారి ఆత్మలు లేదా దెయ్యాలు తిరుగుతున్నాయని చూపించవచ్చు. స్నేహితులు వారి ఉనికికి సంకేతాలను గమనించవచ్చు, ఉదాహరణకు, రాత్రి అరుపులు, అసహజమైన నీడలు లేదా ఎక్కువల స్థానచలనం. ఈ ఆత్మలు స్నేహితులను వేధించడం ప్రారంభించవచ్చు, వారిని భయపెట్టడానికి లేదా వారిని దాడి చేయడానికి ప్రయత్నించవచ్చు.</p> <p>"2. దాగి ఉన్న ప్రాణాలు:" సరస్సులో లేదా దాని మట్టుపట్టుల దాగి ఉన్న ప్రమాదకరమైన బంతువులు లేదా పొరాణిక ప్రాణాలు ఉండవచ్చు. ఉదాహరణకు, ఒక పెద్ద జలవర్ష ప్రాణి, ఒక పాము లేదా ఒక ప్రమాదకరమైన వన్యప్రాణి. ఈ ప్రాణాలు స్నేహితులను వేటాడవచ్చు, వారిని దాడి చేయవచ్చు లేదా వారిని ఒక ప్రమాదంలో ఇరికించవచ్చు.</p> <p>"3. పురాతన శాపం:" సరస్సుకు పురాతన శాపం ఉండవచ్చు, ఇది ఆ ప్రదేశానికి వచ్చే ప్రతి ఒక్కరిని ప్రభావితం చేస్తుంది. ఈ శాపం కొంతకాలం తర్వాత స్నేహితులపై దాడి చేయవచ్చు లేదా వారి మనస్సులపై ప్రభావం చూపవచ్చు, దాన్ని కనుగొనడానికి లేదా అధిగమించడానికి వారిని బలవంతం చేస్తుంది.</p> <p>"4. మానవ దురాచారాలు:" సరస్సు చరిత్రలో జరిగిన మానవ దురాచారాల ఫలితంగా ఈ దృశ్యం ఏర్పడి ఉండవచ్చు. ఉదాహరణకు, పాత, డిబ్బి లేదా క్షణ. ఈ దురాచారాలకు కారణమైనవారు లేదా వారి ఆత్మలు ఇప్పటికీ ఆ ప్రదేశంలో తిరుగుతున్నాయి. స్నేహితులు సరస్సు చరిత్ర గురించి తెలుసుకుని వారి అనుభవాలతో వ్యవహరించవలసి వస్తుంది.</p> <p>"కథాంశ అభివృద్ధికి ఉదాహరణ:"</p> <p>స్నేహితులు ఒక రాత్రి సరస్సు సమయంలో ఉన్న అడవిలో ఒక అసాధారణ శబ్దం వినవచ్చు, ప్రారంభంలో వారు ఏమీ పట్టించుకోరు, కానీ క్షణాలు మరింత తీవ్రతరమవుతాయి. వారు అడవిలోకి వెళ్తే, వారు ఒక పెద్ద, చీకటి వృక్షం చూస్తారు, అది వారిపై దాడి చేస్తుంది. స్నేహితులు పారిపోతారు, కానీ వారు ప్రమాదకర ప్రాణి నుండి తప్పించుకోవడానికి ప్రయత్నిస్తున్నప్పుడు, వారు సరస్సు చరిత్రను కనుగొంటారు, మరియు వారు దానిలో చిక్కుకున్నారు. వారు సరస్సు చరిత్ర నుండి తప్పించుకోవడానికి మరియు ప్రాణాలను కాపాడుకోవడానికి ప్రయత్నించే కథ ఇది.</p> <p>ఈ సూచనలు కథాంశాన్ని అభివృద్ధి చేయడంలో మిమ్మల్ని సహాయపడతాయి అని నేను ఆశిస్తున్నాను.</p>

Figure 22: Pragmaan-Align alignment data example in Creative Writing category with Easy, 1-Turn, Simple-IF, Safe, IC-3, Normal (No Thinking Trails) settings configuration.

[illegible]

Category	Prompt	Preferred Response	Rejected Response
Information Seeking	ತಾರಾ ಅಥವಾ ಗ್ರಹದ ಬೇಳು ಯಾವುದು?	ತಾರಾ ಮತ್ತು ಗ್ರಹಗಳ ನಡುವಿನ ವ್ಯತ್ಯಾಸವನ್ನು ವಿವರಿಸುತ್ತದೆ. ತಾರಾ ಒಂದು ಬೃಹದಾಕಾರದ ಪ್ಲಾಸ್ಮಾ ಗೋಳು, ಆದರೆ ಗ್ರಹವು ದ್ರವ್ಯದಿಂದ ಮಾಡಲ್ಪಟ್ಟಿದೆ.	ತಾರಾ ಮತ್ತು ಗ್ರಹಗಳ ನಡುವಿನ ವ್ಯತ್ಯಾಸವನ್ನು ವಿವರಿಸುತ್ತದೆ. ತಾರಾ ಒಂದು ಬೃಹದಾಕಾರದ ಪ್ಲಾಸ್ಮಾ ಗೋಳು, ಆದರೆ ಗ್ರಹವು ದ್ರವ್ಯದಿಂದ ಮಾಡಲ್ಪಟ್ಟಿದೆ.
Math	ದಿನಾಂಕ 2023-07-01 ರಿಂದ 2023-07-15 ರವರೆಗೆ ಒಟ್ಟು ಎಷ್ಟು ದಿನಗಳಿರುತ್ತವೆ?	ದಿನಾಂಕ 2023-07-01 ರಿಂದ 2023-07-15 ರವರೆಗೆ ಒಟ್ಟು 15 ದಿನಗಳಿರುತ್ತವೆ.	ದಿನಾಂಕ 2023-07-01 ರಿಂದ 2023-07-15 ರವರೆಗೆ ಒಟ್ಟು 15 ದಿನಗಳಿರುತ್ತವೆ.
Reasoning	ಒಬ್ಬ ವ್ಯಕ್ತಿ 10 ವರ್ಷಗಳ ಹಿಂದೆ 30 ವರ್ಷದವನಾಗಿದ್ದಾಗ, ಅವರ ಮಗು 5 ವರ್ಷದವನಾಗಿದ್ದಾಗ, ಅವರ ಮಗು ಈಗ ಎಷ್ಟು ವರ್ಷದವನಾಗಿದ್ದಾನೆ?	ಒಬ್ಬ ವ್ಯಕ್ತಿ 10 ವರ್ಷಗಳ ಹಿಂದೆ 30 ವರ್ಷದವನಾಗಿದ್ದಾಗ, ಅವರ ಮಗು 5 ವರ್ಷದವನಾಗಿದ್ದಾಗ, ಅವರ ಮಗು ಈಗ 40 ವರ್ಷದವನಾಗಿದ್ದಾನೆ.	ಒಬ್ಬ ವ್ಯಕ್ತಿ 10 ವರ್ಷಗಳ ಹಿಂದೆ 30 ವರ್ಷದವನಾಗಿದ್ದಾಗ, ಅವರ ಮಗು 5 ವರ್ಷದವನಾಗಿದ್ದಾಗ, ಅವರ ಮಗು ಈಗ 40 ವರ್ಷದವನಾಗಿದ್ದಾನೆ.

[illegible]

[illegible]

Category	Prompt	Response
Planning	<p>शाश्वत विकासवर लक्ष केंद्रित करून नवीन विद्यापीठ अभ्यासक्रमाच्या विकास आणि सुरुवातीसाठी एक व्यापक योजना विकसित करा. या योजनेत अभ्यासक्रमाची रचना, प्रशिक्षक भरती, विद्यार्थी भरती आणि विपणन, संसाधन वाटप (जगा, उपकरणे, तंत्रज्ञान), मुल्यांकन आणि मुल्यांकन पद्धती आणि अभ्यासक्रमाची दीर्घकालीन शाश्वतता आणि प्रसंगिकता सुनिश्चित करण्यासाठी धोरणे विचारात घेतली पाहिजेत. योजनेत भागधारकांकडून (विद्यार्थी, प्राध्यापक, उद्योग भागीदार) अभिप्राय समाविष्ट केला पाहिजे आणि शाश्वत विकासाच्या विकसित होत असलेल्या लँडस्केपची स्पष्ट समज प्रदर्शित केली पाहिजे.</p>	<p>टप्पा १: नियोजन आणि बांधकामापूर्वीची तयारी (६-१२ महिने)</p> <p>१. पर्यावरणीय परिणाम मूल्यांकन (EIA): प्रकल्पाचे सखोल पर्यावरणीय परिणाम मूल्यांकन (EIA) करणे महत्वाचे आहे. यात वनस्पती, प्राणी, जलस्रोत आणि हवेच्या गुणवत्तेचे तपशीलवार सर्वेक्षण केले जाईल. प्रकल्पाचे संभाव्य परिणाम (उदा. अधिवासाचे नुकसान, आवाजाचे प्रदूषण, दृश्य परिणाम) तपासले जातील आणि ते कमी करण्यासाठी उपाययोजना (उदा. अधिवासाची पुनर्बांधणी, आवाजाचे अडथळे, कमीत कमी दृश्य परिणाम होईल अशी योग्य जागा निवडणे) प्रस्तावित केल्या जातील. निष्पत्तीत आणि सर्व नियमांचे पालन सुनिश्चित करण्यासाठी आम्ही स्वतंत्र पर्यावरणीय सल्लागारांची मदत घेऊ. EIA अहवाल सार्वजनिकपणे उपलब्ध असेल आणि तो पुढील नियामक मंजूरीचा आधार बनेल.</p> <p>२. परवानगांसाठी आणि मंजूरी मिळवणे: या टप्प्यात स्थानिक, प्रादेशिक आणि राष्ट्रीय स्तरावरील गुंतवणूतीच्या नियामक प्रक्रिया पार करायच्या लागतील. आम्ही कायदेशीर आणि नियामक तज्ञांची एक टीम तयार करू, जे सर्व पर्यावरणीय, जमिनीच्या वापराशी संबंधित आणि बांधकाम नियमांचे पालन सुनिश्चित करतील. सर्व संभाव्य चिंतांचा सक्रियपणे विचार करून अर्ज काळजीपूर्वक तयार केले जातील. या संपूर्ण प्रक्रियेदरम्यान नियामक संस्थांशी सतत संवाद ठेवला जाईल.</p> <p>३. सामुदायिक सहभाग: स्थानिक लोकांशी सक्रिय आणि पारदर्शक संवाद साधणे अत्यंत महत्वाचे आहे. वारसाती एक सामुदायिक संघर्ष समिती स्थापन केली जाईल, सार्वजनिक चर्चेसह आयोजित केली जातील आणि स्थानिक लोकांच्या चिंता समजून घेण्यासाठी संघटनेने केली जातील. जमीन वापर, दृश्यावर होणारा परिणाम, मातमतेचे मूल्या आणि संभाव्य शोकरीच्या संधीबद्दलच्या चिंता दूर केल्या जातील. प्रकल्पाचे आर्थिक फायदे (कर, रोजगार) आणि पर्यावरणीय फायदे (कार्बन उत्सर्जन कमी होणे) लोकांना सपजावून सांगितले जातील. संभाव्य विरोधाचे सक्रिय सहकार्य आणि पाठिंब्यामध्ये रूपांतर करण्याचे आमचे ध्येय आहे.</p> <p>४. वित्तपुरवठा आणि गुंतवणूक: वित्तपुरवठा सुरक्षित करण्यासाठी, प्रकल्पाची व्यवहारीत आणि नफा दर्शवणारे एक सविस्तर आर्थिक मॉडेल (financial model) विकसित केले जाईल. प्रकल्पाचे पर्यावरणीय आणि आर्थिक फायदे स्पष्ट करून गुंतवणूकदारांना आकर्षित केले जाईल. ग्रीन बॉन्ड्स, खाजगी इन्व्हेस्ट आणि सरकारी अनुदानाचा समावेश असलेले पर्याय शोधले जातील.</p> <p>टप्पा २: बांधकाम (१२-१८ महिने)</p> <p>१. बांधकाम व्यवस्थापन: एक सविस्तर बांधकाम योजना तयार केली जाईल, ज्यात साइटवर पोहोचणे, सामग्रीची डिलिव्हरी, कर्मचाऱ्यांचे व्यवस्थापन आणि कचरा विल्हेवाट यांचा समावेश असेल. स्थानिक समुदाय आणि परिसंस्थेवर कमीत कमी व्यत्यय येईल याला प्राधान्य दिले जाईल. पर्यावरणीय परिणाम कमी करण्यासाठी टिकाऊ बांधकाम पद्धती लागू केल्या जातील.</p> <p>२. ग्रीडशी जोडणी आणि ऊर्जा वितरण: ग्रीड कनेक्शन सुरक्षित करण्यासाठी आणि ऊर्जा वितरण पायाभूत सुविधांचे नियोजन करण्यासाठी आम्ही ग्रीड ऑपरेटर्ससोबत जवळून काम करू. यात तपशीलवार तांत्रिक वैशिष्ट्ये आणि ग्रीड नियमांचे पालन समाविष्ट आहे.</p> <p>टप्पा ३: संचालन आणि देखभाल (२०+ वर्षे)</p> <p>१. संचालन आणि देखभाल: दीर्घकाळची कार्यक्षमता आणि कार्यक्षमतेसाठी एक मजबूत संचालन आणि देखभाल (O&M) योजना आवश्यक आहे. यात उपकरणांची नियमित तपासणी, प्रतिबंधात्मक देखभाल (preventative maintenance) आणि त्वरित दुरुस्ती समाविष्ट आहे. आम्ही एक स्थानिक O&M टीम स्थापन करू, ज्यामुळे दीर्घकाळासाठी रोजगाराच्या संधी निर्माण होतील.</p> <p>२. प्रकल्प बंद करण्याची योजना: प्रकल्पाचे कार्यशील आयुष्य संपल्यानंतर सोर ऊर्जा प्रकल्प सुरक्षितपणे बंद करण्याच्या प्रक्रियेची तपशीलवार योजना विकसित केली जाईल. यात घटकांचे जबाबदार पुनर्वापर आणि जागेची प्रकल्पापूर्वीच्या स्थितीत पुनर्स्थापना करणे समाविष्ट आहे.</p> <p>जोखीम व्यवस्थापन</p> <p>संपूर्ण प्रकल्प जीवनचक्रात, नियामक विलंबासारख्या संभाव्य आव्हानांना, वित्तपुरवठ्यातील अडथळ्यांना, बांधकामातील अडचणींना आणि समुदायाच्या विरोधाना सामोरे जाण्यासाठी आम्ही एक व्यापक जोखीम व्यवस्थापन योजना लागू करू. या जोखणींना कमी करण्यासाठी आपत्कालीन योजना विकसित केल्या जातील.</p> <p>ही सविस्तर योजना मोठ्या प्रमाणावरच्या नृत्नीकरणीय ऊर्जा प्रकल्पाच्या यशस्वी विकासासाठी एक चौकट प्रदान करते, त्याचबरोबर पर्यावरणीय आणि सामाजिक विघारनाही संबोधित करते. सततचे निरीक्षण, अनुकूली व्यवस्थापन आणि पारदर्शक संवाद याच्या यशसासाठी महत्वाचे ठरतील.</p>
General Question Answering	<p>राबावर कौन बिपन थोक रक्का करुते पात्रे</p> <p>विकल्प:</p> <p>A: ठीका</p> <p>B: लोडा</p> <p>C: बिपुल</p> <p>D: आश्रन</p>	<p>राबावर बिपुलउर कुलरिवाही खलीए ँठिर घदा निर सलज बिपुल परिवारिठ हय ना। राबावरर ँई धपठि ँके पानुसुकर बिपुलएम्पूह १३३या थोक रक्का करार कना कार्यकर बिपुल किमिस रेरिठे साहाय कर। यथन राबावरक (कौन३ वाकि ँर बिपुलउर उलयन पांख राथा हय, यथन ँठि ँई वाकिर लेरर घदा निर बिपुल दरावरक आठिर कय, कल थोक सल्लावा कठि थोक रक्का कर। यमि३ राबावरर अल्लकर धावरि कलन ठीका वा आठि थोडा लोडाउर थोक भाषानु मुदुका कलन कलठ नांन, लर ँठि ँई बिपलरर थोक बीछर कना शीथरिक मुदुकापुलक दारका नय। राबावर अल्लर भास, आठन थोक (कौना मुदुका) श्रधान कर ना।</p>

Figure 27: *Pragyaan-IT* data examples in categories Planning - (*Hard, 1-Turn, Simple-IF, Safe, IC-3, Normal (No Thinking Trails)*) and General Question Answering - (*Easy, 1-Turn, Simple-IF, Safe, IC-1, Normal (No Thinking Trails)*) settings configuration.

[illegible]

Category	Prompt	Response
Information Seeking	<p>ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿಯ ಕುರಿತ ಭಾರತದ ಐತಿಹಾಸಿಕ ಮತ್ತು ತಾಂತ್ರಿಕ ವಾದಗಳನ್ನು ವಿಶ್ಲೇಷಿಸಿ. ಸೈತಿಕ ಹೋಣೆಗಾರಿಕೆ, ಭಾರತೀಯ ಕಾನೂನು ವ್ಯವಸ್ಥೆಗಳು, ಮತ್ತು ವೈಯಕ್ತಿಕ ಗುರುತುಗಳ ಮೇಲೆ ಇದರ ಪರಿಣಾಮಗಳೇನು? ಸಾಮರಸ್ಯವಾದಿ ಮತ್ತು ಅಸಾಮರಸ್ಯವಾದಿ ದೃಷ್ಟಿಕೋನಗಳನ್ನು ಚರ್ಚಿಸಿ. ನಿರ್ಣಾಯಕತೆ ಮತ್ತು ಏಜೆನ್ಸಿಗೆ ಸಂಬಂಧಿಸಿದ ನರವಿಜ್ಞಾನ ಹಾಗೂ ತಾಂತ್ರಿಕ ವಾದಗಳ ಬಲ ದುರ್ಬಲತೆಗಳನ್ನು ಮೌಲ್ಯಮಾಪನ ಮಾಡಿ.</p>	<p>ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿ ಅಂದರೆ ನಮ್ಮ ಆಯ್ಕೆಗಳು ಮತ್ತು ನಿರ್ಧಾರಗಳು ನಿಜಕ್ಕೂ ನಮ್ಮ ಸ್ವಂತದ್ದೇ ಅಥವಾ ಅವು ಪೂರ್ವನಿರ್ದೇಶಿತ ಅಂಶಗಳಿಂದ ನಿಯಂತ್ರಿಸಲ್ಪಟ್ಟವೆಯೇ ಎಂಬ ಪ್ರಶ್ನೆ ಪ್ರಶ್ನೆ ಮನುಷ್ಯರ ನಡುವೆ ನಡೆದ ಚರ್ಚೆಯಲ್ಲಿದೆ. ಇದು ಸೈತಿಕ ಹೋಣೆಗಾರಿಕೆ, ಕಾನೂನು ವ್ಯವಸ್ಥೆಗಳು ಮತ್ತು ವೈಯಕ್ತಿಕ ಗುರುತುಗಳಂತಹ ಮೂಲಭೂತ ಪರಿಕಲ್ಪನೆಗಳ ಮೇಲೆ ಆಳವಾದ ಪರಿಣಾಮಗಳನ್ನು ಬೀರುತ್ತದೆ.</p> <p>ಭಾರತದ ಐತಿಹಾಸಿಕ ಮತ್ತು ತಾಂತ್ರಿಕ ವಾದಗಳು:</p> <p>ಭಾರತೀಯ ತತ್ವಶಾಸ್ತ್ರದಲ್ಲಿ ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿಯ ಕುರಿತ ಚರ್ಚೆಗಳು ಬಹಳ ಪ್ರಾಚೀನ ಮತ್ತು ವೈವಿಧ್ಯಮಯವಾಗಿವೆ.</p> <p>ಕರ್ಮ ಸಿದ್ಧಾಂತ: ಬಹುಶಃ ಭಾರತೀಯ ಆಧ್ಯಾತ್ಮಿಕ ಮತ್ತು ಧಾರ್ಮಿಕ ಸಂಪ್ರದಾಯಗಳಲ್ಲಿ, ವಿಶೇಷವಾಗಿ ಹಿಂದೂ ಧರ್ಮ, ಬೌದ್ಧಧರ್ಮ ಮತ್ತು ಜೈನಧರ್ಮದಲ್ಲಿ, ಕರ್ಮ ಸಿದ್ಧಾಂತವು ಪ್ರಮುಖ ಸ್ಥಾನ ಪಡೆದಿದೆ. ಇದು ನಾವು ಮಾಡುವ ಪ್ರತಿಯೊಂದು ಕ್ರಿಯೆಯೂ (ಕರ್ಮ) ಭವಿಷ್ಯದ ಪರಿಣಾಮಗಳನ್ನು ಹೊಂದಿರುತ್ತದೆ ಎಂದು ಹೇಳುತ್ತದೆ. ಇಲ್ಲಿ ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿಗೆ ಮಹತ್ವದ ಪಾತ್ರವಿದೆ, ಏಕೆಂದರೆ ವ್ಯಕ್ತಿಯು ತನ್ನ ಕರ್ಮಗಳನ್ನು ಆಯ್ಕೆ ಮಾಡುವ ಸಾಮರ್ಥ್ಯವನ್ನು ಹೊಂದಿದ್ದಾನೆ ಮತ್ತು ಆ ಆಯ್ಕೆಗಳಿಗೆ ಹೊಣೆಗಾರನಾಗಿರುತ್ತಾನೆ. ಭಗವದ್ಗೀತೆಯು ಈ ಕರ್ಮ ಸಿದ್ಧಾಂತವನ್ನು ಸ್ಪಷ್ಟವಾಗಿ ವಿವರಿಸುತ್ತದೆ. ಅಲ್ಲಿ ಕ್ರಿಶ್ಚಿಯಾನಿಟಿ ಅರ್ಥಾನುಗುಣಿ ಕರ್ಮ ಮಾಡು, ಫಲದ ನಿರೀಕ್ಷೆ ಇಲ್ಲದೆ ಎಂದು ಹೇಳಿರುವುದು. ಇದು ಆಯ್ಕೆಯ ಸ್ವಾತಂತ್ರ್ಯ ಮತ್ತು ಅದರ ಫಲಾಪ್ನಿಯನ್ನು ಒತ್ತಿಹೇಳುತ್ತದೆ. ವ್ಯಕ್ತಿಯ ಆಯ್ಕೆಗಳು ಅವನ ಭವಿಷ್ಯವನ್ನು ರೂಪಿಸುತ್ತವೆ ಎಂಬುದನ್ನು ಇದು ಸೂಚಿಸುತ್ತದೆ. ಆದರೆ ಅದೇ ಸಮಯದಲ್ಲಿ ಪೂರ್ವಜನ್ಯ ಕರ್ಮಗಳ ಪ್ರಭಾವವನ್ನು ಒಪ್ಪಿಕೊಳ್ಳುತ್ತದೆ.</p> <p>ಯೋಗಸೂತ್ರಗಳು: ಪತಂಜಲಿಯ ಯೋಗಸೂತ್ರಗಳು ಮನಸ್ಸಿನ ನಿಯಂತ್ರಣ ಮತ್ತು ಅಳವಡ ಸ್ವಯಂ ಅರಿವಿನ ಮೂಲಕ ವ್ಯಕ್ತಿಯು ತನ್ನ ಪ್ರಜ್ಞೆಯನ್ನು ಉನ್ನತೀಕರಿಸಬಹುದು ಎಂದು ಹೇಳುತ್ತವೆ. ಇಲ್ಲಿಯೂ, ವ್ಯಕ್ತಿಯು ತನ್ನ ಆಲೋಚನೆಗಳು ಮತ್ತು ಕಾರ್ಯಗಳ ಮೇಲೆ ಹಿಡಿತ ಸಾಧಿಸುವ ಸಾಮರ್ಥ್ಯವನ್ನು ಹೊಂದಿದ್ದಾನೆ ಎಂಬ ಅಂಶವು ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿಗೆ ಅವಕಾಶ ನೀಡುತ್ತದೆ.</p> <p>ಸೈತಿಕ ಹೋಣೆಗಾರಿಕೆ, ಕಾನೂನು ವ್ಯವಸ್ಥೆಗಳು ಮತ್ತು ವೈಯಕ್ತಿಕ ಗುರುತುಗಳ ಮೇಲೆ ಪರಿಣಾಮಗಳು:</p> <p>ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿಯ ಅಸ್ತಿತ್ವದಲ್ಲಿದೆ ಎಂಬ ನಂಬಿಕೆಯು ನಮ್ಮ ಸೈತಿಕ ಮತ್ತು ಕಾನೂನು ವ್ಯವಸ್ಥೆಗಳ ಆಡಿಪಾಯವಾಗಿದೆ.</p> <p>ಸೈತಿಕ ಹೋಣೆಗಾರಿಕೆ: ನೀವು ಒಂದು ಕೆಲಸ ಮಾಡಲು ನಿಮ್ಮದೇ ಇಚ್ಛೆಯಿಂದ ನಿರ್ಧರಿಸಿದರೆ, ಅದರ ಒಳ್ಳೆಯ ಅಥವಾ ಕೆಟ್ಟ ಪರಿಣಾಮಗಳಿಗೆ ನೀವೇ ಜವಾಬ್ದಾರಿಯು. ಉದಾಹರಣೆಗೆ: ನೀವು ಸ್ವತಃ ನಿರ್ಧರಿಸಿ ಒಬ್ಬರಿಗೆ ಸಹಾಯ ಮಾಡಿದರೆ, ಆ ಒಳ್ಳೆಯ ಕಾರ್ಯಕ್ಕೆ ನೀವು ಕಡುಪ್ರಾಣಿರಿ ಪಡೆಯುತ್ತೀರಿ. ಆದರೆ, ಯಾರಾದರೂ ನಿಮ್ಮನ್ನು ಒತ್ತಾಯಿಸಿ ಆ ಸಹಾಯ ಮಾಡಿದರೆ, ಅದರ ಜವಾಬ್ದಾರಿ ನಿಮಗೆ ಸೇರುವುದಿಲ್ಲ. ಅದೇ ರೀತಿ, ನೀವು ನಿಮ್ಮ ಸ್ವಂತ ಇಚ್ಛೆಯಿಂದ ತಪ್ಪು ಮಾಡಿದರೆ, ಅದರ ದೂಷಣೆ ಅಥವಾ ಶಿಕ್ಷೆಯನ್ನು ಎದುರಿಸಬೇಕಾಗುತ್ತದೆ.</p> <p>ಕಾನೂನು ವ್ಯವಸ್ಥೆಗಳು: ನಮ್ಮ ಭಾರತೀಯ ನ್ಯಾಯಾಂಗ ವ್ಯವಸ್ಥೆಯು, ಅವರಾದ ಪ್ರಕರಣಗಳಲ್ಲಿ, ಒಬ್ಬ ವ್ಯಕ್ತಿ ತನ್ನ ಕೆಲಸವನ್ನು ತಾನಾಗಿಯೇ, ಉದ್ದೇಶಪೂರ್ವಕವಾಗಿ ಮಾಡಿದ್ದಾನೆ ಎಂದು ಸಾಮಾನ್ಯವಾಗಿ ಪರಿಗಣಿಸುತ್ತದೆ. ಯಾರಾದರೂ ಮಾಡಿದ ಕೆಲಸಕ್ಕೆ ಅವರೇ ಕಾರಣ ಎಂದು ನಂಬಿದಾಗ ಮಾತ್ರ ಶಿಕ್ಷೆ ನೀಡುವುದು ಸರಿಯಾಗುತ್ತದೆ. ಮನ್ವರ ರಿಯಾ (ಅಪರಾಧ ಮಾಡುವ ಉದ್ದೇಶ) ಎಂಬ ನಿಯಮ, ಒಬ್ಬರು ಮಾಡುವ ಅಪರಾಧದ ಹಿಂದೆ ಅವರ ಅಂತರ ಅಥವಾ ಇಚ್ಛೆ ಇದೆಯೇ ಎಂದು ಪರಿಗಣಿಸುತ್ತದೆ.</p> <p>ವೈಯಕ್ತಿಕ ಗುರುತು: ನಮ್ಮನ್ನು ನಾವು ಯಾರು ಎಂದು ಗುರುತಿಸಿಕೊಳ್ಳುವಲ್ಲಿ ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿ ಮುಖ್ಯ. ನಮ್ಮ ಆಯ್ಕೆಗಳು, ನಿರ್ಧಾರಗಳು ಮತ್ತು ಅವುಗಳ ಪರಿಣಾಮಗಳ ಮೂಲಕವೇ ನಾವು ನಮ್ಮ ವ್ಯಕ್ತಿತ್ವವನ್ನು ರೂಪಿಸಿಕೊಳ್ಳುತ್ತೇವೆ.</p> <p>ಸಾಮರಸ್ಯವಾದಿ (Compatibilist) ಮತ್ತು ಅಸಾಮರಸ್ಯವಾದಿ (Incompatibilist) ದೃಷ್ಟಿಕೋನಗಳು:</p> <p>ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿ ಮತ್ತು ನಿರ್ಣಾಯಕತೆಯ ನಡುವಿನ ಸಂಬಂಧದ ಬಗ್ಗೆ ಎರಡು ಪ್ರಮುಖ ದೃಷ್ಟಿಕೋನಗಳಿವೆ:</p> <p>ಸಾಮರಸ್ಯವಾದಿ (Compatibilism): ಈ ದೃಷ್ಟಿಕೋನವು ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿ ಮತ್ತು ನಿರ್ಣಾಯಕತೆ (Determinism - ಎಲ್ಲ ಘಟನೆಗಳು ಪೂರ್ವನಿರ್ದೇಶಿತವಾಗಿವೆ) ಪರಸ್ಪರ ಹೊಂದಾಣಿಕೆಯಾಗುತ್ತವೆ ಎಂದು ವಾದಿಸುತ್ತದೆ. ನಾವು ನಮ್ಮ ಆಯ್ಕೆಗಳನ್ನು ಮಾಡುವಾಗ ಬಾಹ್ಯ ಒತ್ತಡದಿಂದ ಮುಕ್ತರಾಗಿದ್ದರೆ, ನಮ್ಮ ನಿರ್ಧಾರಗಳು ಹಿಂದಿನ ಕಾರಣಗಳಿಂದ ಪ್ರಭಾವಿತವಾಗಿದ್ದರೂ ಸಹ, ನಾವು ಮುಕ್ತರು ಎಂದು ಸಾಮರಸ್ಯವಾದಿಗಳು ವಾದಿಸುತ್ತಾರೆ. ಇಲ್ಲಿ, ಸ್ವಾತಂತ್ರ್ಯ ಎಂದರೆ ಒತ್ತಾಯವಿಲ್ಲದಿರುವುದು, ಅನಿವಾರ್ಯತೆಯಲ್ಲ.</p> <p>ಅಸಾಮರಸ್ಯವಾದಿ (Incompatibilism): ಈ ದೃಷ್ಟಿಕೋನವು ನಿರ್ಣಾಯಕತೆ ಮತ್ತು ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿ ಪರಸ್ಪರ ಹೊಂದಾಣಿಕೆಯಾಗುವುದಿಲ್ಲ ಎಂದು ವಾದಿಸುತ್ತದೆ. ನಿರ್ಣಾಯಕತೆ ನಿಜವಾಗಿದ್ದರೆ, ನಮ್ಮ ಆಯ್ಕೆಗಳು ನಿಜವಾಗಿಯೂ ಸ್ವಂತ ಸ್ವಂತದ್ದಾಗಿರಲು ಸಾಧ್ಯವಿಲ್ಲ, ಏಕೆಂದರೆ ಅವು ಹಿಂದಿನ ಘಟನೆಗಳ ಸರಣಿಯ ಫಲಿತಾಂಶಗಳಾಗಿರುತ್ತವೆ.</p> <p>ಇಲ್ಲಿ ಎರಡು ಉಪ ವಿಭಾಗಗಳಿವೆ:</p> <p>ಮುಕ್ತ ಆಯ್ಕೆ ಸಿದ್ಧಾಂತ : ಇದು ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿ ನಿಜವಾಗಿದೆ ಮತ್ತು ನಿರ್ಣಾಯಕತೆ ಸುಳ್ಳು ಎಂದು ವಾದಿಸುತ್ತದೆ</p> <p>ನಿರಾಕಾರವಾದ : ಇದು ನಿರ್ಣಾಯಕತೆ ನಿಜವಾಗಿದೆ ಮತ್ತು ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿ ಒಂದು ಭ್ರಮೆ ಎಂದು ವಾದಿಸುತ್ತದೆ.</p> <p>ನಿರ್ಣಾಯಕತೆ ಮತ್ತು ಏಜೆನ್ಸಿಗೆ ಸಂಬಂಧಿಸಿದ ನರವಿಜ್ಞಾನ ಮತ್ತು ತಾಂತ್ರಿಕ ವಾದಗಳು:</p> <p>ಅಧುನಿಕ ನರವಿಜ್ಞಾನವು ಈ ಚರ್ಚೆಗೆ ಹೊಸ ಆಯಾಮವನ್ನು ಸೇರಿಸಿದೆ.</p> <p>ನರವಿಜ್ಞಾನದ ವಾದಗಳು: ಕೆಲವು ನರವಿಜ್ಞಾನದ ಆಧ್ಯಯನಗಳು ಜನರು ತಮ್ಮ ಕ್ರಿಯೆಗಳನ್ನು ನಿರ್ಧರಿಸುವ ಮೊದಲು ಮೆದುಳು ಈಗಾಗಲೇ ಪ್ರತಿಕ್ರಿಯೆಯನ್ನು ಪ್ರಾರಂಭಿಸಿರುತ್ತದೆ ಎಂದು ಸೂಚಿಸುತ್ತವೆ. ಇದು ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿಯು ಒಂದು ಭ್ರಮೆ ಇರಬಹುದೇ ಎಂಬ ಪ್ರಶ್ನೆಯನ್ನು ಹುಟ್ಟುಹಾಕಿದೆ. ಆದಾಗ್ಯೂ, ಈ ಆಧ್ಯಯನಗಳ ವ್ಯಾಖ್ಯಾನದ ಬಗ್ಗೆ ವ್ಯಾಪಕ ಚರ್ಚೆಗಳಿವೆ. ಅವು ಸರಳ ನಿರ್ಧಾರಗಳಿಗೆ ಮಾತ್ರ ಅನ್ವಯಿಸುತ್ತವೆ ಮತ್ತು ಸಂಕೀರ್ಣ, ಉದ್ದೇಶಪೂರ್ವಕ ಯೋಜನೆಗಳಿಗೆ ಅಲ್ಲ ಎಂದು ಕೆಲವರು ವಾದಿಸುತ್ತಾರೆ.</p> <p>ತಾಂತ್ರಿಕ ವಾದಗಳ ಬಲ ಮತ್ತು ದುರ್ಬಲತೆಗಳು:</p> <p>ಬಲ: ನರವಿಜ್ಞಾನದ ಆವಿಷ್ಕಾರಗಳು ನಮ್ಮ ನಿರ್ಧಾರ ಪ್ರಕ್ರಿಯೆಗಳ ಜೈವಿಕ ಆಧಾರದ ಬಗ್ಗೆ ಅಳವಡದ ಒಳನೋಟಗಳನ್ನು ನೀಡುತ್ತವೆ. ಇದು ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿಯು ನಮ್ಮ ಗ್ರಹಿಕೆಯನ್ನು ಪುನರ್ನಿರ್ಮಿಸಲು ಪ್ರೇರೇಪಿಸುತ್ತದೆ. ಕರ್ಮ ಸಿದ್ಧಾಂತವು ವೈಯಕ್ತಿಕ ಜವಾಬ್ದಾರಿಗೆ ಪ್ರಬಲ ಸೈತಿಕ ಘೋಷವನ್ನು ನೀಡುತ್ತದೆ.</p> <p>ದುರ್ಬಲತೆ: ನರವಿಜ್ಞಾನದ ವಾದಗಳು ಸಂಪೂರ್ಣವಾಗಿ ನಿರ್ಣಾಯಕವಾಗಿಲ್ಲ ಮತ್ತು ಅವು ಪ್ರಜ್ಞೆ ಮತ್ತು ಆಯ್ಕೆ ಮಾಡುವ ಸಾಮರ್ಥ್ಯದ ಸಂಕೀರ್ಣತೆಯನ್ನು ಸಂಪೂರ್ಣವಾಗಿ ಗ್ರಹಿಸುವುದಿಲ್ಲ. ಕೇವಲ ಮೆದುಳಿನ ಚಟುವಟಿಕೆಯನ್ನು ಅಳಿಯುವ ಮೂಲಕ ಮಾನವ ಇಚ್ಛಾಶಕ್ತಿಯನ್ನು ಸಂಪೂರ್ಣವಾಗಿ ತಿಳಿದುಕೊಳ್ಳಲು ಸಾಧ್ಯವಿಲ್ಲ ಎಂಬ ವಾದವಿದೆ. ಭಾರತೀಯ ತತ್ವಶಾಸ್ತ್ರದಲ್ಲಿ, ಕರ್ಮ ಸಿದ್ಧಾಂತವು ಭವಿಷ್ಯವನ್ನು ನಿರ್ಧರಿಸುವ ಪೂರ್ವಜನ್ಯದ ಕರ್ಮಗಳ ಬಗ್ಗೆಯೂ ಮಾತನಾಡುತ್ತದೆ, ಇದು ಸಂಪೂರ್ಣ ಸ್ವಾತಂತ್ರ್ಯದ ಪರಿಕಲ್ಪನೆಯನ್ನು ಸಂಕೀರ್ಣಗೊಳಿಸುತ್ತದೆ.</p> <p>ಒಟ್ಟಾರೆ, ಸ್ವಯಂ ಇಚ್ಛಾಶಕ್ತಿಯ ಪ್ರಶ್ನೆಯು ಅಳವಡ ತತ್ವಶಾಸ್ತ್ರೀಯ ಮತ್ತು ವೈಜ್ಞಾನಿಕ ಪರಿಶೋಧನೆಯನ್ನು ಮುಂದುವರಿಸಿದೆ ಮತ್ತು ಭಾರತೀಯ ಚಿಂತನೆಯು ಈ ಜಾಗತಿಕ ಚರ್ಚೆಗೆ ಅನನ್ಯ ಮತ್ತು ಸಮೃದ್ಧ ದೃಷ್ಟಿಕೋನಗಳನ್ನು ಒದಗಿಸುತ್ತದೆ.</p>

Figure 29: *Pragyaan-IT* data examples in category Information Seeking - (*Hard, 1-Turn, Medium-IF, Safe, IC-3, Normal (No Thinking Trails)*) settings configuration.

Figure 30: *Pragyaan-IT* data examples in categories Named Entity Recognition - (*Hard, 1-Turn, Complex-IF, Safe, IC-3, Normal (No Thinking Trails)*), Comprehension - (*Easy, 1-Turn, Simple-IF, Safe, IC-1, Normal (No Thinking Trails)*) and Inference - (*Hard, 1-Turn, Simple-IF, Safe, IC-1, Normal (No Thinking Trails)*) settings configuration.

SOI Matters: Analyzing Multi-Setting Training Dynamics in Pretrained Language Models via Subsets of Interest

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Abstract

This work investigates the impact of multi-task, multi-lingual, and multi-source learning approaches on the robustness and performance of pretrained language models. To enhance this analysis, we introduce Subsets of Interest (SOI), a novel categorization framework that identifies six distinct learning behavior patterns during training, including forgettable examples, unlearned examples, and always correct examples. Through SOI transition heatmaps and dataset cartography visualization, we analyze how examples shift between these categories when transitioning from single-setting to multi-setting¹ configurations. We perform comprehensive experiments across three parallel comparisons: multi-task vs. single-task learning using English tasks (entailment, paraphrase, sentiment), multi-source vs. single-source learning using sentiment analysis datasets, and multi-lingual vs. single-lingual learning using intent classification in French, English, and Persian. Our results demonstrate that multi-source learning consistently improves out-of-distribution performance by up to 7%, while multi-task learning shows mixed results with notable gains in similar task combinations. We further introduce a two-stage fine-tuning approach where the second stage leverages SOI-based subset selection to achieve additional performance improvements. These findings provide new insights into training dynamics and offer practical approaches for optimizing multi-setting language model performance.

1 Introduction

Deep learning has revolutionized natural language processing (NLP), with Transformer-based models (Vaswani et al., 2017) achieving remarkable

success across various tasks. These architectures primarily fall into two categories: decoder-only models, such as GPT-2 (Radford et al., 2019), and encoder-only models, including BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019). Recently, decoder-only large language models (LLMs) have gained prominence, notably following the success of ChatGPT. While newer open-source LLMs, such as the Llama3 family (Dubey et al., 2024), facilitate human-friendly interactions across diverse tasks, they do not consistently outperform traditional models (Abaskohi* et al., 2024; Ghaffarzadeh-Esfahani et al., 2024). Furthermore, current benchmarks for evaluating LLMs emphasize general capabilities such as comprehension and reasoning, frequently neglecting specialized NLP tasks like text classification and named entity recognition. Recent research by Yu et al. (2023) indicates that smaller, fine-tuned encoder-only pretrained language models (PLMs), such as RoBERTa, can match or exceed the performance of larger LLMs across various specialized datasets. Although closed-source LLMs like GPT-4o (Hurst et al., 2024) can occasionally surpass PLMs with extensive prompt engineering, smaller open-source models offer substantial advantages regarding speed, cost-effectiveness, and transparency. Therefore, systematic analyses of PLM training dynamics remain crucial, even as LLMs increasingly dominate NLP research.

Motivated by this, we systematically investigate the impact of multi-task, multi-lingual, and multi-source learning approaches on the robustness and performance of PLMs. Multi-task learning, which leverages shared knowledge across related tasks, has shown considerable promise for enhancing model generalization and robustness, particularly under constraints of limited data and computational resources. Concurrently, multi-source learning exploits diverse data origins to provide models with a broader understanding of target problems,

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¹For brevity, we use "multi-setting" to refer to multi-task, multi-source, or multi-lingual learning, and "single-setting" to refer to single-task, single-source, or single-lingual learning, respectively.

while multi-lingual learning enables the acquisition of language-agnostic knowledge, significantly improving cross-lingual transfer and performance on low-resource languages.

Despite these advances, a key challenge in training PLMs is handling *Forgettable Examples*, samples that are difficult or out-of-scope, leading models to frequently oscillate between correct and incorrect predictions during training. Although fine-tuning on these challenging examples has proven beneficial in enhancing model robustness (Yaghoobzadeh et al., 2021), systematic analysis of their underlying learning patterns is currently lacking.

To address this gap, we introduce *Subsets of Interest* (SOI), a novel framework for categorizing dataset samples based on distinct learning behaviors observed during training. Specifically, SOI consists of six categories: *Unlearned Examples* (UNE), *Always Correct Examples* (ACE), *1-time Forgettable Examples* (1t-FRGE), *At least 2-times Forgettable Examples* (≥ 2 t-FRGE), *Early-Learned Examples* (ELE), and *Late-Learned Examples* (LLE). Collectively, these subsets enable detailed insights into the dynamics of model learning behaviors under single- or multi-setting configurations, spanning different tasks, languages, and sources. Furthermore, we investigate the potential of SOI subsets to enhance out-of-distribution performance through second-stage fine-tuning strategies based on various SOI combinations.

The key contributions of this work are as follows: First, we introduce the SOI framework, systematically classifying training samples into distinct learning behavior subsets (Section 4.1). Second, we visualize model learning dynamics via dataset cartography and SOI transition heatmaps, offering intuitive insights into sample-level training behaviors (Sections 4.2 and 4.3). Third, we provide a comprehensive comparative analysis of multi-task, multi-lingual, and multi-source learning methods, evaluating their impacts on both in-distribution (ID) and out-of-distribution (OOD) performances (Subsection 5.1). Lastly, we extend our OOD evaluations through second-stage fine-tuning on strategically chosen subsets derived from SOI analyses, demonstrating additional performance gains (Subsection 5.2).²

²Our code is publicly available at [this GitHub repository](#). It builds upon the implementation provided [here](#), adapting Hugging Face’s transformers library for multi-setting training.

2 Related Work

In recent years, extensive research has focused on developing multilingual models as well as models capable of performing multiple NLP tasks simultaneously. Multi-task learning leverages shared representations to jointly optimize model performance across various related tasks, enhancing model generalization, robustness, and computational efficiency. Early foundational work by Collobert and Weston (2008) introduced multi-task learning concepts to NLP, illustrating that training multiple tasks concurrently could lead to better feature generalization and more robust representations. Subsequent studies have widely adopted transfer learning techniques (Howard and Ruder, 2018), demonstrating how pretrained language model knowledge can significantly enhance performance on various downstream NLP tasks. Multi-lingual learning, another promising direction, enables models to gain language-agnostic knowledge to understand, generate, and generalize textual information across multiple languages. Conneau et al. (2020) introduced XLM-R, a robust cross-lingual PLM trained on diverse multilingual data, significantly improving performance on low-resource languages and facilitating effective cross-lingual transfer.

Understanding model behavior at the individual example level represents another critical aspect in training language models. The phenomenon of example forgetting, instances where models oscillate between correct and incorrect predictions during training, has been thoroughly investigated by Yaghoobzadeh et al. (2021). Their work demonstrated that fine-tuning models specifically on these challenging, forgettable examples can significantly enhance model robustness and generalization on task-specific OOD datasets. Complementary to this perspective, Swayamdipta et al. (2020) proposed dataset cartography, a visualization technique characterizing training samples based on prediction confidence and variability metrics. Their method categorizes data into easy-to-learn, hard-to-learn, and ambiguous regions, providing intuitive insights into model behavior throughout training. They conclude that training the model from scratch on the ambiguous region achieves the best ID and OOD performances compared to other scenario cases, including training on hard-to-learn and forgetting examples.

Inspired by these foundational works, our study introduces the Subsets of Interest (SOI) framework,

extending beyond previous categorizations with a finer-grained, analytical perspective. Instead of limiting analysis to three regions, SOI systematically classifies training examples into six distinct learning subsets based on their dynamic behaviors during training. Our comprehensive categorization enriches existing analytical tools, offering nuanced insights into model OOD generalization capability across various multi-task, multi-lingual, and multi-source training scenarios.

3 Experiments Setup

In this section we introduce three parallel experimental comparisons: multi-task vs. single-task learning, multi-source vs. single-source learning, and multi-lingual vs. single-lingual learning. For each comparison, we conducted similar experiments to evaluate both performance and generalizability. Our experimental framework encompasses various tasks, languages, datasets, and a unified model architecture detailed below.

3.1 Tasks, Languages and Sources

Our experimental framework spans across multiple dimensions of learning. In the multi-task learning, we utilize three English tasks: entailment (E), paraphrase (P), and sentiment (S). Entailment and paraphrase tasks require binary decisions on semantic relationships between two textual inputs, while sentiment analysis processes single inputs, allowing us to explore combinations of similar tasks (P & E) versus dissimilar ones (S & P, S & E). For the multi-source learning, we focus on sentiment analysis across different data distributions using English datasets, isolating the effects of data source variation from task variation. In our multi-lingual experiments, we conduct intent classification across French (Fr), English (En), and Persian (Fa). This language selection enables us to examine the impact of script and linguistic similarities, as English and French share common features while Persian differs significantly in both script and structure.

3.2 Datasets

We employed several benchmark datasets tailored to different learning settings. For each setting, such as multi-task learning, we construct three pairs of datasets, where each pair includes one in-distribution (ID) and one out-of-distribution (OOD) dataset. Each ID dataset is divided into training, validation, and test splits, whereas the corresponding OOD dataset is treated as a single

evaluation set without internal splits. In the following subsections, we detail the specific datasets chosen for each setting.

3.2.1 Multi-task Learning

For entailment, SciTail (Khot et al., 2018) serves as the ID dataset, comprising 23,097 training examples. The OOD counterpart is the RTE training set from the GLUE benchmark (Wang et al., 2018), comprising 2,490 samples. In the paraphrase detection task, we use the Microsoft Research Paraphrase Corpus (MRPC) (Dolan and Brockett, 2005) as the ID dataset, which includes 3,668 training instances. The OOD dataset in this case is a reduced version of the Quora Question Pairs (QQP) training set from the GLUE (Wang et al., 2018), subsampled to 4,000 examples.

For sentiment classification, we utilize a modified version of the Twitter US Airline Sentiment dataset (Rane and Kumar, 2018), containing 8,078 samples after removing "neutral" labels to enforce binary sentiment polarity. For the corresponding OOD dataset, we adopt a reduced version of the Stanford Sentiment Treebank (SST-2) (Socher et al., 2013) dataset, limited to 4,000 examples to maintain balance across tasks.

3.2.2 Multi-source Learning

For multi-source experiments, we use three sentiment analysis datasets as our ID datasets, each containing 50,000 examples sampled from the full dataset with an 80-10-10 train-eval-test split, resulting in 40,000 training instances per dataset. The IMDB movie reviews dataset (Rudra and Gopalakrishnan, 2023) serves as our first source, the Yelp Reviews dataset (Hemalatha and Ramathmika, 2019) comprises business reviews with binary sentiment labels, and Sentiment140 (Habib and Sultani, 2021) provides sentiment-labeled Twitter content for social media analysis.

As the OOD dataset, we use the Stanford Sentiment Treebank (SST-2) (Socher et al., 2013), comprising 5,000 examples. Since all sources share the same task, we use the same OOD dataset for all three sources.

3.2.3 Multi-lingual learning

For our multilingual experiments, we adopted three intent classification datasets as the ID datasets: Persian subset of MASSIVE (FitzGerald et al., 2023) (11,514 training examples), *Small* subset of CLINC150 (Larson et al., 2019) for English (7,600

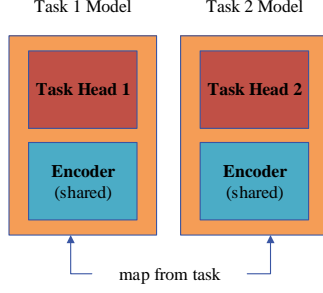


Figure 1: Unified Architecture for Our Multi-Setting Learning Experiments.

training samples), and LORIA subset of MIAM (Colombo et al., 2021) for French (8,465 training samples).

Since the number of intent classes can differ across datasets in the intent classification task, we translated each ID dataset into Burmese, a very low-resource language, and treated these translated versions as the OOD datasets. For translation, we employed the No Language Left Behind machine translation model³ (NLLB Team et al., 2022).

3.3 Architecture

Our experiments employ a unified architecture (see Figure 1) that leverages shared knowledge through a common encoder. For multi-task and multi-source experiments, we use BERT-base⁴ (Devlin et al., 2019), while multi-lingual experiments utilize the multilingual XLM-R⁵ (Conneau et al., 2020) model. Each setting maintains specialized classification heads (task-specific, source-specific, or language-specific) attached to the shared encoder. For multi-setting experiments, training occurs with pairs of tasks/sources/languages: sentiment-entailment (SE), sentiment-paraphrase (SP), and paraphrase-entailment (PE) for tasks; IMDB-Yelp (IY), Sentiment140-Yelp (SY), and IMDB-Sentiment140 (IS) for sources; and finally, English-Persian (En-Fa), French-English (Fr-En), and French-Persian (Fr-Fa) for languages.

4 Subsets of Interest

In this section, we present a comprehensive framework for analyzing deep learning models through the lens of training dynamics. We introduce the concept of *Subsets of Interest* (SOI), a novel categorization system that partitions training examples based on their unique learning patterns observed

during the training process. Our analysis unfolds in three complementary parts: first, we formally define the six distinct SOI categories and their characteristics; second, we employ dataset cartography to visualize how these subsets manifest in the confidence-variability space; and third, we introduce transition heatmaps to track how examples migrate between SOI categories under different training configurations. Together, these components provide a systematic approach to understanding and analyzing the complex dynamics of neural network training.

4.1 SOI Framework and Definitions

In this section, we introduce a novel approach to analyzing deep learning models by extracting specific samples from the training set, based on unique learning patterns observed during training. Based on these patterns, the training set spans six distinct subsets, which we call *Subsets of Interest* (SOI): 1. *Unlearned Examples* (UNE), 2. *Always Correct Examples* (ACE), 3. *1-time Forgettable Examples* ($1t$ -FRGE), 4. *At least 2-times Forgettable Examples* ($\geq 2t$ -FRGE), 5. *Early-Learned Examples* (ELE), and 6. *Late-Learned Examples* (LLE).

UNE refers to samples that show no sign of learning from a certain point onward in the training process. A representative prediction pattern over ten epochs of fine-tuning, assuming the true label is 1, might be $[1, 0, 0, 0, 0, 0, 0, 0, 0, 0]$. ACE denotes samples that the model finds particularly easy to learn, exhibiting consistently correct predictions across all epochs, such as $[1, 1, 1, 1, 1, 1, 1, 1, 1, 1]$.

$1t$ -FRGE and $\geq 2t$ -FRGE represent samples that undergo forgetting events, inspired by Toneva et al.’s (2019) work on forgetting dynamics during training. In that framework, our UNE is interpreted as a subset of forgettable examples exhibiting an infinite number of forgetting events, denoted by ∞t -FRGE. A more recent study by Yaghoobzadeh et al. (2021) defined forgettable examples as those that experience at least one forgetting event (i.e., $\geq 1t$ -FRGE), or are never learned at all (i.e., UNE).

In our framework, a forgettable example is defined as one that exhibits at least one forgetting and one recollecting event. A *forgetting event* occurs when a previously correct prediction becomes incorrect in a subsequent epoch, while a *recollecting event* is the reverse, an incorrect prediction followed by a correct one. This distinction ensures that FRGE includes dynamic behav-

³We used “nllb-200-3.3B” model.

⁴We used “bert-base-uncased” model.

⁵We used “xlm-roberta-base” model.

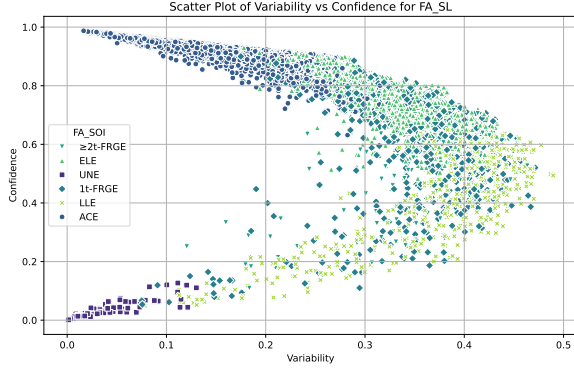


Figure 2: Dataset cartography Map for Single-Lingual Learning in Persian (Fa), showing confidence (average highest prediction probabilities) vs. variability (standard deviation across training epochs).

ior, separating it from UNE, which lacks recollection. For example, a prediction pattern such as $[0, 1, 0, 0, 0, 1, 0, 1, 0, 0]$ contains three forgetting and two recollecting events, and would be categorized as $\geq 2t\text{-FRGE}$.

ELE and **LLE** refer to samples that initially elude correct classification but eventually reach a point of consistent accuracy. If the first correct prediction occurs on or before epoch 5, the sample is considered ELE; otherwise, it is categorized as LLE, reflecting late-stage learning. For instance, prediction patterns such as $[0, 0, 1, 1, 1, 1, 1, 1, 1, 1]$ and $[0, 0, 0, 0, 0, 0, 0, 0, 1, 1]$ represent ELE and LLE, respectively. All training was conducted over 10 epochs, meaning the ELE/LLE classification is influenced by this hyperparameter. However, the broader notion of early- vs. late-stage learning generalizes across training durations.

4.2 SOI Visualization via Dataset Cartography

To better illustrate our definition of SOI, we use dataset cartography analysis, following the approach of Swayamdipta et al.’s (2020), to visualize how the model learns over time. This method maps training examples onto a two-dimensional space based on two metrics: *confidence* (the average of the model’s highest prediction probabilities) and *variability* (the standard deviation of these predictions across training epochs). This mapping helps us understand how the model behaves with different examples during training.

With cartography we divide the examples into three main regions: (1) *easy-to-learn*, with high confidence and low variability; (2) *hard-to-learn*, with low confidence and low variability; and (3)

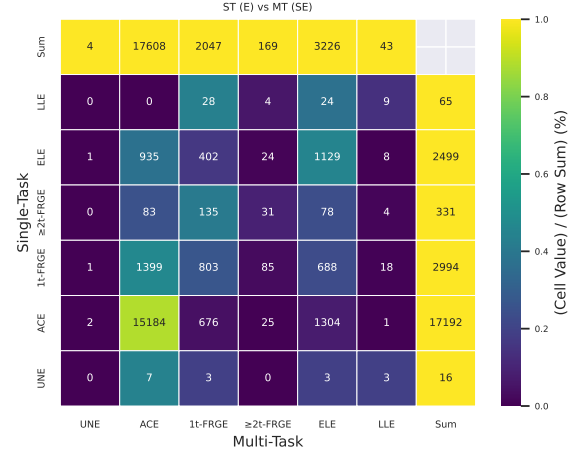


Figure 3: SOI Transition Heatmap: Tracking Training Example Migrations from Single-task (E) to Multi-task (SE). Each cell $H_{i,j}$ shows the number of examples transitioning from SOI category i in single-task to category j in multi-task learning, with the final row and column representing total sums.

ambiguous, with high variability.

Figure 2 shows the cartography plot for single-lingual learning in Persian. In this plot, the UNE category mainly appears in the hard-to-learn region, while ACE is mostly found in the easy-to-learn region. The LLE class spreads across the hard-to-learn and ambiguous regions, showing a wide range of variability but generally low confidence. On the other hand, ELE stretches from the ambiguous to the easy-to-learn region, suggesting higher confidence even when variability differs. Both $1t\text{-FRGE}$ and $\geq 2t\text{-FRGE}$ appear in all three regions, with more examples found in the ambiguous area, which suggests less stable learning behavior. A full version of our cartography visualization is provided in Appendix B.

4.3 SOI Transitions through Heatmaps

To analyze how training dynamics evolve under different configurations, we introduce *SOI transition heatmaps*, which capture how examples shift between learning behavior categories when moving from a *single-setting* (e.g., single-task) to a *multi-setting* configuration (e.g., multi-task).

Each transition is represented as a one-to-one mapping from a subset of training examples in a given SOI category under the single-setting to a potentially different category under the multi-setting. This mapping highlights how the training setup influences the model’s ability to learn or forget

certain examples.

To visualize these transitions, we construct 7×7 heatmaps. The first 6 rows and columns correspond to the defined SOI categories, while the final row and column represent the *row sums* and *column sums*, respectively. Each cell $H_{i,j}$ in the heatmap records the number of training examples that transitioned from category i (row, under the single-setting) to category j (column, under the multi-setting). For instance in Figure 3, if 24 examples labeled as LLE in single-task learning become ELE in multi-task learning, then the corresponding cell is $H_{\text{LLE,ELE}} = 24$.

5 Results & Analyses

In this section, we present our experimental results and analyses, focusing on the impact of different multi-setting configurations on ID and OOD performance, relative to their corresponding single-setting baselines.

5.1 First-Stage Fine-Tuning

The goal of first-stage fine-tuning is to adapt PLMs introduced in Subsection 3.3 to the in-distribution (ID) training sets under both single-setting and multi-setting configurations. Evaluation is then performed using the corresponding **ID test sets** and **OOD test sets**.

5.1.1 In-Distribution Performance

Overall, we observed no substantial improvements in **ID** performance when moving from single-setting to multi-setting fine-tuning. A notable exception was the entailment task, which exhibited a performance gain of 2.6% when trained jointly with the sentiment task. Additionally, five cases showed marginal improvements (between 0.5% and 1.0%), mostly attributed to multi-source learning. The remaining configurations either showed negligible changes ($\leq 0.5\%$) or experienced slight performance degradation (see middle columns of Tables 1, 2, and 3).

5.1.2 Out-of-Distribution Performance

OOD performance across both single-setting and multi-setting configurations was consistently lower than ID performance. However, the comparative OOD performance between the two configurations revealed insightful trends.

Referencing Table 1, we observed similar OOD behavior for French and Persian, while English exhibited a distinct pattern. Specifically, French

showed one performance decline (in the French-English pair) and one improvement (French-Persian), while Persian followed a symmetric trend with a drop in the Persian-French case and an increase in Persian-English. In contrast, English experienced performance drops in both of its OOD pairings. These results suggest that multilingual OOD behavior cannot be easily generalized from single-lingual learning. Notably, the positive impact of one language on another’s OOD performance (e.g., Persian improving French) does not imply reciprocal benefit (i.e., French may not enhance Persian).

Turning to Table 2, the multi-source learning configuration demonstrated consistent OOD improvements across all six evaluated cases. For Sentiment140, we observed the most significant gain, with a 7% improvement in OOD accuracy. Other datasets exhibited improvements exceeding 3%, confirming the effectiveness of multi-source learning in enhancing generalization beyond the training distribution.

Finally, Table 3 echoes the patterns seen in Table 1, with one key distinction: in multi-task learning, when one task enhances another’s OOD performance, the improvement is typically mutual. This is evident in the Paraphrase-Entailment configuration (similar tasks), where OOD performance increased by 1.8% for Entailment and 6.9% for Paraphrase. In contrast, dissimilar task combinations such as Sentiment-Paraphrase led to performance drops in both tasks under OOD evaluation.

Overall, OOD performance improves most when we hold the task and language fixed (e.g., English sentiment analysis) and vary only the data sources (multi-source). With a fixed task but varying languages (multilingual intent classification), the effect is language-dependent—some language pairs improve while others regress. When tasks differ (multitask), gains are conditional and appear primarily when the tasks are closely related (e.g., entailment and paraphrase).

5.2 Second-Stage Fine-Tuning

In the second-stage fine-tuning, we investigate whether the multi-setting models fine-tuned in Subsection 5.1 can be further improved to enhance OOD performance. The fine-tuning sets for this stage are selected based on the heatmaps introduced in Section 4.3, which reveal SOI transitions for a given task, language, or source. For instance, referring to Figure 3, we can subsample the En-

tailment training set by extracting all *ELLE* examples from the single-task configuration (e.g., all entries along row $H_{LLE,-}$). Using this approach, we experimented with multiple subsampled sets, each defined by a specific heatmap-based criterion, and selected the one that achieved the best average OOD performance across the three multi-task combinations. The selected strategy was then applied to the multi-source and multi-lingual setups as well (see below). Fine-tuning was conducted for 4 epochs, and evaluation was performed solely on OOD sets under multi-setting conditions.

5.2.1 Heatmap-Based Fine-Tuning Set Selection

We evaluated several fine-tuning set selection strategies based on the transition patterns identified from the heatmaps: **I.** Transitions representing shifts from more favorable to less favorable learning behaviors (9 out of 36 heatmap transitions: $[ACE, ELE, LLE] \rightarrow 1t-FRGE$, $[LLE, ELE, ACE, 1t-FRGE] \rightarrow \geq 2t-FRGE$, and $[ACE, ELE] \rightarrow LLE$); **II.** Diagonal entries excluding both $ACE \rightarrow ACE$ and $ELE \rightarrow ELE$; **III.** Diagonal entries excluding only $ACE \rightarrow ACE$; **IV.** All forgettable examples identified in single-task learning; **V.** All forgettable examples identified in multi-task learning; and **VI.** The entire training set. Among these strategies, method **III** produced the highest average out-of-distribution (OOD) performance across various multi-task configurations.

5.2.2 Out-of-Distribution Performance

We compare the second-stage results against first-stage OOD performance (Subsection 5.1.2). In multi-lingual learning (Table 1), English-French continued to decline, while English-Persian and French-Persian each showed marginal improvements of about 0.3%. Here, one possible explanation for the overall limited improvements lies in the nature of the OOD test language—*Burmese*, a low-resource language that XLM-R may struggle to represent effectively. As a result, improvements made through training on English, French, or Persian datasets may not transfer well to Burmese, regardless of the fine-tuning strategy. In multi-source learning (Table 2), no further gains were observed, likely because the first-stage fine-tuning had already maximized performance. In multi-task learning (Table 3), each combination showed a clear improvement for one task and a slight decline

for the other. These improvements often occurred where first-stage fine-tuning had previously led to performance drops (e.g., Paraphrase dropped from 62.7% to 57.3% in the first stage, then improved to 58.8%).

Based on our analysis, we found that second-stage fine-tuning was most beneficial in the multi-task setting, had limited or no effect in the multi-source setting, and largely preserved performance in the multi-lingual setting. These results suggest that optimizing the fine-tune set selection with the help of SOI transitions heatmaps is a promising direction for improving OOD robustness in multi-setting configurations.

6 Conclusion & Future Work

In this work, we conducted a comprehensive investigation into the effects of multi-task, multi-source, and multi-lingual training on PLMs, emphasizing the learning dynamics through the introduction of SOI. By leveraging SOI transition heatmaps and dataset cartography, we provided novel insights into how different training configurations influence both ID and OOD performance. Our results reveal that multi-source learning consistently enhances OOD generalization, while multi-task and multi-lingual learning exhibit more nuanced behavior, offering benefits primarily when task or language similarities exist. The proposed two-stage fine-tuning approach, particularly when guided by SOI-based sample selection, showed further gains in OOD performance, especially in multi-task settings. To sum up, our work highlights the potential of multi-setting configurations in creating more adaptable, robust PLMs capable of generalizing across tasks, languages, and sources.

While our study focused on encoder-based PLMs, future work could apply the SOI framework to large decoder-based language models, such as GPT-style models, to gain insights into their training behaviors and generalization capabilities. Additionally, expanding beyond pairwise combinations to train models on multiple (three or more) tasks, sources, or languages simultaneously could provide a deeper understanding of scaling trends in multi-setting learning. Another direction involves investigating curriculum learning strategies where training is staged according to SOI categories.

Tables 1, 2, and 3 summarize experimental results from initial (first stage) and SOI-guided fine-tuning (second stage). The **initial fine-tuning** trains PLMs separately (single-setting) or jointly (multi-setting) on ID datasets; ID columns report in-distribution evaluations, while OOD columns show out-of-distribution performance. The **SOI-guided fine-tuning** (second stage) further optimizes multi-setting models using targeted subsets strategically selected via SOI transition heatmaps (Section 5.2.1), with improvements measured under the second-stage OOD columns. To interpret these tables, first compare single-setting to multi-setting performances from the initial fine-tuning, then evaluate the additional gains obtained from the subsequent SOI-guided (second stage) fine-tuning.

Table 1: Single and Multi-lingual learning performances. For the multi-lingual setting, we translate each ID dataset (in English, French, or Farsi) into Burmese, and treat the translated samples as OOD evaluation set.

Model Type	Language	First stage fine-tuning		Second stage fine-tuning
		ID	OOD	OOD
Single-lingual	English	84.5	52.8	-
	French	88.5	49	-
	Persian	87.4	62.9	-
Multi-lingual (En-Fr)	English	84.4	51.9	51.8
	French	88.7	41.6	40.9
Multi-lingual (En-Fa)	English	84.7	48	48.1
	Persian	87.4	63.3	63.6
Multi-lingual (Fr-Fa)	French	89.4	52.2	52.2
	Persian	87.2	61	61.4

Table 2: Single and Multi-source learning performances. OOD dataset: SST-2 is used for all three sources.

Model Type	Dataset	First stage fine-tuning		Second stage fine-tuning
		ID	OOD	OOD
Single-source	IMDB	89.4	79.4	-
	Yelp	93.8	79.6	-
	Sentiment140	82.7	76	-
Multi-source (IY)	IMDB	90.2	83.9	83.6
	Yelp	94.1	84.3	84.1
Multi-source (SY)	Sentiment140	83.6	79	79.4
	Yelp	93.7	83.2	82.7
Multi-source (IS)	IMDB	90.2	85.5	84.9
	Sentiment140	83.5	83	83.1

Table 3: Single and Multi-task learning performances. OOD dataset: RTE for entailment, QQP for paraphrase, and SST-2 for sentiment.

Model Type	Task	First stage fine-tuning		Second stage fine-tuning
		ID	OOD	OOD
Single-task	Entailment	89.3	43.9	-
	Sentiment	94.6	76.7	-
	Paraphrase	81.7	62.7	-
Multi-task (SP)	Sentiment	95	75.3	74.4
	Paraphrase	80.3	57.3	58.8
Multi-task (SE)	Sentiment	95.1	62.7	64.9
	Entailment	91.9	38.6	38.2
Multi-task (PE)	Paraphrase	79.3	69.6	70
	Entailment	89.6	45.7	45.1

Limitations

We outline the known limitations of our current implementation: (1) The subsets of interest (SOI) categorize dataset samples by aggregating their learning pattern—the binary status of learned vs. not learned per epoch—over 10 epochs, yielding six learning categories. However, SOI (i) does not account for the per-epoch class probability distributions and therefore does not fully capture the training dynamics of the samples, and (ii) we did not validate the optimal number of epochs (here, 10), defined as the epoch at which samples within each SOI category exhibit the least shift to another category when the epoch increases by one. (2) The SOI concept is limited to discriminative tasks (e.g., deciding whether a sentence entails another sentence) that require ground-truth labels; for generative models trained on unlabeled text, it does not generalize. (3) The multi-task/multi-source/multilingual experiments were conducted on two datasets; exploring a larger number of datasets remains unexplored. (4) For computational efficiency, we applied the multi-task heatmap-based subsampling (which defines the second-stage fine-tuning set) to both the multi-source and multilingual configurations. However, a single subsampling policy may not generalize across distinct multi-setting configurations.

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A Experiments Environment

All of the experiments were conducted on the Google Colab virtual systems with around 12.7GB of available RAM and an Nvidia T4 GPU with around 15GB available VRAM.

B Complete Dataset Cartography Visualizations

To complement our dataset cartography analysis in Section 5, we provide here the complete set of cartography visualizations across all learning configurations: Figures 4, 5, and 6 present the confidence-variability distributions for single-setting learning across tasks, sources, and languages, respectively.

C Complete Heatmap Visualizations

As part of our experimental analysis, we generated 18 transition heatmaps - six for each learning mode (multi-task, multi-source, and multi-lingual). While Section 6 presents a detailed analysis of these transitions, here we provide the complete set

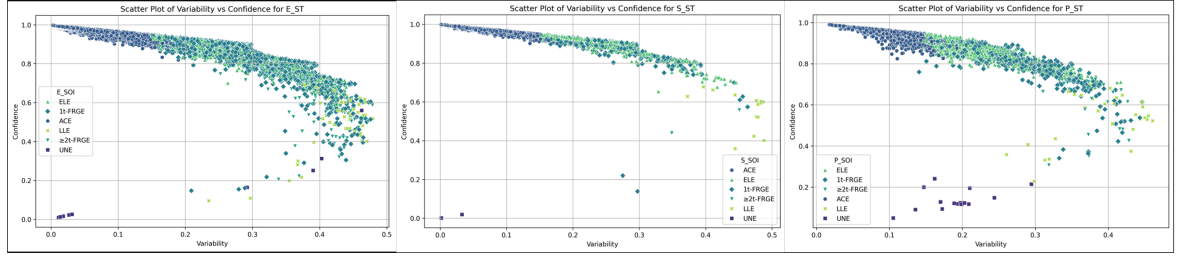


Figure 4: Single-Task Learning (ST) cartography showing the distribution of examples for Entailment, Sentiment, and Paraphrase tasks.

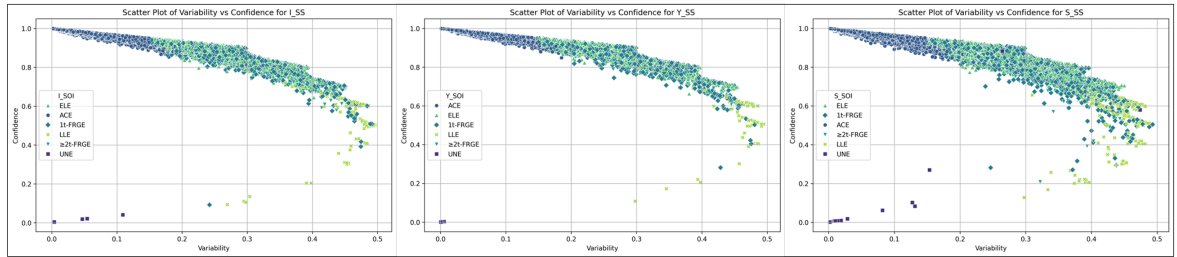


Figure 5: Single-Source Learning (SS) cartography showing the distribution of examples for IMDB, Sentiment140, and Yelp sources.

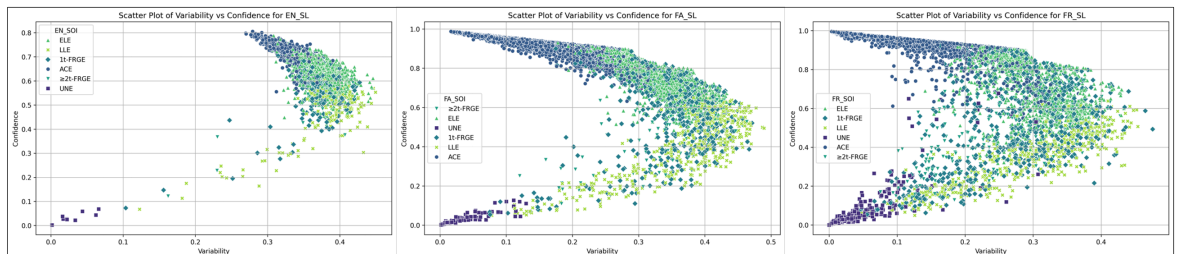


Figure 6: Single-Lingual Learning (SL) cartography showing the distribution of examples for English, French, and Farsi languages.

of heatmaps for reference: Figures 7, 8, and 9 show how samples transition happen between different SOI categories when moving from single-mode to multi-mode learning. Each cell indicates the number of samples that moved from one category to another, with rows representing the initial (single-mode) categories and columns showing the final (multi-mode) categories.

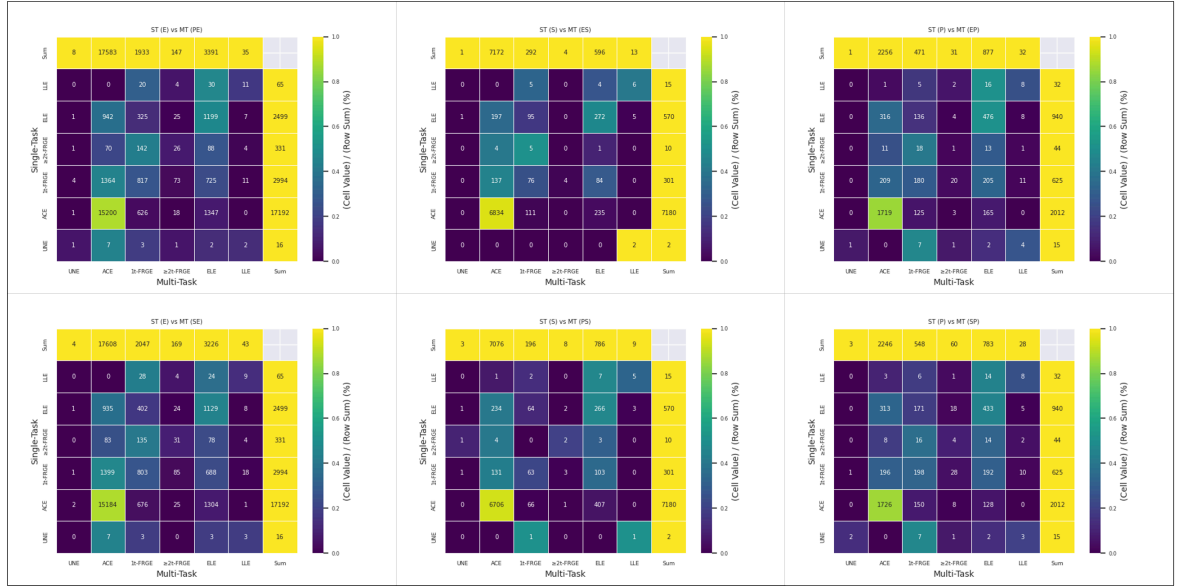


Figure 7: Multi-Task Learning (MT) transition heatmaps showing SOI transitions for all task combinations.

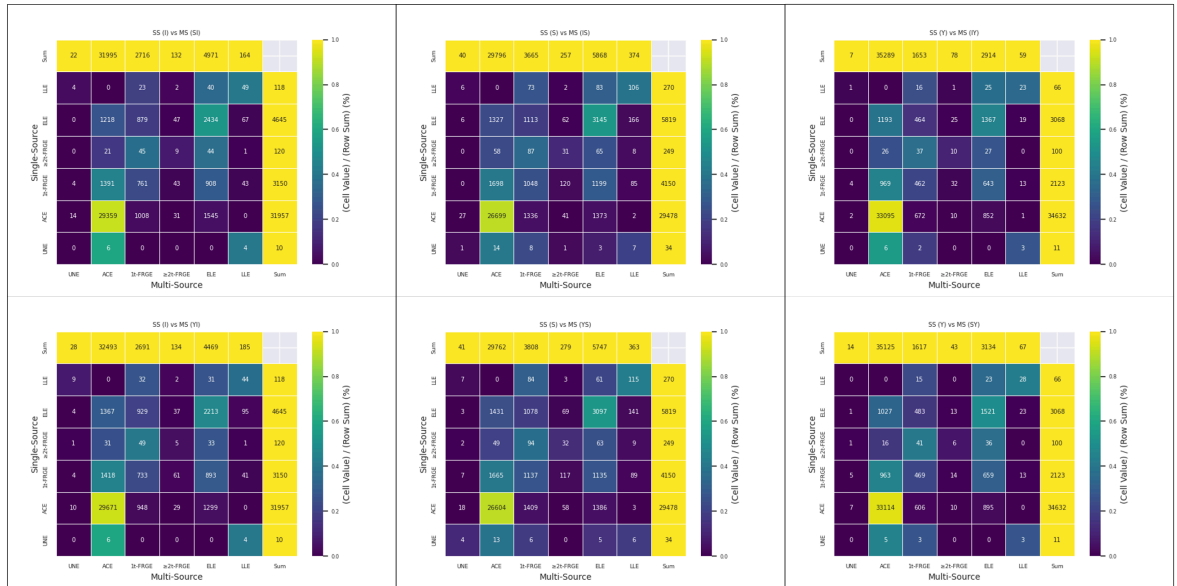


Figure 8: Multi-Source Learning (MS) transition heatmaps showing SOI transitions for all source combinations.

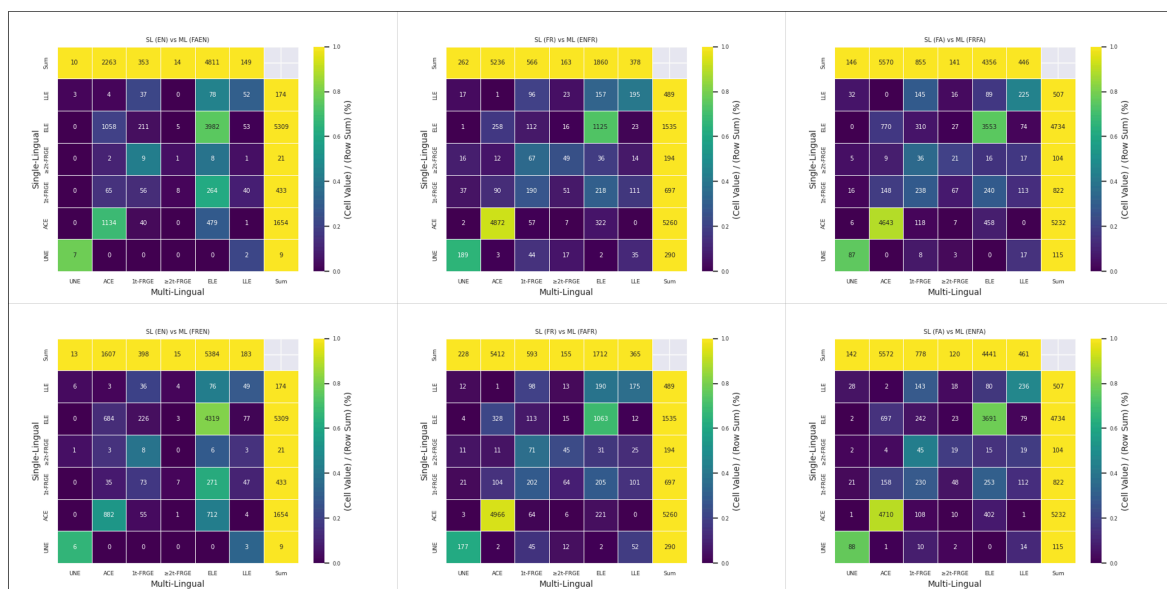


Figure 9: Multi-Lingual Learning (ML) transition heatmaps showing SOI transitions for all language combinations.

When Scripts Diverge: Strengthening Low-Resource Neural Machine Translation Through Phonetic Cross-Lingual Transfer

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Abstract

Multilingual Neural Machine Translation (MNMT) models enhance translation quality for low-resource languages by exploiting cross-lingual similarities during training—a process known as knowledge transfer. This transfer is particularly effective between languages that share lexical or structural features, often enabled by a common orthography. However, languages with strong phonetic and lexical similarities but distinct writing systems experience limited benefits, as the absence of a shared orthography hinders knowledge transfer. To address this limitation, we propose an approach based on phonetic information that enhances token-level alignment across scripts by leveraging transliterations. We systematically evaluate several phonetic transcription techniques and strategies for incorporating phonetic information into NMT models. Our results show that using a shared encoder to process orthographic and phonetic inputs separately consistently yields the best performance for Khmer, Thai, and Lao in both directions with English, and that our custom Cognate-Aware Transliteration (CAT) method consistently improves translation quality over the baseline.

1 Introduction

A common approach to enhancing Neural Machine Translation (NMT) for low-resource languages involves leveraging the knowledge from similar high-resource languages. One approach to this is **multilingual learning**, in which a high-resource language pair is combined with a low-resource language pair within a single multilingual model (Chen et al., 2019)

This method is effective with large models that support dozens of languages (Aharoni et al., 2019; Gala et al., 2023). The method also performs well on a smaller scale when pairing related languages, such as low-resource Haitian Creole with

high-resource French (Robinson et al., 2023), Vietnamese and French (Ngo et al., 2020), or Catalan and several higher-resource Indo-European languages (Chen and Abdul-Mageed, 2021). In these cases, the low-resource language improvements are enabled by the token overlap with the higher-resource languages (Aji et al., 2020; Patil et al., 2022). This token overlap relies on the shared scripts between the high- and low-resource languages, a benefit not all low-resource languages have (Muller et al., 2021).

Some low-resource languages have a related high-resource counterpart but use a different writing system. Despite strong phonetic and lexical similarities, the lack of a shared writing system almost completely eliminates token overlap, potentially limiting the benefits of transfer learning. One way to address this problem is by increasing token overlap; for example, Limisiewicz et al. (2023) achieve this by modifying the tokenizer, though our approach differs.

In this work, we propose and evaluate a method for increasing token overlap in NMT models through the use of phonetic transliterations. Specifically, we incorporate both phonetic information and the original orthographic representations of three Southeast Asian languages into a Multilingual NMT (MNMT) model. Our evaluation focuses on Thai, Lao, and Khmer—closely related languages spoken in Thailand, Laos, and Cambodia, respectively. Although these languages share many lexical and grammatical similarities, each employs a distinct orthographic system.

We compare a baseline multilingual NMT (MNMT) system, which uses only the orthographic representations of the languages, against three transliteration methods. The transliteration methods include International Phonetic Alphabet (IPA) transcriptions, Romanization, and a custom method we call Cognate-Aware Transliteration (CAT). These transcriptions are integrated

with the original orthographies in three ways: 1) by concatenating the orthographic and transliterated representations as a single input to a vanilla transformer, 2) by using a single encoder that processes the two inputs separately before concatenating their embeddings for a shared decoder, and 3) by using two separate encoders—one for the orthographic input and one for the transliterated input—combined with a shared decoder. More details can be found in Section 3.

Incorporating phonetic information allows MNMT models to overcome divergent orthographies and improve knowledge transfer between languages, boosting translation quality by up to 3.4 BLEU points and 4.4 chrF points for low-resource Southeast Asian languages. Additional results show that IPA and CAT generally outperform Romanization, with shared-encoder models achieving the largest gains over the baseline. Overall, we contribute:

- A framework for integrating phonetic transliterations into multilingual NMT.
- Cognate-Aware Transliteration (CAT), a novel method for capturing cross-lingual similarities.
- A comprehensive evaluation of transliteration and integration strategies on Thai, Lao, and Khmer.

2 Related Works

Previous research has been conducted for the cross-lingual transfer of various NLP tasks in Chinese, Japanese, Korean, and Vietnamese (CJKV). [Nguyen et al. \(2023\)](#) utilize the International Phonetic Alphabet (IPA) to produce transcriptions in an attempt to improve the cross-lingual transfer for CJKV languages. They show improvements in cross-lingual transfer for POS tagging and NER tasks. [Nguyen et al. \(2024\)](#) build on that work by creating more benchmark data for additional tasks beyond token-level POS tagging and NER. Romanization is also included in experiments in addition to the phonetic transcriptions, finding the romanization to perform better than the phonetic transcriptions. Both of these works focus on the alignment of the transcriptions/romanization to the orthographic tokens. [Moosa et al. \(2023\)](#) further study transliteration as a cross-lingual signal for Indic languages, showing that transliteration can im-

prove multilingual language modeling and downstream task performance across scripts.

Recent work extends these ideas to large language models (LLMs). [Purkayastha et al. \(2023\)](#) propose a large-scale romanization-based adaptation approach for multilingual LLMs, demonstrating improved transfer to low-resource and non-Latin languages. Similarly, [J et al. \(2024\)](#) introduce RomanSetu, which leverages romanization to improve multilingual capabilities in LLMs while reducing training costs. [Nguyen et al. \(2025\)](#) explore phoneme-based prompting for LLMs, finding that phonemic representations enhance multilinguality for non-Latin-script languages.

Romanization has been used to enhance knowledge transfer in multilingual NMT models. A universal parent model trained with a Romanized vocabulary was found to achieve improved knowledge transfer in a many-to-one translation scenario ([Gheini and May, 2019](#)). [Amrhein and Sennrich \(2020\)](#) extended this approach to many-to-many NMT models and found that while romanization does not consistently improve results across all languages, it is beneficial in cases where related languages use different scripts. In such scenarios, romanization facilitates knowledge transfer. Additionally, [Salesky et al. \(2023\)](#) address this problem by abstracting vocabularies entirely. They utilize multilingual pixel representations, enabling the model to generalize to new and even unseen scripts as inputs.

While prior work has applied romanization and phonetic representations to well-resourced language families, our study focuses on lower-resource Southeast Asian languages with limited transliteration tools in the underexplored domain of Neural Machine Translation.

3 Methodology

In Section 3.1, we describe the non-transliterated baseline inputs and the three transliteration methods we intend to compare. In section 3.2 we describe the methods for computing token overlap between transliterated texts. Finally, section 3.3 describes the methods for integrating the phonetic transcriptions into NMT models.

3.1 Phonetic Transcriptions

There are multiple levels of granularity at which phonetic transcriptions can be applied. In this work, we explore whether different translitera-

tion strategies affect downstream model performance. By varying the degree of token overlap across languages—from none at all to a highly customized scheme designed to maximize overlap—we aim to understand how transcription choices influence cross-lingual modeling. The following subsections describe the four approaches we evaluate, ranging from no transliteration to a cognate-aware system.

No transliteration. As a baseline, we evaluate the models without any transliteration, using the original orthographic representations of the text for all languages. We expect this to have the lowest amount of token overlap between related languages of different scripts.

International Phonetic Alphabet (IPA). We consider the most granular method for transliteration to be converting text into IPA transcriptions. IPA would maintain the most subtle differences between languages and dialects, which could be detrimental to this methodology. Despite this, we expect that the unified alphabet will still yield much more token overlap than original orthographies.

Romanization. Romanization is the process of converting text from another script into the Latin alphabet. We expect that transliterating non-Latin scripts into Latin would be result in simpler transcriptions compared to IPA, but still be granular enough to be useful in distinguishing sounds.

Cognate-Aware Transliteration (CAT). *Regular sound correspondences* are systematic phoneme changes that occur in cognates across related languages (Brown et al., 2013). For example, the /tɕʰ/ sound in Thai is systematically replaced by the /s/ sound in Lao. Similarly, the Thai /r/ is replaced by /h/ or /l/ in Lao. Additionally, similar substitutions occur between some German and English words, such as the replacement of the English /ð/ sound in "this" and "that" with the /d/ sound in their German equivalents, "dies" and "das."

For this method, sound correspondences would be represented by unified characters for both languages in the transliteration, with the purpose of representing cognates uniformly. There are currently no automatic methods for finding regular sound correspondences and thus CAT rules would need to be created manually for a set of languages, though one potential method could be to automatically detect cognates based on parallel data (Grönroos et al., 2018) and then use those to create a CAT system. We hypothesize that a high quality

transliteration system based on the regular sound correspondences between languages would yield the highest overlap of tokens, compared to the previous methods.

3.2 Vocabulary Overlap

In multilingual NLP models, shared vocabularies between languages are commonly used. Previous work has shown that larger vocabulary overlap leads to improved model performance (Pires et al., 2019; Wu and Dredze, 2019). Our work seeks to determine whether this applies to Neural Machine Translation, and more specifically if the amount of vocabulary overlap between the transliterations (not the original orthographies) correlates with downstream translation performance.

To assess the degree of vocabulary overlap between languages, we employ two metrics. These metrics are based on discrete token-level overlap comparisons using the Jaccard Index (Jaccard, 1901), defined as:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|} \quad (1)$$

Corpus-level Jaccard (CJ). This is the simplest metric for quantifying vocabulary overlap. We compute the Jaccard Index at the corpus level, where set A contains all unique tokens in Language A, and set B contains all unique tokens in Language B. This metric provides a general sense of phonetic overlap between the two languages based on their transliterations. However, it does not capture whether semantically equivalent sentences share a high degree of lexical overlap.

Mean Pairwise Jaccard (MPJ). We define Mean Pairwise Jaccard (MPJ) as the average Jaccard Index computed between aligned sentence pairs across two languages. For each sentence pair i , let A_i denote the set of unique tokens in sentence i in language A, and B_i denote the corresponding set of unique tokens in the translated sentence in language B.

We define two vectors of sets:

$$\mathbf{a} = (A_1, \dots, A_n), \quad \mathbf{b} = (B_1, \dots, B_n)$$

MPJ is then computed as:

$$\text{MPJ}(\mathbf{a}, \mathbf{b}) = \frac{1}{n} \sum_{i=1}^n J(A_i, B_i) \quad (2)$$

where $J(A_i, B_i)$ is the Jaccard Index between the token sets of sentence i .

This metric better captures whether semantically equivalent sentences share a high degree of lexical overlap.

3.3 Phonetic Integration

Neural Machine Translation (NMT) models aim to generate a target sentence $\mathbf{y} = (y_1, y_2, \dots, y_n)$ given a source sentence $\mathbf{x} = (x_1, x_2, \dots, x_m)$. The model defines a conditional probability distribution:

$$P(\mathbf{y} | \mathbf{x}) = \prod_{i=1}^n P(y_i | y_1, \dots, y_{i-1}, \mathbf{x}) \quad (3)$$

Each term in the product represents the probability of generating the token y_i at step i given all previously generated tokens y_1, \dots, y_{i-1} and the entire source sentence \mathbf{x} .

To incorporate phonetic information, we introduce a transcription function $\tau(\mathbf{x})$ that maps the source sentence to its phonetic representation. The conditional probability is then modified to condition each target token not only on the previously generated tokens and the source sentence in its original script, but also the phonetic transcription:

$$P(\mathbf{y} | \mathbf{x}) = \prod_{t=1}^n P(y_i | y_1, \dots, y_{i-1}, \mathbf{x}, \tau(\mathbf{x})) \quad (4)$$

The target output of the NMT model can be conditioned on a given transcription function $\tau(\mathbf{x})$ in various ways. We propose the following methods for integrating the phonetic transcriptions:

Concatenated Input. Orthographic and phonetic sequences are concatenated into a single input.

Shared Encoder. A single encoder processes both inputs; their embeddings are concatenated before decoding.

Dual Encoder. Separate encoders process orthographic and phonetic inputs, with a shared decoder attending to both.

4 Experiments

4.1 Data

To evaluate the various phonetic transcription and integration methods, we study the following set of South-East Asian languages: Khmer, Lao, and

Language Pair	Uncleaned	Cleaned
Thai - English	2,175,880	1,080,329
Lao - English	1,994,050	612,836
Khmer - English	1,501,301	501,955

Table 1: Approximate number of parallel segments for each language pair. Extensive cleaning was performed to ensure higher quality data.

Thai. Although each language uses a distinct writing system, they share significant linguistic similarities because of common historical and geographical background, with roots in Pali and Sanskrit (Enfield, 2019).

We utilize the Paracrawl Bonus dataset which focuses on better coverage for South and East Asian languages (Koehn, 2024). This data is noisy, so we applied the guidelines found in the GILT Leaders Forum’s Best Practices in Translation Memory Management.¹ Details of the cleaning pipeline are provided in Appendix A; the most impactful step was validating that Unicode characters correspond to the intended language. Table 1 shows the number of parallel sentence pairs for each language pair before and after cleaning.

We use all the cleaned data for training, in both English \rightarrow X and X \rightarrow English directions. For validation and testing, we use the FLORES+ (NLLB Team et al., 2024) dev and devtest datasets for each language direction, ensuring that there was no data contamination in the training set.

4.2 Transliteration

Although several IPA transliteration tools are available for Thai (Phatthiyaphaibun et al., 2023), and the Uroman package (Hermjakob et al., 2018) provides coverage for all three languages under study, we chose to develop our own transliteration software and typology for IPA, romanization, and CAT (Cognate-aware Transliteration), which we release on our public Github repository.² This ensured that our comparisons remained consistent and fair, avoiding the inconsistencies that can arise when relying on multiple tools created by different designers. Additionally, there is currently a distinct lack of quality, openly-available transliteration software for Khmer and Lao.

¹<https://github.com/GILT-Forum/TM-Mgmt-Best-Practices/blob/master/best-practices.md>

²<https://github.com/byu-matrix-lab/sea-transliteration-mnmt>

Transliteration Method	Thai Sentence	Khmer Sentence	Token Overlap
None	คุณสามารถเรียนภาษา ที่มหาวิทยาลัยได้	អ្នកអាចរៀនភាសានៅ មហាវិទ្យាល័យបាន។	0
IPA	k ^h unsa:ma:rt ^h rianp ^h a:sa: t ^h i:mha:uait ^h ja:lajajd	?nk?a:crienp ^h a:sa:naw mha:vjetja:ljbam.	4
Romanization	khunsaamaarthrianphaasaa thiimhaauaithyaalaiaid	qnkqaacrienphaasaanao mhaavityaalybaan.	4
CAT	khonsaamaarthrianphaasaa teimhaauaityaalaetaet	onkvaacrianphaasaanao mhaavityaalybaan.	5

Table 2: Example Thai and Khmer translations of the English sentence: "You can learn languages at a university." Each sentence is transliterated using the International Phonetic Alphabet (IPA), romanization, and a custom Cognate-Aware Transliteration (CAT). Each representation is tokenized using the XLM-RoBERTa (Conneau et al., 2020) tokenizer and the overlap of tokens between the two sequences is calculated as the intersection between the two token sets.

To unify our transliteration methods, we created a simple transliteration script that replaces specified Unicode characters with others based on a JSON file containing all mappings. This supports single Unicode characters and sequences of Unicode characters.

For our IPA transliterations, we used the Wikipedia script descriptions from the Khmer³, Thai⁴, and Lao⁵ script pages. For romanization, we used the mappings described in the Uroman (Hermjakob et al., 2018) source code.⁶

To create a transliteration scheme that heavily encourages token overlap between languages, we created CAT for the three South-East Asian languages. This was designed by categorizing each consonant and vowel character in each of the languages according to both orthographic similarity and phonetic similarity. More details on the creation of CAT for Khmer, Lao, and Thai are contained in Appendix B.

To showcase the differences for each of these methods, we provide an example in Table 2. In this example, we take a Thai and a Khmer translation of the sentence "You can learn languages at a university." and transliterate using the four methods: None, IPA, Romanization, and CAT. These transliterations are tokenized using the XLM-RoBERTa (Conneau et al., 2020) tokenizer to demonstrate token overlap differences.

³https://en.wikipedia.org/wiki/Khmer_script

⁴https://en.wikipedia.org/wiki/Thai_script

⁵https://en.wikipedia.org/wiki/Lao_script

⁶<https://github.com/isi-nlp/uroman>

4.3 Training Implementation

For our experiments, we compare a baseline Transformer (Vaswani et al., 2017) model to each combination of transliteration and integration method, resulting in nine model variants. The transliteration methods are (1) IPA transcriptions, (2) Romanization, and (3) our proposed Cognate-Aware Transliteration (CAT). Each is integrated into the model using one of three approaches: (a) concatenating orthographic and transliterated inputs, (b) processing them separately within a shared encoder before concatenation at the embedding level, or (c) using two separate encoders combined with a shared decoder.

All experiments are based on the Transformer-base architecture. We use the *BARTForConditionalGeneration* implementation (Lewis et al., 2019), modified to support both the shared-encoder and dual-encoder configurations.

Each model contains 6 encoder layers and 6 decoder layers, with the dual-encoder setup allocating 6 layers to each encoder. The feed-forward network has a dimensionality of 2048, each encoder and decoder uses 8 attention heads, and the hidden size (d_{model}) is 512. We employ ReLU activations and apply dropout with a rate of 0.1.

Models are trained to convergence using 8 A100 GPUs, with an effective batch size of 8,192. Validation is performed every 4,000 steps, and convergence is determined using the validation set.

For tokenization, we train Byte-Level BPE tokenizers using the HuggingFace *Tokenizers* li-

		Orth.	IPA	Rom.	CAT
Tha–Lao	CJ	0.024	0.230 [†]	0.198	0.719
	MPJ	0.029	0.113 [†]	0.093	0.394
Tha–Khm	CJ	0.007	0.055	0.107 [†]	0.694
	MPJ	0.011	0.062 [†]	0.060	0.202
Khm–Lao	CJ	0.007	0.042	0.080 [†]	0.637
	MPJ	0.011	0.065 [†]	0.064	0.198

Table 3: Corpus-level Jaccard (CJ) and Mean Pairwise Jaccard (MPJ) scores for Thai (Tha), Lao (Lao), and Khmer (Khm) across four transliteration methods: native orthography (Orth.), IPA, Romanization (Rom.), and CAT. Bold = highest overlap; [†] = second highest.

brary.⁷ We build separate multilingual tokenizers for each representation—orthography-only, IPA, Romanization, and CAT—each with a vocabulary size of 32K, trained on uniformly sampled sentences from the training set. For the shared-encoder and concatenation models, we train joint tokenizers that include both orthographic and transliterated text, using a larger vocabulary size of 56K, also drawn from uniformly sampled training data.

5 Results and Discussion

5.1 Vocabulary Overlap

To determine vocabulary overlap for each transliteration method, we first created the “complete” (Freitag and Firat, 2020) aligned data so we can compare sentences across non-english centric pairs, using English as a pivot to find the $X \rightarrow Y$ translation directions. This resulted in 19,525 sentences translated into Khmer, Lao, and Thai.

We calculated Corpus-level Jaccard (CJ) and Mean Pairwise Jaccard (MPJ) for the following language pairs across each transliteration method: Thai \leftrightarrow Lao, Thai \leftrightarrow Khmer, and Khmer \leftrightarrow Lao. Each language was transliterated into IPA, Romanization, and CAT and we report overlap metrics in Table 3, with the original orthography overlap calculations included as a baseline reference. Overlap is determined using the tokenizers trained for each transliteration method, as described in Section 4.3.

As expected, the overlap between tokens when using the native orthographies is close to 0, indicating almost zero overlap. The little overlap that is included is likely to be punctuation and numerals common to all three languages. Meanwhile, we

see that CAT achieves the highest amount of overlap both globally and at the sentence-level. For the more linguistically related Thai–Lao pair, IPA yields greater token overlap than Romanization, whereas the Khmer–Thai and Khmer–Lao pairs show lower values and mixed outcomes between IPA and Romanization.

5.2 Multilingual Neural Machine Translation (MNMT)

We report chrF++ (Popović, 2017) and BLEU (Papineni et al., 2002) scores for all language directions calculated using SacreBLEU (Post, 2018). For language directions with English as the target, we utilize the default tokenization for BLEU. For language directions with English as the source, we utilize the Flores-200 tokenizer to calculate an spBLEU score instead, as the South-East Asian languages do not use spaces as word delimiters.

A summary of all chrF++ and BLEU/spBLEU scores are shown in Table 4. Overall, all transliteration methods and integration methods generally improve over the baseline, as indicated by a higher score with statistical significance. The gains appear to be larger when translating into English, reflecting the baseline’s struggle to encode and comprehend the South-East Asian languages. Using a shared encoder with IPA transliterations achieves the highest scores in all but 1 direction, all of which are statistically significant compared to the baseline. The one exception is that CAT with dual encoders achieves the highest scores for the English \rightarrow Lao pair. These results suggest that integrating any form of transliteration not only helps boost performance for lower-resource languages such as Khmer and Lao, but can also provide measurable gains for higher-resource languages like Thai.

To isolate the effects of the integration methods, we average the results over the three transliteration methods (romanization, IPA, and CAT) and report the corresponding chrF++ scores compared to the baseline in Table 5. We focus on chrF++ scores because it provides a more reliable metric for these South-East Asian languages, which do not use spaces to delimit word boundaries. Across all language directions, using a shared encoder to integrate transliterations consistently improves translation performance, with gains ranging from +0.4 to +3.4 chrF++ points over the baseline. In contrast, the Concat and Dual approaches show smaller improvements or even declines when translating from English to , with changes ranging from

⁷<https://github.com/huggingface/tokenizers>

System	Khm → Eng	Lao → Eng	Tha → Eng	Eng → Khm	Eng → Lao	Eng → Tha
Baseline	37.8/9.3	39.3/11.4	39.4/11.3	40.4/18.1	44.3/21.0	42.6/25.0
CAT Concat	40.0*/ 11.7*	42.3*/14.0*	41.6*/12.4*	40.7*/18.4	44.7*/21.5*	43.2*/25.7*
CAT Shared	40.5*/11.5*	41.5*/12.8*	40.9*/11.9*	40.7/18.2	45.0*/21.6*	42.8/25.4
CAT Dual	39.9*/10.5*	42.6*/14.2*	42.2*/12.8*	41.4*/19.0*	45.5*/22.4*	43.6*/26.4*
IPA Concat	39.2*/10.7*	41.6*/13.7*	41.1*/11.4	39.0*/16.7*	43.2*/19.9*	41.0*/23.4*
IPA Shared	42.2*/11.6*	43.4*/14.8*	43.2*/13.5*	41.5*/19.3*	45.4*/22.2*	43.9*/26.8*
IPA Dual	39.9*/10.1*	41.5*/13.4*	40.7*/12.0*	38.8*/16.1*	42.9*/19.5*	40.5*/22.6*
Rom. Concat	38.9*/10.6*	41.9*/13.7*	41.1*/12.3*	40.3/17.9	44.2/21.0	42.3/25.0
Rom. Shared	40.8*/11.0*	41.7*/13.3*	40.3*/11.6	40.1*/17.9	44.3/21.2	42.3/24.9
Rom. Dual	39.2*/10.4*	41.2*/13.9*	40.0*/11.5	39.8*/17.2*	43.3*/20.1*	41.4*/23.8*

Table 4: chrF++/BLEU scores for each transliteration method and architecture across all language directions. Scores are reported as chrF++/BLEU. Bold values indicate the best score within a language direction. An asterisk (*) marks scores that are significantly different from the Baseline ($p < 0.05$).

-0.8 to +2.6. These results highlight that the shared encoder is the most robust method for integrating transliterations for this dataset.

Focusing on the transliteration methods themselves, we average the results over the integration methods (concatenation, shared encoder, dual encoder) and report the chrF++ scores in Table 6, again comparing the averaged scores to the baseline. Unlike the integration methods, there is no single transliteration approach that consistently achieves the largest gains across all directions. IPA performs best on average when translating into English, with improvements ranging from +2.3 to +2.6 chrF++, but it underperforms when translating from English, with declines between -0.8 and -0.5. However, CAT performs best on average for English → X directions, as well as providing more consistent improvements across all language directions, with score increases ranging from +0.5 to +2.8. Romanization generally improves over the baseline but tends to achieve smaller gains than IPA or CAT.

According to these experiments, there is not a clear transliteration method which performs better than all the others. We see that both IPA and CAT enhance these MNMT models more than romanization, but not by much. Despite the much larger token overlap when using CAT, it does not do much better than the IPA performance. Though CAT results in much higher token overlap across languages, its performance is not substantially better than IPA. We hypothesize that this may be due to CAT’s tendency to overgeneralize: it creates shared tokens between languages that do not necessarily share semantics, which can introduce ambiguity. Conversely, IPA enforces stricter token sharing, resulting in more precise and less ambiguous representations that facilitate effective knowledge

transfer.

Both IPA and CAT provide larger improvements to the MNMT models compared to romanization, though the differences are relatively modest. Overall, all three transliteration methods contribute to improved translation, particularly in low-resource settings, despite the apparent lack of correlation to the amount of vocabulary overlap as described in Section 5.1.

Future work should investigate whether the shared tokens for each transliteration method actually preserve semantic equivalence across languages, or if their overlap introduces misleading or ambiguous representations.

6 Conclusion

Low-resource languages with unique writing systems pose challenges for traditional Neural Machine Translation (NMT) knowledge transfer techniques. In this work, we proposed methods for integrating phonetic transliterations to address the lack of shared orthographies between related high- and low-resource languages in Multilingual NMT (MNMT) systems. Specifically, we compared three transliteration schemes—International Phonetic Alphabet (IPA), romanization, and our custom Cognate-Aware Transliterations (CAT)—together with three integration methods in a Transformer model: concatenating inputs, using a shared encoder, and using dual encoders. We evaluated this methodology for Khmer, Lao, and Thai in both directions with English, leveraging knowledge transfer from the higher-resource Thai to the lower-resource Lao and Khmer.

Overall, integrating any transliteration method via any integration strategy improves translation performance in the X → English direction, while

System	Khmer → Eng	Lao → Eng	Thai → Eng	Eng → Khmer	Eng → Lao	Eng → Thai
Baseline	37.8 (+0.0)	39.3 (+0.0)	39.4 (+0.0)	40.4 (+0.0)	44.3 (+0.0)	42.6 (+0.0)
Concat Average	39.4 (+1.6)	41.9 (+2.6)	41.3 (+1.9)	40.0 (-0.4)	44.0 (-0.3)	42.2 (-0.4)
Shared Average	41.2 (+3.4)	42.2 (+2.9)	41.5 (+2.1)	40.8 (+0.4)	44.9 (+0.6)	43.0 (+0.4)
Dual Average	39.7 (+1.9)	41.8 (+2.5)	41.0 (+1.6)	40.0 (-0.4)	43.9 (-0.4)	41.8 (-0.8)

Table 5: chrF++ scores for the three phonetic integration methods, averaged over all transliteration methods (Romanization, IPA, CAT) compared to the Baseline. Bold values indicate the best score within a language direction. Values in parentheses indicate the change relative to the Baseline.

System	Khmer → Eng	Lao → Eng	Thai → Eng	Eng → Khmer	Eng → Lao	Eng → Thai
Baseline	37.8 (+0.0)	39.3 (+0.0)	39.4 (+0.0)	40.4 (+0.0)	44.3 (+0.0)	42.6 (+0.0)
CAT Average	40.1 (+2.3)	42.1 (+2.8)	41.6 (+2.2)	40.9 (+0.5)	45.1 (+0.8)	43.2 (+0.6)
IPA Average	40.4 (+2.6)	42.2 (+2.9)	41.7 (+2.3)	39.8 (-0.6)	43.8 (-0.5)	41.8 (-0.8)
Rom. Average	39.6 (+1.8)	41.6 (+2.3)	40.5 (+1.1)	40.1 (-0.3)	43.9 (-0.4)	42.0 (-0.6)

Table 6: chrF++ scores for the three transliteration methods, averaged over all integration methods (concatenated input, shared encoder, dual encoder) compared to the Baseline. Bold values indicate the best score within a language direction. Values in parentheses indicate the change relative to the Baseline.

translations from English → X show less consistent gains. Among all combinations, using a shared encoder with IPA or CAT transliterations achieves the largest improvements. Notably, the Khmer → English direction—our lowest-resource scenario—achieves the highest chrF++ improvement of +4.4 points, providing strong evidence of effective knowledge transfer between these South-East Asian languages.

This approach can be extended to other language groups that share linguistic features but not orthography, such as Maltese (Latin script) and Tunisian Arabic (Arabic script), with the potential to enhance translation for lower-resource languages. Future work could also explore additional transliteration and integration methods, as well as leverage larger datasets such as OPUS for South-East Asian languages, which would likely further improve performance above the baseline. Beyond multilingual learning for knowledge transfer, additional work could explore whether integrating transliterations benefits parent-child fine-tuning (Zoph et al., 2016; Neubig and Hu, 2018) in which a parent model is first trained on a high-resource language pair and then fine-tuned on the low-resource language pair.

Limitations

This study focuses on a single group of related languages and may not generalize to other language families containing different orthographies. All models were trained under fixed architectural conditions, and results could differ when scaling mod-

els up or down. We trained using Paracrawl Bonus data only, without incorporating additional OPUS data, in order to maintain smaller models. While this allows for controlled and informative experiments, we acknowledge that including all available data would likely improve overall translation metrics.

We note that creating a Cognate-Aware Transliteration (CAT) system requires expertise in the languages involved. Unlike IPA or romanization schemes, which are more widely available and easier to apply across languages, there is currently no automated way to generate a CAT system for a given set of languages.

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A Cleaning Steps

We apply the following cleaning steps in our data cleaning pipeline:

1. Remove pairs containing empty source or target segments.
2. Remove pairs when the source segment exactly or nearly matches the target segment.
3. Remove duplicate source-target pairs.
4. Remove pairs with segments containing mostly non-alphabetic characters.
5. Remove pairs with segments containing abnormally long sequences of characters without spaces, including segments that are only URLs.
6. Remove pairs containing segments with unbalanced brackets.
7. Remove pairs containing fewer than 3 words in the English source segment.
8. Remove pairs with segments containing a higher number of characters than 5 standard deviations above the mean for that language (sentences that are too long).
9. Remove pairs in which the ratio of the lengths of the source and target segments exceeds a certain cutoff.
10. Normalize escaped Unicode characters.
11. Validate and normalize character encodings for each language.
12. Normalize whitespace
13. Shorten sequences of excessively repeated punctuation.
14. Normalize quotation marks.
15. Normalize HTML entities.
16. Remove all markup tags.

B Khmer, Lao, and Thai Cognate-Aware Transliteration (CAT)

Creation of a Cognate Aware Transliteration (CAT) system requires familiarity with the languages it is designed to incorporate. The ideal CAT system uses examples of known cognates to detect common, predictable mappings between phonemes across multiple languages, including both vowels

and consonants. We did this manually, but finding these mappings automatically is likely possible and a topic for future research.

For Thai, Lao, and Khmer, we created these mappings based on cognates, borrowed words, and place names that could be found in both languages. Specifically, we constructed these mappings through a comparative dictionary-based approach. Each language was examined letter by letter, and for each grapheme we identified potential correspondences by consulting cognates, loanwords, and place names attested across the three languages. When a candidate word exhibited both phonological similarity and a plausible semantic match across the languages, we treated it as evidence of a sound correspondence for that grapheme. This procedure relied on the combined expertise of the researchers, who brought working knowledge of the relevant languages, ensuring that proposed correspondences were grounded in linguistic judgment. We also considered similarities in orthography when creating mappings, such as when two graphemes exhibited a large degree of visual similarity, such as when two graphemes had closely aligned visual features—length, curvature, and positioning—making them appear almost identical (e.g., Khmer vowel ្ើ and Thai vowel ำ).

For this example, we designed the system to maximize overlap and cognates, allowing for cognates with different romanization and pronunciations to be successfully identified. However, this may have led to the creation of false cognates, negating some of the benefits of transfer learning. In addition, because Khmer is not tonal, we chose not to map the tones between Thai and Lao for commonality. Mapping these may improve transfer learning between Thai and Lao at the cost of transfer learning between these two languages and Khmer.

To reduce complexity, we modeled cognate consonant phonemes based on beginning consonants only, but mapping final consonants would lead to a more complete CAT system. We chose not to do this because of the complexity of determining whether a consonant is beginning or final in Thai and Khmer.

Conditions for Catastrophic Forgetting in Multilingual Translation

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Abstract

Fine-tuning multilingual foundation models on specific languages often induces catastrophic forgetting, degrading performance on languages unseen in fine-tuning. While this phenomenon is widely-documented, the literature presents fragmented results about when forgetting occurs. To address this ambiguity, we conduct a systematic empirical study using machine translation as a testbed to identify the conditions that trigger catastrophic forgetting in multilingual fine-tuning. Through controlled experiments across different model architectures, data scales, and fine-tuning approaches, we reveal that the relative scale between model and data size is a primary determinant of forgetting. Moreover, we demonstrate that a model’s instruction-following ability is more critical for retaining multilingual knowledge than its architecture. Contrary to assumptions, parameter-efficient fine-tuning offers no clear advantage over full fine-tuning in mitigating forgetting. Lastly, we show that cross-lingual alignment can mitigate forgetting while also facilitating positive transfer to unseen target languages.

1 Introduction

Foundation models pretrained on vast amounts of multilingual data have become the standard backbone for modern natural language processing systems. To achieve optimal performance, however, these models typically require fine-tuning on downstream tasks. This specialization introduces a critical trade-off: while performance on the target task improves, the model may suffer from *catastrophic forgetting* (McCloskey and Cohen, 1989), a substantial degradation of capabilities on tasks or languages not present in the fine-tuning data.

A common use case is to fine-tuning multilingual models to focus on specific languages or language pairs. Ideally, this process would not harm, and might even improve, performance on unseen languages through positive transfer, as illustrated on

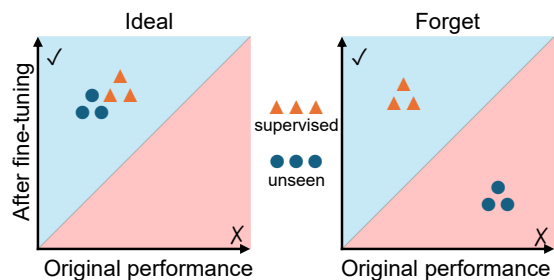


Figure 1: Selectively fine-tuning on some languages or translation directions may lead to positive transfer (left) or catastrophic forgetting (right).

the left of Figure 1. However, empirical evidence often shows the opposite. Models frequently lose proficiency in languages they were not fine-tuned on (Vu et al., 2022b; Sun et al., 2023; Winata et al., 2023), as shown on right of Figure 1.

Machine translation (MT) serves as a compelling testbed for studying multilingual catastrophic forgetting. First, a model supporting n languages encompasses $n(n - 1)$ directed translation pairs, offering a large and structured space to analyze forgetting patterns. Second, languages can be “unseen” in different roles. For example, a language may be present only as a source language, only as a target language, or in specific source-target pairs that were never explicitly trained. This enables fine-grained analysis of how different types of exposure during fine-tuning affect retention. Moreover, forgetting can occur asymmetrically, where a model may retain the ability to translate from language A to B while losing the reverse direction.

Despite its practical importance, the literature presents a fragmented and sometimes contradictory picture of when catastrophic forgetting occurs in MT. On one hand, studies on traditional NMT models trained from scratch (Berard, 2021) and some large pretrained models (Vu et al., 2022a; Liu and Niehues, 2022; Liu et al., 2023; Lai et al., 2023) report severe forgetting after standard fine-tuning,

where the ability to translate unseen directions is almost entirely lost. These findings suggest that catastrophic forgetting is an inevitable consequence of selective specialization. On the other hand, recent works on large language models (LLMs) provided mixed evidence. Richburg and Carpuat (2024) demonstrated that fine-tuning Llama 2 (Touvron et al., 2023) and Tower (Alves et al., 2024) models on specific language pairs could improve performance on unseen pairs, indicating positive transfer. Conversely, Zan et al. (2024) found that their fine-tuned Llama 2 models performed very poorly on unseen directions, again indicating issues with forgetting.

These conflicting results raise fundamental questions about the factors leading to catastrophic forgetting. Has the emergence of large language models altered the dynamics of catastrophic forgetting? To what extent do model architecture (encoder-decoder versus decoder-only), scale, or fine-tuning methodology determine whether a model forgets or generalizes? How do factors like the volume of fine-tuning data, the use of parameter-efficient fine-tuning (PEFT), or instruction-following capabilities influence the retention of multilingual abilities? To resolve these ambiguities, we conduct a systematic study to identify the conditions that trigger catastrophic forgetting in multilingual MT. We systematically control for key variables, including model architecture and size, fine-tuning data composition and scale, full-parameter vs. parameter-efficient fine-tuning, and instruction-following versus standard fine-tuning approaches. With a series of controlled experiments, we demonstrate that:

- The relative scale between pre-trained model parameters and fine-tuning data volume is a critical factor in catastrophic forgetting, with smaller models fine-tuned on larger datasets being most vulnerable (§4.1).
- Whether a model supports instruction-following, rather than its underlying architecture (encoder-decoder versus decoder-only), is a primary factor impacting catastrophic forgetting (§4.2).
- Contrary to common assumptions, parameter-efficient fine-tuning with LoRA (Hu et al., 2022) provides no significant advantage over full fine-tuning in preventing catastrophic forgetting under our experimental conditions (§4.4).
- Besides mitigating forgetting, cross-lingual alignment methods may facilitate positive transfer, with improvements observed on translation directions with unseen target languages (§5).

2 Related Work

Catastrophic Language Forgetting in MT

Catastrophic forgetting in machine translation has been extensively studied. Dakwale and Monz (2017); Thompson et al. (2018, 2019) established that domain-specific fine-tuning degrades performance on previously learned domains with specific subject areas or text styles. Many subsequent works have investigated the underlying mechanisms and mitigation strategies for domain forgetting in MT, e.g., Gu and Feng (2020); Saunders and DeNeefe (2024); Eschbach-Dymanus et al. (2024); Wu et al. (2024); Hu et al. (2024). Compared to domain forgetting, the multilingual dimension of forgetting has received less attention. Berard (2021) demonstrated severe language forgetting in conventional encoder-decoder-based MT models during standard fine-tuning on selected languages, while Vu et al. (2022a) showed that domain-specific fine-tuning compounds forgetting across both domains and languages. Liu and Niehues (2022); Liu et al. (2023) confirmed that standard fine-tuning consistently triggers catastrophic forgetting of unseen language pairs, even in pre-trained models with large language coverage, such as M2M-124 (Goyal et al., 2022) and mBART-50 (Tang et al., 2021). Besides language and domain forgetting, models also lose in-context learning abilities after fine-tuning (Alves et al., 2023).

Model Factors Influencing Forgetting The scale of both the model and its pretraining data has been identified as a key factor in mitigating catastrophic forgetting (Ramasesh et al., 2022). Our study extends this analysis by examining the relative scale between the model and the fine-tuning data. The choice of fine-tuning methodology is another contested factor. Kalajdziewski (2024) suggests that LoRA does not resolve catastrophic forgetting, while Biderman et al. (2024) suggest that LoRA “learns less and forgets less”. The finding by Zhang et al. (2024) that the optimal fine-tuning method is highly task-dependent warrants a specific investigation for the task of multilingual MT.

3 Controlled Setting to Study Catastrophic Forgetting in MT

Our controlled experiments are structured along two dimensions, namely the choice of base model and the characteristics of the training dataset.

Model	Size	Model Type
M2M-124-0.2B	175M	Translation-specific
M2M-124-0.6B	615M	
Qwen2.5-0.5B-Instruct	494M	Instruction-following
Qwen2.5-7B-Instruct	7B	
Llama-3-8B-Instruct	8B	

Table 1: Base models and their configurations.

3.1 Base Models

An overview of all base models and their configurations is provided in Table 1.

Translation-Specific Models We choose M2M-124¹ (Goyal et al., 2022) with two sizes:

- M2M-124-0.2B: smallest-scale baseline
- M2M-124-0.6B: larger-scale comparison to isolate model size effects

Instruction-Following Models We evaluate and fine-tune models from two prominent families, Qwen 2.5 (Qwen Team et al., 2025) and Llama 3 (AI @ Meta et al., 2024):

- Qwen2.5-0.5B-Instruct : similar to M2M-124-0.6B in size for comparison between translation-specific and instruction-following models²
- Qwen2.5-7B-Instruct: larger-scale instruction-following baseline
- Qwen2.5-7B-Instruct (LoRA): identical to full fine-tuning but using LoRA as a PEFT approach
- Llama-3-8B-Instruct (LoRA): similar scale to above but from another family

3.2 Data

Dataset Overview As shown in Table 2, we experiment on datasets of different scales:

- **SMALL**: training dataset in ALMA (Xu et al., 2024), covering five languages paired with English: Czech (cs), German (de), Icelandic (is), Russian (ru), and Chinese (zh). The unseen languages include Hebrew (he), Japanese (ja), and Ukrainian (uk).
- **LARGE**: from the WMT 21 Shared Task on Large-Scale Multilingual Machine Translation (Wenzek et al., 2021), focusing on three related Austronesian languages paired with English: Javanese (jv), Malay (ms), and Tagalog (tl). The unseen language is Indonesian (id).

¹We choose M2M-124 over NLLB-200 models of similar sizes (NLLB Team, 2024) as the former showed stronger performance in our preliminary experiments.

²We note that this is not fully controlled setup contrasting M2M-124-0.6B due to different pre-training data.

Dataset	Details
SMALL	Training Data: ALMA (117K sentence pairs) Test (supervised): WMT23 (Kocmi et al., 2023) Test (unseen pair): WMT24 (Kocmi et al., 2024) Test (unseen source): WMT23 Test (unseen target): WMT23 Training directions: {cs, de, is, ru, zh} ↔ en Testing directions: - Unseen pair (20): {cs, de, is, ru, zh} ↔ {cs, de, is, ru, zh} - Unseen source (3): {he, ja, uk} → en - Unseen target (3): en → {he, ja, uk}
LARGE	Training Data: WMT21 large-scale multilingual track (54M sentence pairs) Test (unseen pair): FLoRes (Goyal et al., 2022) Test (unseen source): FLoRes Test (unseen target): FLoRes Training directions: {jv, ms, tl} ↔ en Unseen testing directions: - Unseen pair (6): {jv, ms, tl} ↔ {jv, ms, tl} - Unseen source (4): id → {en, jv, ms, tl} - Unseen target (4): {en, jv, ms, tl} → id

Table 2: Dataset overview for training and testing configurations for both small and large-scale experiments.

- **subsampled LARGE**: sampled from the LARGE dataset with 12K, 120K, and 1.2M sentences per language pair respectively.

Unseen Language Pairs We evaluate catastrophic forgetting on three types of unseen language pairs. Our analysis focuses on pairs where at least one language was seen during fine-tuning, as pairs with two unseen languages consistently showed severe performance degradation in preliminary experiments. The three categories are:

- **Unseen Pair**: Both the source and target languages are present in the fine-tuning data, but not in combination. This is the most challenging category as explained next.
- **Unseen Source**: The source language has not been seen during fine-tuning, but the target language has.
- **Unseen Target**: The target language has not been seen during fine-tuning, but the source language has.

Among the three evaluated categories, the “unseen pair” scenario presents a unique challenge. While counterintuitive, this case is often more difficult than scenarios involving languages completely unseen during fine-tuning. The primary reason for this difficulty lies in the English-centric nature of the fine-tuning dataset. Because all training examples are paired with English, the model learns an implicit association that a specific source language uniquely predicts English as the target lan-

guage, which represents a spurious correlation (Gu et al., 2019).³ In contrast, the other two conditions do not present this conflict to the same level. For an unseen source language, the model has not formed any directional association during fine-tuning. Therefore, there is no learned association to be overridden. The unseen target language scenario is also comparatively less difficult. Specifically, as long as the source language has to translate into multiple different target languages during training or has not been seen in training, the model does not learn a one-to-one mapping to a single output. This condition applies to four of the seven unseen target language scenarios ($\text{en} \rightarrow \{\text{he}, \text{ja}, \text{uk}, \text{id}\}$), where the source language was part of a multi-target translation setup. This configuration discourages overspecialization toward a single output language, reducing the overall difficulty of translating into a unseen target language for this category.

Language Control Mechanisms Following the original models, we use different language specification methods. For M2M-124, we follow their token-based control, prepending source and target sentences with their respective language tokens:

```
<source_lang_token> source sentence
<target_lang_token> target sentence
```

For instruction-following models, we use the system prompt “Translate the given sentence from [source language] to [target language]” followed by the source sentence. In ablations, we also test instructions in the target language⁴.

3.3 Training and Inference

For full fine-tuning, we update all model parameters. For LoRA, we adopt a rank of 8 and α of 16, applying adapters to all components within self-attention (Query, Key, Value, Output, Gate) and linear projections. This LoRA configuration was chosen after initial experiments applying LoRA to fewer components showed weaker supervised performance. It also creates conditions more analogous to full fine-tuning than selective adapter application, minimizing potential confounding factors related to parameter coverage. More training and inference details are available in [Appendix A](#).

³For instance, when translating from German-Czech after fine-tuning on English-Czech and German-English, the model has been implicitly trained to associate German inputs with English outputs. Direct German-Czech translation requires the model to override this spurious correlation.

⁴We translate English instructions with DeepL. For languages not supported by DeepL, we use Google Translate.

3.4 Metrics

For evaluation, we primarily use COMET-22 (Rei et al., 2022) as our main quality metric due to its strong correlation with human judgments (Freitag et al., 2022). However, COMET has known limitations when models generate unintended languages (Zouhar et al., 2024), which is particularly relevant for catastrophic forgetting. Therefore, we include BLEU⁵ (Papineni et al., 2002) as a complementary string-matched metric. When appropriate, we also report language accuracy using the language identification tool by Lui and Baldwin (2011).

4 Gain-Forgetting Analyses

We investigate the trade-off between performance gains on fine-tuned language pairs and potential catastrophic forgetting on those unseen during fine-tuning. To visualize this relationship, we create scatter plots ([Figure 2](#) and [Figure 3](#)) where each point represents a language pair’s performance before (x -axis) and after (y -axis) fine-tuning. The diagonal line ($y = x$) is a reference boundary, where points below indicate catastrophic forgetting, while those above indicate performance improvement.

4.1 Model Scale and Fine-Tuning Data Size

Impact of Model Size Larger model variants consistently exhibit greater resistance to catastrophic forgetting. For M2M-124 models, the 0.6B parameter variant shows fewer language pairs in the forgetting zone compared to its 0.2B counterpart. Similarly for Qwen2.5, the 7B model demonstrates substantially less forgetting than the 0.5B model across all language pairs. This confirms the finding from Ramasesh et al. (2022) that the base model scale helps mitigate forgetting.

Impact of Fine-Tuning Data Volume We additionally observe that the amount of fine-tuning data plays a crucial role in forgetting. By contrasting [Figure 2](#) ($\sim 100\text{K}$ sentences FT data) and [Figure 3](#) ($\sim 54\text{M}$ sentences FT data), it becomes clear that higher-data-volume fine-tuning leads to stronger forgetting across all model variants. This observation extends the findings of Ramasesh et al. (2022), by demonstrating that catastrophic forgetting is impacted not only by base model scale, but also by the intensity of task-specific training.

⁵with default tokenizer “13a” in sacreBLEU (Post, 2018), and the dedicated tokenizers for Chinese and Japanese.

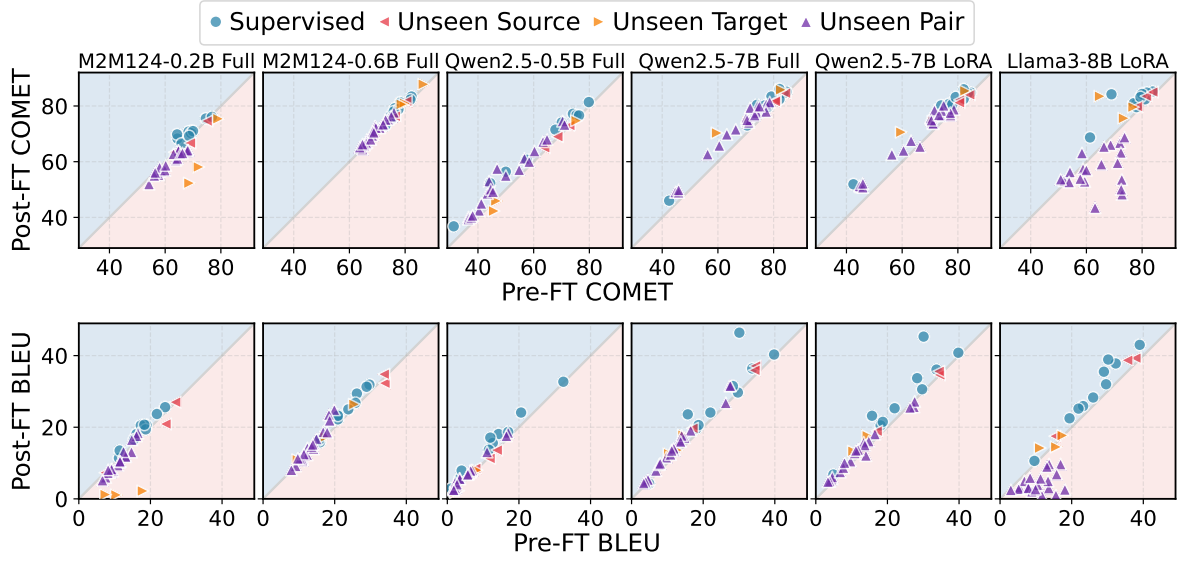


Figure 2: Gain-forgetting plots on the SMALL dataset (117K sentence pairs). Catastrophic forgetting is minimal, except unseen language pairs on Llama (addressed later in Table 4).

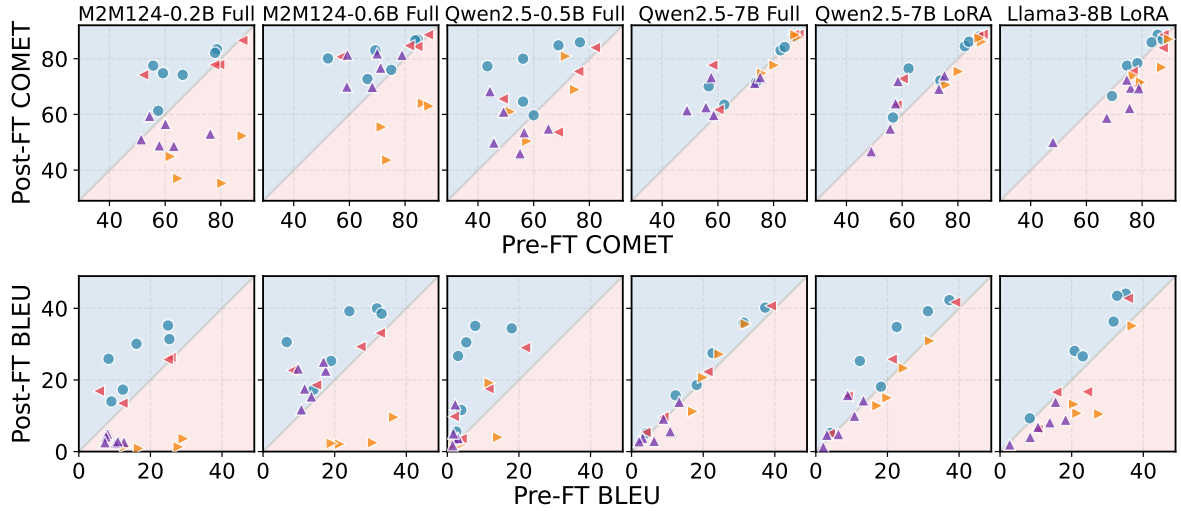


Figure 3: Gain-forgetting plots on the LARGE dataset (54M sentence pairs). Catastrophic forgetting is more severe, especially with translation-specific models where they show performance collapse approaching 0 BLEU.

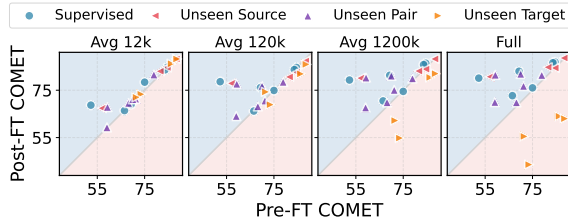


Figure 4: Controlled analysis of data volume effects by subsampled portions of the LARGE dataset. Forgetting becomes severe as fine-tuning data amount increases.

Controlled Analysis of Data Volume Effects To isolate the impact of data volume from dataset-specific factors (e.g., the ALMA dataset has higher-quality data), we conduct controlled experiments

using subsampled portions of the WMT21 dataset. We systematically vary the amount of fine-tuning data while maintaining a consistent data source. Starting with 12K sentences per language pair (matching ALMA), we increase the volume by an order of magnitude at each step: 12K \rightarrow 120K \rightarrow 1,200K sentences per language pair. Figure 4 demonstrates the progressive increase in catastrophic forgetting as training volume grows. At 12K sentences per language pair, the gain-forgetting pattern resembles ALMA results, with most language pairs clustered near the diagonal line and minimal performance changes. At 120K sentences, a shift toward forgetting emerges, particularly for target languages unseen in fine-tuning.

Model	Average		en→id	
	COMET	BLEU	COMET	BLEU
Qwen2.5-0.5B-Instruct	64.0	8.0	71.6	11.8
+ Instruction-based FT	65.3	6.8	80.9	19.2
+ Token-based FT	60.9	5.2	72.1	14.0

Table 3: Effectiveness of different language control mechanisms on unseen target languages compared to the base model without fine-tuning. Instruction-based language control outperforms token-based control.

At 1,200K sentences, severe catastrophic forgetting occurs, though not to the full extent observed in the complete dataset. The progressive degradation suggests that the intensity of fine-tuning on specific language pairs impacts the forgetting patterns.

4.2 Architecture and Language Control Mechanism

To isolate the impact of model architecture and pretraining objectives on catastrophic forgetting, we compare two models of comparable scale but different designs: M2M-124-0.6B, a translation-specific encoder-decoder model, and Qwen2.5-0.5B, a general-purpose decoder-only model pre-trained for instruction following. While these two models differ in their pre-training data, which precludes a fully controlled comparison, we also replicate M2M-124’s language control mechanism on Qwen2.5 to reduce potential confounding factors.

Forgetting Patterns Across Architectures In Figure 3 on the LARGE dataset, where forgetting effects are strongest due to large-scale fine-tuning data, both models exhibit catastrophic forgetting with multiple language pairs falling below the diagonal. However, they differ in their forgetting patterns: M2M-124-0.6B exhibits severe performance degradation on unseen target languages, while Qwen2.5-0.5B shows modest forgetting. We hypothesize that this is related to the target language control mechanisms by the models. As discussed in §3.2, M2M-124 relies on language-specific tokens prepended to both source and target sentences, with the target-side token determining the output language. In contrast, with Qwen, we use natural language instructions to specify the target language, leveraging its existing instruction-following capabilities. This instruction-based mechanism may support more generalizable language control and help mitigate catastrophic forgetting on unseen target languages. We examine this hypothesis next.

Isolating Language Control Mechanisms To test the previous hypothesis that natural language instructions facilitate language control, we conduct a controlled experiment by fine-tuning Qwen2.5-0.5B using the same token-based language specification format as M2M-124, as described in §3.2. This format eliminates natural language instructions entirely, allowing fairer comparisons between models while holding the language control method unchanged. The results support our hypothesis that instruction-following paradigms provide superior language control. As shown in Table 3, when trained with token-based language control, Qwen2.5’s performance on unseen target languages drops substantially from 65.3 to 60.9 COMET over 4 unseen target language pairs. To account for low initial performance in some non-English language pairs, we specifically examine the English-Indonesian pair, which has a stronger baseline. In this case, performance still degrades substantially from 80.9 to 72.1 COMET and from 19.2 to 14.0 BLEU. These results on Qwen show that it is the instruction-following ability, rather than the decoder-only architecture, that provides stronger protection against target language forgetting.

Impact of In-Language Instructions Building on our previous findings regarding instruction-following for language control, we investigate whether using instructions in the target language (in-language instructions) can mitigate catastrophic forgetting on unseen language pairs. While prior work on in-language instructions for multilingual LLMs shows mixed results (Marchisio et al., 2024; Mondshine et al., 2025; Liu et al., 2025; Romanou et al., 2025; Enomoto et al., 2025), these studies primarily evaluate models out-of-the-box. In contrast, we focus specifically on the training effects of in-language instructions.

We focus on the Llama3-8B trained on the SMALL dataset, which exhibits strong catastrophic forgetting (rightmost plots in Figure 2). As the results in Table 4 suggest, for unseen language pairs affected by forgetting, in-language instructions substantially outperform English instructions. Specifically, average language accuracy improves dramatically from 22.1% to 82.0%, with corresponding translation quality gains as measured by COMET increasing from 57.2 to 70.9. It is worth noting that this does not impact performance on supervised language pairs, and slightly improves performance on unseen target languages (COMET 79.6→80.3).

	Metric	Supervised	Unseen Pair	Unseen Source	Unseen Target
Original	COMET	76.9	63.8	81.1	71.8
	BLEU	26.0	10.9	29.5	14.8
	LangID	97.9	85.1	97.9	93.5
English instruction	COMET	81.4	57.2	82.8	79.6
	BLEU	30.0	4.4	31.8	15.5
	LangID	96.7	22.1	98.4	94.1
In-language instruction	COMET	81.7	70.9	82.9	80.3
	BLEU	30.3	14.4	32.4	16.1
	LangID	97.5	82.0	98.5	95.1

Table 4: With Llama3 on the SMALL dataset, in-language instructions recover catastrophic forgetting on unseen pairs, reversing a 6.6 COMET loss (63.8→57.2) into a 7.1 COMET gain (63.8→70.9).

4.3 Analyses by Language Pair Types

The results in Figure 2 and Figure 3 also suggest that catastrophic forgetting patterns are strongly dependent on the language pair type. As shown in the previous section, a major issue for language pairs unseen during fine-tuning is generating incorrect output languages. Therefore, we separately discuss the two language control mechanisms.

Token-Based Control and Target Language Forgetting For translation-specific models (M2M-124 variants) which use specialized tokens for language control, performance degradation is most acute for unseen target languages. This is expected, as if the language token for a target language is never encountered during fine-tuning, the model’s ability to interpret it and generate the correct language catastrophically degrades.

Unseen Pairs as Main Vulnerability for Instruction-Following Models In contrast, instruction-following models demonstrate greater resilience on unseen target languages, a capability we attribute to the generalizable nature of natural language prompts (§4.2). However, these models are not immune to forgetting and are most susceptible when handling unseen language pairs, where both source and target languages are absent from the fine-tuning set. This is particularly evident with the Llama3-8B model. We hypothesize this vulnerability is compounded by the fact that these unseen pairs are often non-English-centric. Base models typically possess weaker zero-shot capabilities for such translation directions due to the prevalence of English in their pre-training data. Fine-tuning on a different, often English-centric, set of pairs appears to accelerate the forgetting of these already fragile,

non-English-centric translation abilities.

4.4 Comparing LoRA and Full Fine-Tuning

We observe that LoRA and full fine-tuning result in comparable levels of catastrophic forgetting (fourth and fifth columns of Figure 2 and Figure 3). Note that we applied LoRA adapters to all components of self-attention and linear projections, thereby minimizing differences in parameter coverage as a confounding factor. Our finding differs from that of Biderman et al. (2024), who observed that LoRA mitigates forgetting when adapting models to dissimilar domains like code and math. We hypothesize that this difference is because our fine-tuning task (translation) requires a smaller domain shift for the base models, which already exhibit strong zero-shot translation capabilities, whereas adapting to code or math requires a larger deviation.

5 Evaluating Cross-Lingual Alignment for Forgetting Mitigation

Having identified the architectural and training factors that impact catastrophic forgetting, we pose a question about mitigation strategies: Do established forgetting mitigation methods primarily restore lost performance, or do they also improve cross-lingual transfer? We focus on cross-lingual alignment methods, as they encourage similar representations for semantically equivalent content across languages, which could mitigate forgetting.

5.1 Evaluated Methods

We evaluate three prominent cross-lingual alignment techniques that encourage shared representations across languages:

- **Adversarial language identification** (Ganin et al., 2016; Arivazhagan et al., 2019): includes an adversarial language classifier that encourages language-agnostic representations by penalizing the model’s ability to predict the source language from hidden states.
- **Similarity-only loss** (Arivazhagan et al., 2019; Pham et al., 2019): pulls together translation pairs without negative examples. While a naive implementation would lead to representation collapse, joint training with the translation loss mitigates this by maintaining discriminative power for the primary task (Duquenne et al., 2023).
- **Contrastive loss** (Pan et al., 2021): employs a contrastive objective that pulls together representations of translation pairs while pushing apart representations of unrelated sentence pairs.

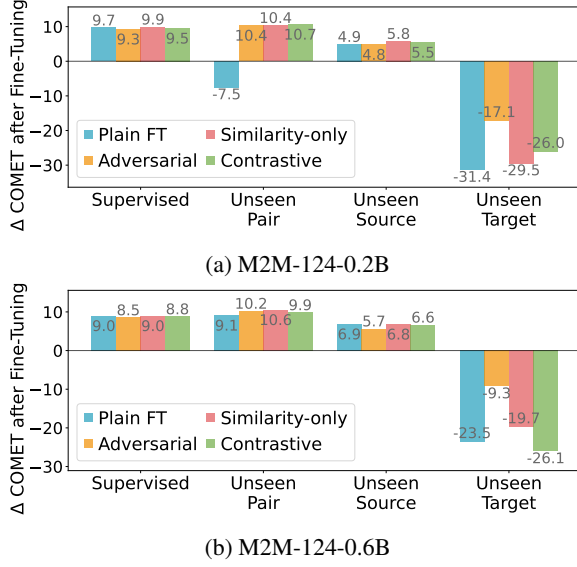


Figure 5: Cross-lingual alignment effects on translation-specific models on the LARGE dataset. Alignment methods bring gains in unseen language pairs, but suffer from persistent forgetting in unseen target languages.

The losses are applied on encoder for encoder-decoder models, and on the middle layers of decoder-only model (Liu and Niehues, 2025).

5.2 Translation-Specific Models

We first evaluate the three alignment methods on translation-specific models: the 0.2B and 0.6B variants of M2M-124. The results are shown in Figure 5, displaying change in translation quality for various language categories, comparing each alignment method against the plain fine-tuning baseline.

Gains in Unseen Language Pairs Among the three unseen categories, alignment methods primarily improve performance on unseen language pairs. These improvements are observed when plain fine-tuning causes forgetting (Figure 5a) and when it brings improvements (Figure 5b). For the 0.2B model, these methods reverse a -7.5 COMET loss by plain fine-tuning (60.5→53.0) into a gain of over 10 COMET. On the larger 0.6B model, the gains are more modest but consistent, ranging from +0.8 to +1.5 COMET over the plain fine-tuning baseline. Besides this category, alignment techniques do not benefit unseen source or target languages, as discussed next.

Persistent Forgetting in Unseen Target Languages The last column of Figure 5 shows that all three approaches still result in drastic, double-digit COMET degradation for this category. This sug-

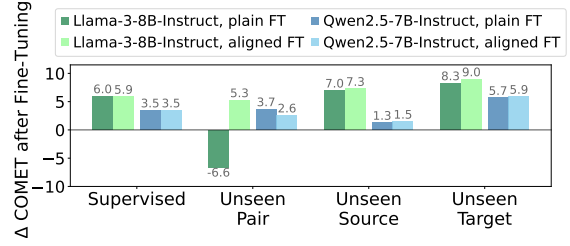


Figure 6: Cross-lingual alignment effects on instruction-following models on the SMALL dataset.

gests an inherent weakness of the token-based language control mechanism discussed in §4.3. Cross-lingual alignment, while beneficial for transfer, struggle to overcome this fundamental limitation.

Similar Performance Patterns Across Alignment

Methods The three evaluated alignment methods exhibit highly similar performance patterns. While the adversarial approach shows an advantage for unseen target languages (Figure 5), the improvement is insufficient to overcome the severe forgetting in this category. We argue this difference is of limited practical relevance, as the degradation results from an inherent limitation in the token-based language control that none of the methods fully resolve. Moreover, the instruction-based language control already demonstrates superior baseline performance in this setting (§4.2). Therefore, given their comparable overall effectiveness, we select a single representative alignment method for the subsequent analysis of instruction-following models.

5.3 Instruction-Following Models

We choose the contrastive approach for studying instruction-following models due to its generality, as the other two approaches require joint training with task-specific loss to avoid collapse. In Figure 6, results are shown for both Llama3-8B and Qwen2.5-7B with LoRA fine-tuning on both the SMALL and LARGE fine-tuning data configurations.

Impact on Unseen Source and Target Languages

On unseen source languages, cross-lingual alignment generally leads to performance comparable to standard LoRA fine-tuning, in line with previous observations on task-specific models (§5.2). On unseen target languages, cross-lingual alignment provides a modest gain of 0.7 COMET (79.6→80.3) for Llama, whereas it offers no significant improvement for the Qwen model. These results suggest that the primary advantage of cross-lingual alignment is its ability to reverse forgetting on un-

seen language pairs. In conditions where standard fine-tuning already yields improvements, the additional gains from alignment are much milder. This forgetting pattern here, especially in the unseen target category, differs from those observed on translation-specific models in §5.2. The persistent strong forgetting observed previously is substantially reduced, with alignment occasionally surpassing the performance of standard fine-tuning. This suggests that as models move forward in their instruction-following capabilities, their potential for cross-lingual transfer is also enhanced.

Why Gains Concentrate on Unseen Pairs The most significant performance improvements are observed on unseen pairs, where both the source and target languages were included in the training data but never appearing together. As discussed in §3.2, this category is particularly challenging because fine-tuning can cause the model to overfit to spurious source-target associations, leading to outputs in an incorrect target language.

We interpret these results as evidence that cross-lingual alignment methods directly counteract this degradation. Encourage more language-invariant representations leads to disentangling semantic content from language-specific features. By breaking the spurious associations learned during training, alignment mitigates the effects of forgetting and restores the model’s ability to generate the correct target language. Consequently, the performance gains are most substantial on these unseen pairs. Considering that the number of translation directions in a multilingual system scales quadratically, and that many languages may only have parallel data to English, breaking the spurious correlations that affect unseen pairs is of high practical importance for scalable translation models.

In contrast, for translation directions involving entirely unseen languages, the central challenge is a general lack of exposure rather than spurious correlations. Therefore, the impact of this alignment mechanism is much milder in those scenarios.

6 Conclusion

In this work, we aim to resolve ambiguities in the literature regarding when catastrophic forgetting occurs for multilingual fine-tuning for MT. Based on our findings, we provide the following practical recommendations: **1)** Consider the relative scale between model size and fine-tuning data. Larger datasets may require larger base models to pre-

vent forgetting. **2)** Prioritize models with strong instruction-following abilities over specific architectural choices. **3)** Do not rely solely on parameter-efficient fine-tuning methods as a forgetting mitigation strategy. **4)** For models exhibiting forgetting, cross-lingual alignment is promising for unseen pairs where both source and target languages have been separately seen in fine-tuning. For instruction-following models, we recommend training with in-language instructions as an initial data-oriented approach before proceeding with cross-lingual alignment approaches.

Limitations

Our study has several limitations that should be considered when interpreting the results:

- Our translation experiments focus on English-centric language pairs, which reflects real-world data availability. Extension to non-English pivot scenarios would provide additional validation of our findings’ generalizability.
- While we vary model and data scales systematically, computational constraints limit our exploration to larger size ranges. The dynamics of forgetting in even larger models remain to be investigated.
- We focus on machine translation as it provides a well-structured testbed for studying multilingual forgetting with clear evaluation metrics. Whether similar patterns emerge across other multilingual tasks remains an open question beyond the current scope.

Acknowledgement

We thank the reviewers for their helpful feedback. Part of this work was funded by the KiKIT (The Pilot Program for Core-Informatics at the KIT) of the Helmholtz Association. The authors gratefully acknowledge the computing time provided on the high-performance computer HoreKa by the National High-Performance Computing Center at KIT (NHR@KIT). This center is jointly supported by the Federal Ministry of Education and Research and the Ministry of Science, Research and the Arts of Baden-Württemberg, as part of the National High-Performance Computing (NHR) joint funding program (<https://www.nhr-verein.de/en/our-partners>). HoreKa is partly funded by the German Research Foundation (DFG).

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A Training and Inference Details

Implementation Frameworks: The M2M-124 experiments were conducted using FairSeq (Ott et al., 2019), while Qwen and Llama experiments utilized Hugging Face Transformers (Wolf et al., 2020).

Training For M2M-124, we used a batch size of 16,384 target tokens. For Qwen and Llama models, we used a batch size of 128 sentences. With M2M-124, we applied a warmup period of 2,500 steps

with a learning rate of $1e-4$. Training was limited to a maximum of 500K updates, with validation runs every 2,000 steps. Early stopping was triggered if validation loss does not improve for 10 consecutive runs. With Qwen and Llama, we used a warmup period of 200 steps with a default learning rate of $5e-4$. For full fine-tuning of Qwen-7B and Llama-8B, the learning rate was reduced to $1e-4$ to due to training instability with higher rates. Validation was conducted every 200 steps, with early stopping applied after 5 consecutive runs without improvement. Both model families employed an inverse square root learning rate schedule.

Decoding During inference, we used beam search with a beam size of 5 for M2M-124 experiments, while greedy search was applied for Qwen and Llama models, following Alves et al. (2024).

Monolingual Adapter Networks for Efficient Cross-Lingual Alignment

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Abstract

Multilingual alignment for low-resource languages is a challenge for embedding models. The scarcity of parallel datasets in addition to rich morphological diversity in languages adds to the complexity of training multilingual embedding models. To aid in the development of multilingual models for under-represented languages such as Sanskrit, we introduce GitaDB: a collection of 640 Sanskrit verses translated in 5 Indic languages and English. We benchmarked various state-of-the-art embedding models on our dataset in different bilingual and cross-lingual semantic retrieval tasks of increasing complexity and found a steep degradation in retrieval scores. We found a wide margin in the retrieval performance between English and Sanskrit targets. To bridge this gap, we introduce Monolingual Adapter Networks: a parameter-efficient method to bolster cross-lingual alignment of embedding models without the need for parallel corpora or full finetuning.

1 Introduction

Sanskrit is one of the oldest languages in human history, actively spoken by 25k people in India. The collection of scriptures, written in Vedic and Classic Sanskrit, include Vedas, Bhramanas, Arkanyas, Upnishads, Vedangas, Upvedas, Mahapurans, Upapurans, Darsanas, Smritis, Itihasa, and the Bhagvada Gita. These works have received so little attention that there is no consensus on the total verse count for Brahmanas, Aranyakas, Upanishads, Smritis, Vedangas, Upavedas, and Darsanas. The rest (Vedas, Puranas, Itihasas, and Bhagvada Gita) have an estimated total of 600,000 Sanskrit verses. It is estimated that 30 million documents of Sanskrit exist that are partly digitized (Aralikatte et al., 2021). Being silos of knowledge and wisdom, these are prominent works for cultural and historical studies. However, their accessibility is limited due to a

lack of good quality translations and applications to search and analyze these works.

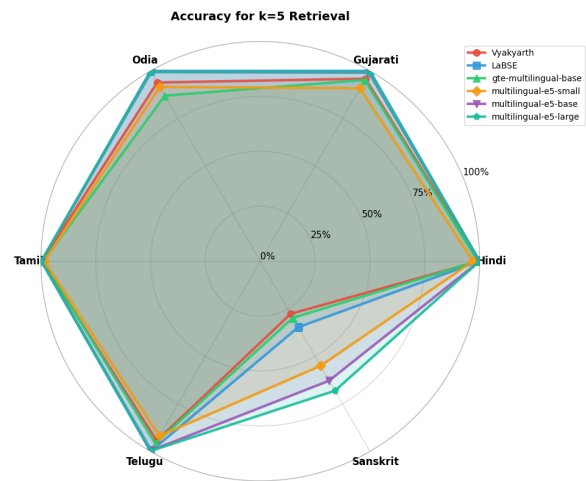


Figure 1: Bilingual retrieval accuracy of embedding models across Indic languages and Sanskrit (k=5) for English translations. SOTA models that excel in Indic-English retrieval, struggle with English-Sanskrit retrieval.

Retrieval-augmented generation (RAG) has emerged as the dominant paradigm for extending large language models’ generative question-answering capabilities to new domains (Lewis et al., 2021, Gao et al., 2024, Guo et al., 2025, Han et al., 2025). Their multilingual and cross-lingual performance on question answering tasks have also been evaluated (Liu et al., 2025, Artetxe et al., 2020). The core challenge in creating a RAG system is retrieval of high-quality documents to be passed as part of the context to a LLM for generation. A standard retrieval pipeline uses a variation of semantic retrieval in addition to statistical methods such as BM-25 (Robertson et al., 1994) or graphs (Han et al., 2025, Guo et al., 2025). Semantic retrieval is based on similarity of vector embeddings of a given query and documents in the dataset. The quality of embeddings generated from an embedding model play a crucial role in the retrieval performance of

this pipeline.

A large proportion of the population interested in surveying Sanskrit texts are non-native English speakers and often use their mother tongue, not English for most, as the preferred mode of communication and interaction with applications. The problem for Sanskrit verse retrieval is trivial if both query and translation is available in English or Indic languages (Figure 1). The Sanskrit verse can be retrieved based on semantic similarity of a translation (available in English or Indic language) with the query. The non-trivial cases include:

- Query in English against dataset of Sanskrit documents.
- Query in language X (low-resource indic language) against dataset of Sanskrit documents.
- Retrieving parallel pairs from an unlabeled corpora of Sanskrit/English/Indic languages.

Thus, multilingual embedding models capable of retrieving Sanskrit documents for English and Indic language queries will bolster the efforts in making accessible applications for the analysis of Sanskrit texts.

In our survey we found that existing corpora (Aralikatte et al., 2021, Bakrola and Nasariwala, 2023, Jagadeeshan et al., 2025, Maheshwari et al., 2024, Gala et al., 2023, Ramesh et al., 2022) lacked multilingual parallel translations for Sanskrit verses to benchmark multilingual and cross-lingual retrieval performance of embedding models. To aid in the development of models and applications, we introduce **GitaDB**: a parallel aligned dataset of high quality translations of Sanskrit verses in 5 Indic languages and English to support the development of new models in the field of retrieval, embedding, and question answering. Using our dataset we benchmark the performance of various multilingual embedding models in bilingual and cross-lingual retrieval.

In our analysis, we found a wide gap in the retrieval performance of these models in retrieving Sanskrit documents for English/Indic queries. To bridge this gap we created **Monolingual Adaptation Networks**, as a method to expand coverage of multilingual models to weakly represented languages. Monolingual Adaptation Networks are dense feed-forward neural networks that learn to transform the embeddings for an under-represented language (Sanskrit) to be closer to a pivot language

(English) in a parameter and resource efficient manner.

Our main contributions in this paper include:

- **GitaDB** - A parallel aligned corpus of classic Sanskrit in 6 languages: English, Hindi, Gujarati, Odia, Tamil, Telugu
- **Monolingual Adapter Network** - A method to bolster the performance of embedding models for under-represented languages in a resource efficient way.
- **Cross-lingual Alignment** - We showcase the benefits of using a pivot language as training target for contrastive learning in cross-lingual alignment of translations.

2 Related Work

In our survey we found various datasets for Sanskrit translations. Itihasa (Aralikatte et al., 2021) has a collection of 93,000 pairs of Sanskrit and English translations created from two epics: Ramayana and Mahabharata. Sahayaak (Bakrola and Nasariwala, 2023) is a collection of 1.5M pairs of Sanskrit-Hindi translations covering various domains such as daily conversations, Sports, News, History, and ancient Indian literature including the 700 verses from Bhagvada Gita. Anveshana is a dataset of 3400 Sanskrit document-English query pairs used to study the efficacy of translation based retrieval over direct retrieval for cross-lingual retrieval of ancient texts (Jagadeeshan et al., 2025). Samayik (Maheshwari et al., 2024) has a collection of 53,000 Sanskrit-English pairs written in prose form, distinct from the poetic form of verses present in datasets like Itihasa. Other datasets such as IndicTrans2 (Gala et al., 2023) and IndicGenBench (Singh et al., 2024) cover modern Sanskrit, distinct from the Vedic and Classic forms of Sanskrit used in historic literature.

Most of the datasets we surveyed were either bilingual datasets for Sanskrit or were multilingual datasets for low-resource Indic languages *excluding Vedic and Classic Sanskrit*. GitaDB is the first dataset that contains multilingual verse aligned translations of 640 verses in 5 low-resource Indic languages along with English.

Our primary objective is to identify embedding models’ ability to retrieve similar verses for a given query, presented in different Indic languages. Roy et al., 2020 introduced the concept of strong cross-lingual alignment and its necessity in a multilin-

gual embedding model’s output. Strong cross-lingual alignment is achieved by maximizing inter-cluster distance and minimizing intra-cluster distance for multilingual embeddings of the same information. A model which exhibits low intra-verse distance and high inter-verse distance has strong cross-lingual alignment of translations which produces a high-quality retriever. Thus, we use the concept of strong alignment in our study.

Multilingual alignment methods typically depend on parallel data or bilingual dictionaries, which are scarce for under-represented languages like Sanskrit. More recent multilingual embedding models (e.g., LaBSE (Feng et al., 2020), mE5 (Wang et al., 2024)) aim to create shared representation spaces but still exhibit performance degradation on low-resource languages. Parameter-efficient adaptation methods such as adapter layers (Houlsby et al., 2019) and MAD-X (Pfeiffer et al., 2020) have proven effective for cross-lingual transfer, yet they primarily target task adaptation rather than language alignment. In contrast, *Monolingual Adapter Networks* focus specifically on resource-efficient language-space realignment, enabling embeddings of low-resource languages to be pushed closer to a pivot language without requiring parallel corpora in multiple languages or sacrificing performance on other languages.

3 Dataset

Our dataset is a collection of 640 verses taken from the Bhagvada Gita. The Bhagvada Gita is a subset of 700 verses from the Mahabharata structured as a poetic discourse between Arjuna and Lord Krishna, covering various parts of one’s life: duty, knowledge, and devotion. It is also referred to as the summary of the Vedas - the scriptures that form the roots of Sanatan Dharma. The Bhagvada Gita contains a total of 700 verses. After data cleanup, we were left with 640 verses with translations in 6 languages: Hindi, English, Gujarati, Tamil, Telugu, and Odia for a total of 4480 sentences in our dataset.

We sourced our translations from various online sources and align them at the verse level. For each verse, we store the Sanskrit verse along with its translation in each language available: Hindi, English, Gujarati, Tamil, Telugu, and Odia. Each language uses a different script that adds a rich complexity in our dataset.

After initial data collection, we found certain

verses were fused together. These verses are translated in pairs/triplets as they provide necessary context for the pair/triplet of verses to be interpreted correctly. We translated each verse of the pair/triplet independently and found the meaning to be skewed without the appropriate context. Thus, we decided to leave the fused verses as a single entity in our dataset. This brought our total verse count from down from 700 to 640.

Our dataset along with all our code for this paper can be found here ¹

4 Methods

4.1 Base Model

We adopt LaBSE (Feng et al., 2020) as the underlying multilingual encoder due to its strong bilingual retrieval performance for Indic queries against a corpus of English translations (Table 1). LaBSE provides sentence-level embeddings for more than 100 languages, but like other multilingual encoders, it performs poorly on low-resource languages such as Sanskrit (Table 2).

4.2 Adapter Network Architecture

On top of the frozen LaBSE encoder, we introduce an *Adapter Network* implemented as a lightweight two-layer feed-forward neural network. This adapter maps Sanskrit embeddings into a space more closely aligned with English embeddings, serving as a post-hoc correction without requiring changes to the base model. By restricting training to the adapter, our approach remains computationally efficient and avoids catastrophic forgetting across other languages. The training and inference setup are showcased in figures 2 and 3 respectively.

4.3 Training Data

We train the Adapter Network on the Itihasa corpus ² (Aralikatte et al., 2021), which provides paired Sanskrit and English translations. Importantly, only the Sanskrit embeddings are passed through the adapter during training, while the English embeddings from LaBSE remain fixed and serve as alignment targets.

¹<https://github.com/tickloop/gitadb>

²The Bhagvada Gita is a part of the Mahabharata. To avoid test set leakage, we remove the chapters of Mahabharata that cover the Bhagvada Gita from our training set.

Model	Top-k	Hi (Acc/MRR)	Gu (Acc/MRR)	Od (Acc/MRR)	Ta (Acc/MRR)	Te (Acc/MRR)
Vyakyarth	k=5	99.8 / 98.3	95.9 / 89.5	93.9 / 86.2	99.5 / 98.6	94.4 / 89.1
LaBSE	k=5	100.0 / 99.9	100.0 / 100.0	100.0 / 100.0	99.8 / 99.7	100.0 / 100.0
gte-multilingual-base	k=5	99.2 / 96.6	95.2 / 89.4	87.0 / 75.9	98.9 / 97.2	95.8 / 90.6
multilingual-e5-small	k=5	97.7 / 94.3	90.9 / 79.4	91.6 / 83.7	98.4 / 94.9	91.9 / 83.3
multilingual-e5-base	k=5	100.0 / 98.7	99.1 / 96.1	99.4 / 97.3	99.7 / 99.3	99.5 / 97.7
multilingual-e5-large	k=5	100.0 / 99.5	99.4 / 98.5	99.5 / 98.9	99.8 / 99.5	99.7 / 98.8
Vyakyarth	k=10	99.8 / 98.3	98.0 / 89.8	96.4 / 86.6	99.8 / 98.7	97.3 / 89.5
LaBSE	k=10	100.0 / 99.9	100.0 / 100.0	100.0 / 100.0	99.8 / 99.7	100.0 / 100.0
gte-multilingual-base	k=10	99.5 / 96.7	97.2 / 89.7	92.5 / 76.7	99.4 / 97.2	97.5 / 90.8
multilingual-e5-small	k=10	98.8 / 94.4	95.0 / 80.0	95.5 / 84.2	99.1 / 95.0	95.5 / 83.8
multilingual-e5-base	k=10	100.0 / 98.7	99.5 / 96.1	99.7 / 97.4	99.7 / 99.3	99.8 / 97.8
multilingual-e5-large	k=10	100.0 / 99.5	99.7 / 98.5	100.0 / 99.0	100.0 / 99.5	99.8 / 98.8

Table 1: Top-k retrieval accuracy (Acc) and mean reciprocal rank (MRR) for queries in Indic languages with targets from English translation corpora. Each cell shows Acc / MRR.

4.4 Objective Function

Training is performed with the InfoNCE contrastive loss (van den Oord et al., 2018). For each Sanskrit-English pair, the adapter output for Sanskrit serves as the query, and the corresponding English embedding is treated as the positive key among a set of in-batch negatives. This formulation encourages the adapted Sanskrit embeddings to be “pulled” closer to their English counterparts while being pushed away from non-matching English samples. Use of more advanced loss functions is left as part of future work.

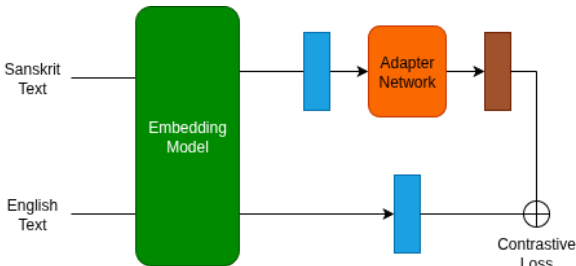


Figure 2: Adapter Network training setup. The embedding model is kept frozen and only the Adapter Network is trained using a contrastive loss. This creates embeddings for Sanskrit that are better aligned with English while the alignment between other languages is unaltered.

5 Experiments

We selected the following models for evaluation on our retrieval benchmarks:

- **Vyakyarth** (Pushkar Singh, 2024) is a 270M

sentence embedding model designed for Indic languages, built upon the STSB-XLM-R-Multilingual architecture.

- **GTE-Multilingual** (Zhang et al., 2024) is a 305M parameter General Text Embedding model which is trained on 70+ languages and ranks high on MMTEB (Enevoldsen et al., 2025).
- **LaBSE** (Feng et al., 2020) is a 471M parameter multilingual model that scores well on low-resource languages.
- **Multilingual-e5** (Wang et al., 2024) family of models trained on 100+ languages offer three models: small (118M), base (278M), and large (560M) parameters.

We tested the models in scenarios that resemble real-world application of high-quality embeddings: Bilingual English-Indic Retrieval, Retrieval without translation availability, and Bitext mining in multilingual corpora. Each task requires high bilingual and cross-lingual alignment of embeddings. We use cosine similarity as our distance metric in all our experiments. Since our dataset does not contain queries, we use the translations as a proxy for queries.

5.1 Retrieval from English Corpus

Task: Given a query in Indic language and a corpora of English translations, retrieve the parallel translation of the query. We expect all models

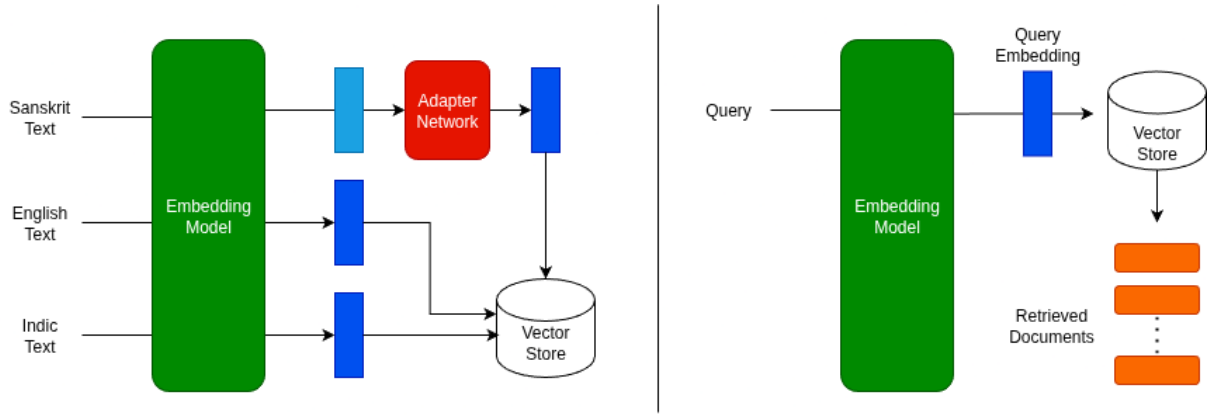


Figure 3: During inference, English and Indic text embeddings are generated via the embedding model while Sanskrit embeddings are generated as a combination of the embedding model and the adapter network. The embeddings are stored in a vector store for retrieval. Queries are embedded using the same embedding model and relevant documents are retrieved from the vector store. Since the adapted embeddings for Sanskrit are better aligned with English (and consequently Indic Languages), the retrieval performance is better for Sanskrit documents against queries from different languages.

to perform well on this task due to the increase in availability of multilingual corpora for all languages tested. This task also serves as a benchmark to identify any language bias in embedding models.

We created embeddings for each English translation in our corpora and stored them in a vector database. Then, for each query we retrieved top-k English translations using Cosine similarity as the distance metric from our vector store. We report the Accuracy@k and Mean Reciprocal Rank (mRR@k) values in Table 1. All models performed near perfectly in this task as we expected. The MRR scores being close to 100 indicate that majority of correct retrievals were the highest scoring result. This showcases a high bilingual alignment between English and Indic language embeddings.

5.2 Retrieval from Sanskrit Corpora

Task: Given a query in language X (En/Indic) and a corpora of Sanskrit verses, retrieve the parallel verse for the query. This task benchmarks the bilingual alignment between English/Indic languages and Sanskrit for each embedding model.

We created embeddings for each Sanskrit verse in our corpora and stored them in a vector database. Then, for each query we retrieved top-k Sanskrit verses using Cosine similarity as the distance metric from our vector store. The results for this study are presented in Table 2.

The multilingual-e5 model family was the dominant model for this task. The base LaBSE model achieves an average score of 29.82. Adding the Adapter Network (+ada) increases performance

to 43.3, a 45.2% improvement, highlighting the effectiveness of the adapter. The Adapter Network also aids in alignment between Sanskrit verses and translations in Indic languages which the models was not trained on. For English retrieval, the model exhibited an absolute improvement of 12.6%, whereas for Indic languages it demonstrated a comparatively higher average absolute gain of 13.7%, highlighting the enhancement in cross-lingual alignment. Having a good alignment between pivot and non-pivot languages, as we noted in Task 1, aids in a consistent improvement across all languages (Table 2).

5.3 Bitext Retrieval

Task: Given a Sanskrit verse and a multilingual corpora of English and Indic language translations, retrieve all the parallel translations for the verse. This task benchmarks the cross-lingual alignment and retrieval ability of embedding models.

For each verse in our Sanskrit corpora, we retrieve top-k results from a multilingual corpora of English and Indic translations. We report the Accuracy@k for k=6 in Table 3. We use k=6 as there are 6 parallel translations for each verse in our dataset. Since there are multiple correct candidates for retrieval, we also report Mean Average Precision (mAP) (Roy et al., 2020) values in Table 4 along with average accuracy (count of correct retrievals / total correct translations in dataset).

The base LaBSE model achieves an average score of 11.9 which is a massive drop compared to the bilingual setting with only one target lan-

guage. The presence of multiple correct translations was a challenge for every embedding model. The sharp drop in performance indicates that the embedding space contains clusters with low inter-verse distance resulting in weak alignment between Sanskrit and English/Indic languages. Incorporating the Adapter Network (+ada) raises the average to 23.9, highlighting that the adapter helps align low-resource language embeddings even without full fine-tuning. It provided a +25.6% absolute improvement in retrieval accuracy for English translations, while also providing a consistent improvement in cross-lingual alignment for non-pivot languages: +3.2% in Hindi, +9.5% in Gujarati, +13.6% in Odia, +10.3% in Tamil, and +10.4% in Telugu.

We also note a wide variation in the performance of multilingual-e5 models across languages. Their performance for English retrieval dropped significantly in the presence of multiple translations from Indic languages. The e5-large model’s top-k retrieval accuracy for Gujarati was 61.6 whereas for English it was only 11.1. There are similar language biases in e5-base and e5-small embedding models. To investigate this bias, we trained an Adapter Network for e5-base model.

While the performance of m-e5-base (+ada) on English, Odia, and Tamil increased by an absolute average of 23.8%, it dropped for Hindi, Gujarati and Telugu by an absolute average of 10.2%. The top-6 average retrieval accuracy for m-e5-base was 30.7, which was boosted to 37.5 with the help of Adapter Networks. The average retrieval performance of this combination of multilingual-e5-base with Adapter networks (37.5) is comparable to multilingual-e5-large (38.1). It is clear that

Model	En	Hi	Gu	Od	Ta	Te
Vyakyarth	27.7	29.2	24.2	22.7	22.8	19.7
gte-m-base	29.8	41.4	25.8	24.2	27.5	27.3
m-e5-small	55.0	63.4	56.1	53.6	50.8	56.4
m-e5-base	62.8	70.8	66.9	66.7	59.7	67.5
m-e5-large	68.1	75.8	77.5	74.1	68.9	77.5
LaBSE	34.7	26.7	30.2	29.2	25.8	32.3
LaBSE (+ada)	47.3	40.5	42.7	42.8	42.0	44.5

Table 2: Top-5 retrieval accuracy for queries in English/Indic language with targets from Sanskrit verse corpora. (+ada) uses adapted embeddings for retrieval targets. The Adapter Network not only increased performance on English, but also across non-pivot languages that were not included in training.

multilingual-e5 family of models’ Indic language embeddings do not cluster around English as a pivot language and an interesting future work will be to investigate the choice of pivot language for different embedding models.

6 Results

Overall, our experiments reveal a clear stratification in model performance across tasks and languages. While nearly all multilingual embedding models exhibited decent performance in bilingual retrieval from parallel corpora, their effectiveness dropped substantially when moving to tasks that required cross-script and cross-lingual alignment with Sanskrit. The multilingual-e5 family consistently ranked at the top for bilingual scenarios, particularly the large variant, which demonstrated strong resilience to performance degradation.

In the Indic/English-to-Sanskrit retrieval task (Table 2), the models encountered a significant challenge. The shift from modern language corpora to a under-represented, morphologically rich language introduced substantial difficulty in semantic alignment. Even top-performing models exhibited a marked decline in retrieval accuracy, indicating that bi-lingual alignment learned from contemporary corpora does not directly transfer to Sanskrit. The relative resilience of the multilingual-e5 family suggests that broader multilingual coverage and larger model capacity help preserve alignment in low-resource or structurally distant target languages, but performance gaps remain large enough to affect real-world applicability in downstream RAG systems. Adapter Networks consistently improved retrieval accuracy for English and Indic

Model	En	Hi	Gu	Od	Ta	Te
Vyakyarth	12.0	15.0	10.2	6.9	6.1	9.7
gte-m-base	19.8	17.5	8.4	7.5	9.8	11.7
m-e5-small	2.3	14.4	44.2	15.5	5.0	19.4
m-e5-large	11.1	38.3	61.6	48.9	21.1	48.0
LaBSE	10.0	12.3	13.0	10.0	8.8	17.3
LaBSE (+ada)	35.6	15.0	22.5	23.6	19.1	27.7
m-e5-base	8.4	41.7	49.2	27.8	19.1	38.0
m-e5-base (+ada)	59.7	40.3	28.1	33.1	33.8	29.8

Table 3: Top-6 parallel alignment accuracy for each language. There is a stark decline in performance for all models as compared to retrieval from English corpora in Task 1 and for bilingual retrieval with Sanskrit targets in Task 2. The multilingual-e5 family also showcases a heavy language bias.

Model	acc@6	acc@10	mAP@6	mAP@10
Vyakyarth	9.97	13.26	0.18	0.19
gte-m-base	12.47	16.67	0.26	0.25
m-e5-small	16.80	20.44	0.39	0.37
m-e5-large	38.15	46.35	0.63	0.60
LaBSE	11.90	16.09	0.18	0.18
LaBSE (+ada)	23.91	31.30	0.35	0.34
m-e5-base	30.70	37.16	0.52	0.50
m-e5-base (+ada)	37.47	46.28	0.54	0.52

Table 4: Average accuracy and mAP values for parallel translation retrieval. mAP values closer to 1 are better. All models struggled in retrieving parallel translations in the presence of multiple targets from different languages. A stark contrast from the bilingual performance highlights the complexity of this task.

languages, even with the lack of parallel corpora or full-finetuning of embedding models.

The bitext retrieval task (table 3-4), which required retrieving all valid translations of a Sanskrit verse from a multilingual pool, proved the most difficult. The presence of multiple correct answers across diverse scripts and languages compounded alignment complexity, amplifying the effects of language bias and imperfect semantic clustering. Here, accuracy dropped sharply for most models, and mAP values were substantially below 1 indicating the lack of correct answers in majority of retrievals. The multilingual-e5 models again emerged as the most robust, though their performance in English retrieval degraded noticeably in this multi-target setting, suggesting that even strong multilingual alignment is strained when faced with semantically overlapping candidate sets. This result underscores the need for embedding strategies explicitly optimized for multi-answer, multilingual retrieval scenarios in low-resource languages. While the use of Adapter Networks showed improvement in cross-lingual alignment for all non-pivot languages for LaBSE, the lack of strong cross-lingual alignment between English and Indic language translations resulted in a split performance for the E5 family of models.

7 Conclusion

In this work, we introduced GitaDB, a parallel-aligned multilingual dataset of 640 Bhagavad Gita verses in Sanskrit with translations in five Indic languages and English. We benchmarked a range of multilingual embedding models on retrieval tasks

of increasing complexity, revealing the strengths and limitations of current embedding models for cross-lingual and cross-script retrieval in a classical language setting. While state-of-the-art models such as the multilingual-e5 family demonstrated strong performance in parallel multilingual retrieval, their performance dropped substantially in bilingual Sanskrit alignment and multilingual bitext retrieval scenarios. These results underscore the unique challenges of handling morphologically rich, low-resource languages with diverse scripts, even for models trained on extensive multilingual corpora. Our method of creating resource efficient Adapter Networks proved effective in extending the capabilities of embedding models to an under-represented languages without full finetuning or parallel multilingual corpora.

8 Future Work

Our findings suggest several promising directions for future work. There is a clear need for embedding models explicitly trained on classical language corpora and capable of handling cross-script alignment without relying solely on translations. This work has uncovered the use of Adapter Networks as a strategy to improved cross-lingual retrieval performance with a simple architecture. Adapter Networks can be further studied with varying architectures, loss functions, and pivot languages based on the choice of underlying embedding model. Using hard in-batch negatives has also shown promising results in contrastive training. We leave the exploration of using hard in-batch negatives for a future study.

The multi-answer retrieval setting presents an open challenge; techniques that better cluster semantically equivalent translations while maintaining separation between distinct verses could yield significant zero-shot improvements. For RAG systems in particular, such advances could enable more accurate context retrieval across languages, improving both coverage and relevance for end users who query in non-English languages. By closing the alignment gap between Sanskrit and modern Indic languages, future systems will be better equipped to serve as multilingual gateways to the cultural and philosophical heritage embedded in these texts.

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Culturally-Nuanced Story Generation for Reasoning in Low-Resource Languages: The Case of Javanese and Sundanese

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Abstract

Culturally grounded commonsense reasoning is underexplored in low-resource languages due to scarce data and costly native annotation. We test whether large language models (LLMs) can generate culturally nuanced narratives for such settings. Focusing on Javanese and Sundanese, we compare three data creation strategies: (1) LLM-assisted stories prompted with cultural cues, (2) machine translation from Indonesian benchmarks, and (3) native-written stories. Human evaluation finds LLM stories match natives on cultural fidelity but lag in coherence and correctness. We fine-tune models on each dataset and evaluate on a human-authored test set for classification and generation. LLM-generated data yields higher downstream performance than machine-translated and Indonesian human-authored training data. We release a high-quality benchmark of culturally grounded commonsense stories in Javanese and Sundanese to support future work.¹

1 Introduction

Reasoning, the ability to draw conclusions, make inferences, and relate concepts, is a core evaluation target in recent LLM work (Dubey et al., 2024; OpenAI et al., 2024; Hurst et al., 2024; Almazrouei et al., 2023). Yet widely used English benchmarks such as StoryCloze (Mostafazadeh et al., 2016, 2017), WinoGrande (Sakaguchi et al., 2021), and HellaSwag (Zellers et al., 2019) encode Western norms. Because reasoning is culturally shaped, relying on machine-translated English datasets (Ponti et al., 2020; Lin et al., 2022; Hershovich et al., 2022) risks erasing local context.

Recent datasets for medium-resource languages (e.g., Indonesian (Koto et al., 2024) and Arabic (Sadallah et al., 2025)) add cultural grounding but

mainly target sentence-level classification. Story-level commonsense, how people interpret events across narratives, remains underexplored in low-resource languages due to limited speaker access, high annotation costs, and scarce culturally relevant materials.

We address story comprehension in two under-represented languages, Javanese and Sundanese, spoken by roughly 80M and 32M people respectively (Badan Pusat Statistik, 2025; Eberhard et al., 2025). Beyond sheer scale, both carry rich sociolinguistic systems: Sundanese encodes politeness and hierarchy phonologically, while Javanese employs elaborate speech levels (Wolff and Poedjosoedarmo, 1982). We adopt a StoryCloze-style setup (Mostafazadeh et al., 2016, 2017): given a four-sentence story, models either generate a plausible fifth sentence (generation) or choose the correct continuation from two options (classification).

We compare three dataset creation strategies for culturally grounded story comprehension: (1) LLM-assisted generation with culturally informed prompts, (2) machine translation from Indonesian benchmarks, and (3) native-authored stories. Each has distinct benefits, scalability, resource reuse, and authenticity, respectively. Human evaluation shows LLM outputs are culturally plausible and comparable to native-written stories.

To assess cultural reasoning on narratives, we use the native-authored set as a zero-shot testbed. As in Figure 1, Indonesian/SEA-centric models, though covering the target languages, often produce culturally inappropriate endings, showing that language support alone is insufficient. We then fine-tune on synthetic data and find that LLM-generated training yields stronger results than machine-translated data for both classification and generation.

Our contributions are as follows:

- We release the **first benchmark** for culturally grounded commonsense reasoning in

*Equal contribution

¹The dataset can be accessed at https://huggingface.co/datasets/rifoag/javanese_sundanese_story_cloze

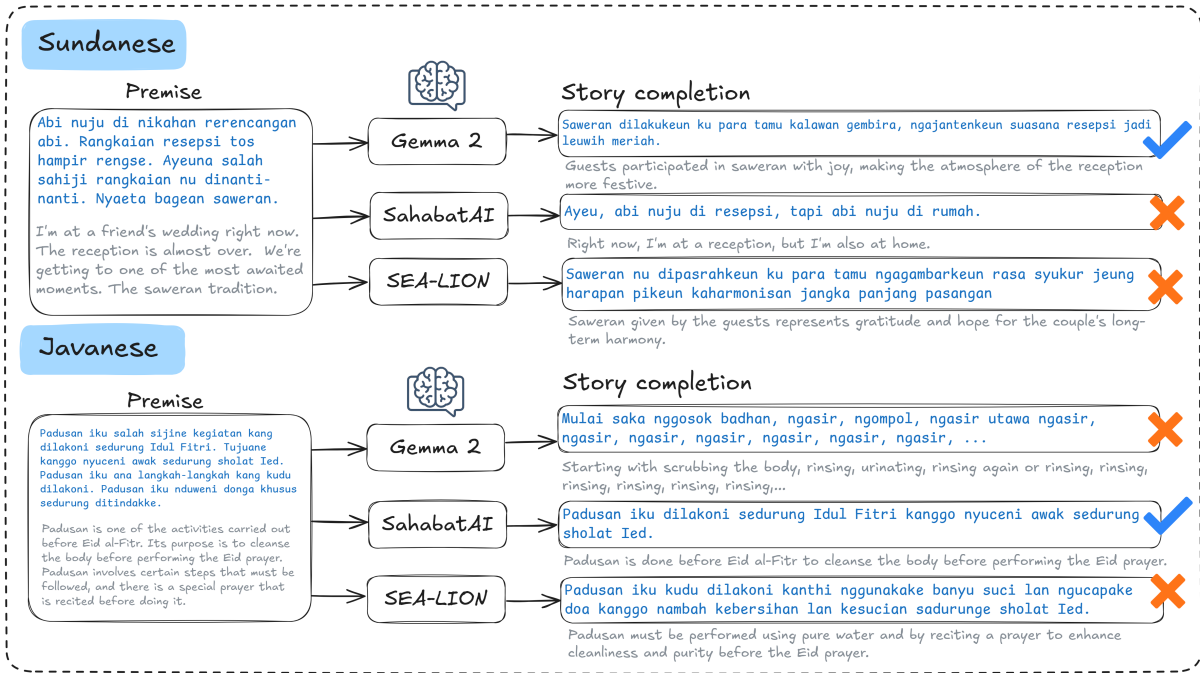


Figure 1: Examples of human-written stories in Sundanese and Javanese. English translations in gray color are provided for reference. A cross (X) indicates a culturally irrelevant ending, generated by LLMs

Javanese and Sundanese, comprising 3.3K high-quality stories. This includes 1.12K human-written samples, 1K human-reviewed machine-translated texts, and 1.22K filtered LLM-generated samples.

- We conduct extensive human evaluation of multiple dataset creation strategies, including (i) LLM-assisted generation, (ii) direct machine translation, (iii) culturally localized translation, and (iv) native-authored stories.
- We evaluate model performance through zero-shot inference and supervised fine-tuning in both classification and generation settings to assess their cultural reasoning capabilities.

2 Related Works

2.1 Commonsense Reasoning in English Story Comprehension

Story comprehension in NLP involves reasoning over causal, temporal, and commonsense relations within narratives. The StoryCloze test, introduced by Mostafazadeh et al. (2016, 2017) is a landmark benchmark, requiring models to select the most plausible ending for a short four-sentence story. Many commonsense reasoning datasets, however, focus on sentence-level challenges include WinoGrande (Sakaguchi et al., 2021) for pronoun resolution, COPA (Gordon et al., 2012) for

causal reasoning, and HellaSwag (Zellers et al., 2019) for adversarial sentence completion. While effective for probing localized reasoning, these do not capture broader discourse coherence or character motivations.

Recent work has shifted toward narrative-level reasoning with longer contexts and richer event dynamics. NarrativeQA (Kočiský et al., 2018) covers full books and movie scripts, CosmosQA (Huang et al., 2019) infers implicit causes and intentions, and TellMeWhy (Lal et al., 2021) targets causal and motivational “why” questions. Yet these remain English-centric and question-answering-oriented. Our work instead addresses narrative completion in low-resource languages, particularly in Javanese and Sundanese, providing a culturally grounded alternative to high-resource, English-dominant benchmarks.

2.2 Commonsense Reasoning in Languages Beyond English

Early multilingual commonsense benchmarks often extended English datasets via translation. XCOPA (Ponti et al., 2020) translated COPA into 11 typologically diverse languages, including Indonesian, while X-CSQA (Lin et al., 2021) adapted CommonSenseQA across languages. Although useful for cross-lingual evaluation, such resources inherit Anglocentric biases, as progress in English

does not always transfer culturally or linguistically (Lin et al., 2022; Shwartz et al., 2020). Direct translations risk embedding English social contexts rather than local commonsense (Lin et al., 2021).

Story comprehension tasks like StoryCloze (Mostafazadeh et al., 2016) have been similarly extended. One such extension is XStoryCloze (Lin et al., 2022), by translating English narratives into multiple languages. Yet such approaches still struggle to capture culture-specific narrative norms.

For Indonesian, culturally grounded datasets such as COPAL-ID (Wibowo et al., 2024) and IndoCulture (Koto et al., 2024) model regional practices and norms across 11 provinces, advancing evaluation in a medium-resource language. However, they primarily focus on short-form, sentence-level reasoning such as multiple-choice or cloze-style questions, rather than full-narrative comprehension. Beyond Indonesia, CultureBank (Shi et al., 2024) compiles large-scale cultural knowledge from community narratives to support culturally aware language technologies, while CultureLLM (Li et al., 2025) incorporates cultural differences into LLMs via semantic data augmentation. However, these resources primarily focus on short-form, structured tasks rather than full-narrative comprehension. Our work fills this gap by introducing the first benchmark for **story-level commonsense reasoning** in low-resource languages, specifically Javanese and Sundanese, two of Indonesia’s most widely spoken local languages.

2.3 LLM-Generated Data Creation

One possible solution to tackle data scarcity in NLP is applying data augmentation (Feng et al., 2021; Ding et al., 2020; Ahmed and Buys, 2024; Liu et al., 2024; Yong et al., 2024; Guo and Chen, 2024; Liu et al., 2022), with LLMs increasingly used to produce high-quality synthetic data that complements or substitutes manual annotation. Most prior work targets classification tasks. For example, WANLI (Liu et al., 2022) used GPT-3 (Brown et al., 2020) to generate synthetic English natural language inference data (Bowman et al., 2015) refined by humans, while Yong et al. (2024) generated English sentiment and topic classification data before translating it into low-resource languages using bilingual lexicons.

For low-resource languages, Putri et al. (2024) employed GPT-4 (OpenAI et al., 2024) to create question-answering datasets, showing LLM potential in under-resourced settings. However, such

efforts often overlook cultural reasoning and narrative coherence. Our work instead focuses on culturally nuanced story generation in Javanese and Sundanese, targeting story-level commonsense reasoning. We compare multiple data creation strategies, including LLM-assisted generation with open- and closed-weight models, machine translation from Indonesian, and native-authored stories.

3 Dataset Construction

As in Figure 2, we build two parallel streams: training and test. For training, the IndoCloze (Koto et al., 2022) train split serves both as seeds for LLM-guided generation and as sources for machine translation into Javanese and Sundanese. For testing, we translate the IndoCloze test split and human-verify it for linguistic quality and cultural relevance, and we add a fully new set of native-authored stories from predefined topics. Each instance follows the StoryCloze format: a four-sentence premise with one correct and one incorrect ending.

Indonesian is chosen as the seed language for its national status and cultural proximity to Javanese and Sundanese. To ensure authenticity, native speakers authored and validated stories, embedding local names, places, foods, and customs. Following Mostafazadeh et al. (2016); Koto et al. (2022), the dataset targets everyday commonsense reasoning grounded in local culture

3.1 Training Data

We construct our training set using three strategies: (1) LLM-assisted data generation, (2) direct machine translation, and (3) machine translation followed by cultural localization using an LLM.

3.1.1 LLM-Assisted Data Generation

We synthesize training data with three open models: Gemma2-27B-it (Rivière et al., 2024), Llama3.1-70B (Dubey et al., 2024), Mixtral-8x7B-Instruct (Jiang et al., 2024), and three closed models: GPT-4o (Hurst et al., 2024; OpenAI et al., 2024), Cohere Command-R-Plus (Cohere, 2024), Claude-3-Opus (Anthropic, 2024).

For each language and LLM, we supply seed examples and topics. We manually translate 50 IndoCloze train samples into Javanese and Sundanese with cultural localization (e.g., foods like *Gudeg* and rituals like *Sawéran*). Topics are de-

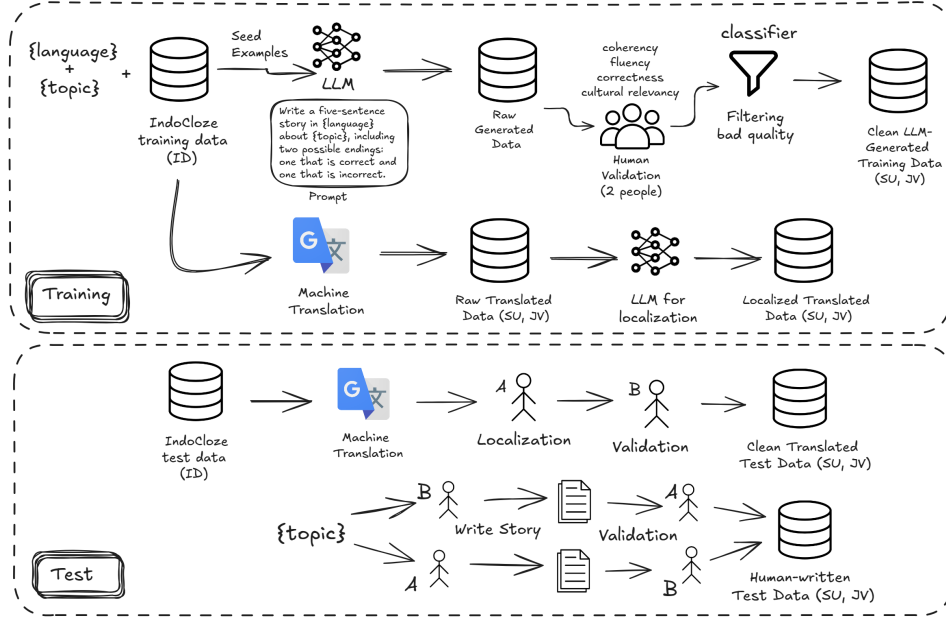


Figure 2: Overall pipeline of dataset creation.

rived from IndoCulture (Koto et al., 2024). The full prompt appears in Figure 4.

Each LLM produces 2,000 stories (1,000 per language), yielding six training sets. Per call, five random seeds guide generation at temperature 0.7; we repeat until each model reaches 1,000 valid samples per language (≈ 166 per topic on average).

To filter quality, we train an XLM-R binary classifier on 600 human-rated outputs (Section 4.2)². Applied to all 12,000 generations, it retains 1.2K high-quality stories (592 Sundanese, 628 Javanese). Roughly half of Claude and GPT-4o outputs pass, while far fewer from other LLMs, especially Mixtral, survive (Appendix B).

3.1.2 Machine Translation (MT_{train})

We translate 1,000 IndoCulture training instances into Javanese and Sundanese (1,000 each) using Google Translate³ (see Appendix F for quality). As a training resource, this set is *not* human-validated. We refer to it as MT_{train} .

3.1.3 Machine Translation + Localization ($\text{MT}_{\text{train}} + \text{GPT4o}$)

We prompt GPT-4o to culturally localize the MT outputs, following the same guidelines given to human annotators. The model adapts names,

events, foods, settings, and social norms to Javanese/Sundanese contexts. This probes whether LLMs can align literal translations with local cultural values to produce more authentic, context-appropriate narratives.

3.2 Test Set

We carefully construct the test set using two strategies: (1) machine translation with human verification, resulting in 500 Javanese and 500 Sundanese instances, and (2) manual writing by native speakers based on pre-defined topics, producing roughly 529 Javanese instances and 595 Sundanese instances. Each strategy undergoes rigorous quality control to ensure accuracy and reliability. In total, we create a high-quality test set of 2,124 instances across both languages.

To ensure the authenticity and quality of the dataset, we recruited 4 expert workers (2 per language) who are not only native Indonesian speakers but also fluent in Javanese and Sundanese. Each expert worker has a deep understanding of their respective language, culture, and customs. They have at least 10 years of experience speaking Javanese or Sundanese and possess strong linguistic and cultural expertise. The recruited workers, aged between 21 and 35 years, hold bachelor’s degrees and were carefully selected for their proficiency in both language and cultural knowledge.

²68.33% accuracy on the dev split (20% of train); setup in Appendix A.

³<https://translate.google.com/>, accessed September 2024.

Dataset	Sundanese				Javanese			
	Coherence	Fluency	Correctness	Cultural Rel.	Coherence	Fluency	Correctness	Cultural Rel.
Human Written (HW)	5.0	5.0	100	96	5.0	5.0	100	66
LLM Generated Data								
GPT-4o	4.7	4.2	80	96	4.9	4.5	97	91
Claude	4.7	4.4	86	92	4.9	4.3	96	93
Cohere	3.4	3.0	28	46	4.6	4.1	80	65
Llama3.1	3.7	3.4	56	70	4.5	4.2	65	50
Gemma2	3.9	3.1	42	78	4.8	3.6	83	81
Mixtral	2.0	1.5	0	4	2.0	1.9	3	22
Translated								
MT _{train}	3.24	4.36	80	20	4.36	4.46	98	12
Translated Data + Localization								
MT _{train} + GPT4o	4.36	4.68	86	80	4.6	4.64	98	76
MT _{test} + Human	5.0	5.0	100	14	5.0	5.0	100	18

Table 1: Quality analysis of models on Sundanese and Javanese. Higher scores indicate better performance in each category.

Dataset	Sundanese				Javanese			
	#data	#vocab	LW (%) ↓	MATTR ↑	#data	#vocab	LW (%) ↓	MATTR ↑
Human Written (HW)	594	4693	0	0.84	529	3497	0	0.80
LLM Generated Data								
GPT-4o	1000	3444	0	0.82	1000	3073	0	0.80
Claude	1000	3898	0	0.80	1000	3104	0	0.79
Cohere	1000	2654	3	0.65	1000	2254	3	0.68
Llama3.1	1000	3126	0	0.69	1000	2836	2	0.69
Gemma2	1000	3758	5	0.72	1000	3334	4	0.71
Mixtral	1000	4584	16	0.71	1000	4215	13	0.67
Translated Data								
MT _{train}	1000	5272	0	0.83	1000	5007	1	0.81
Translated Data + Localization								
MT _{train} + GPT4o	1000	4985	1	0.82	1000	4692	1	0.81
MT _{test} + Human	500	3877	0	0.82	500	3620	3	0.81

Table 2: Lexical diversity analysis of different models on Sundanese and Javanese. “LW” denotes the percentage of loanword.

3.2.1 Machine translation with human verification (MT_{test}+Human)

As shown in Figure 2, we translate 500 randomly selected samples from the IndoCloze test set into Javanese and Sundanese using Google Translate.⁴ To ensure accuracy and naturalness of the machine-translation, we employ two native speakers for each language and implement a two-stage quality control process (Winata et al., 2023). In Stage 1, the first worker manually corrects translation errors and localizes content by replacing entities (e.g., names, buildings, food) with culturally relevant alternatives.⁵ In Stage 2, a second worker validates the revised text and directly corrects any remaining errors from the first stage. From this point forward, we refer to this data as **MT_{test}+Human**.

⁴Google Translate was accessed in September 2024

⁵Note that while we applied cultural localization, not all examples could be fully adapted to Javanese or Sundanese contexts, as some stories reflect general Indonesian cultural elements that are not specific to either group.

3.2.2 Human-written Dataset (HW)

Each expert worker in Sundanese and Javanese is tasked with writing 600 short stories following the IndoCloze format: a four-sentence premise, a correct fifth sentence, and an incorrect fifth sentence. Stories are written based on 12 predefined topics, adhering to the same topic taxonomy used for training (see Section 3.2). See Appendix E for further details on the writing guidelines.

To ensure quality, each expert worker reviewed their peer’s written stories. The reviewing worker was presented with a premise and two randomized alternate endings from another worker’s story and was asked to identify the correct one. Instances incorrectly identified by the second worker were discarded, as they likely contained incorrect endings or exhibited ambiguity. After quality control, 529 Javanese and 595 Sundanese instances remained from the original 600 per language. From this point forward, we refer to this human-written dataset as **HW**.

4 Data Analysis

4.1 Overall Statistics

For LLM-assisted dataset creation, GPT-4o and Claude demonstrated the highest efficiency, generating nearly 1,000 clean samples with minimal discarded output, while Mixtral was the least efficient, requiring significantly more samples to reach the same threshold. The LLM-generated data does not have a uniform topic distribution due to variations in broken samples.

In total, the LLM-generated datasets contain 72K sentences and approximately 557K words. The word distribution across sentence positions remains consistent across the six LLMs, with word counts per position relatively uniform and a median sentence length ranging from 5 to 10 words. MT_{test}+Human (both with and without localization) and HW datasets exhibit a similar word distribution pattern to the LLM-generated datasets. MT contains around 6K sentences with 44,5K words, while HW has 6,7K sentences with 58,2K words. Despite the slight difference in word count, both datasets maintain a consistent distribution, with a median sentence length ranging from 4 to 11 words.

4.2 Quality Analysis based on Human Evaluation

We evaluate the quality of all the constructed dataset based on four key criteria: coherence, fluency, correctness, and cultural relevance. Specifically, we randomly select 50 samples (5–10% of the total dataset) for both Sundanese and Javanese and engage two native speakers for evaluation. Coherence and fluency are rated on a Likert scale from 0 to 5, while correctness and cultural relevance are assessed using binary annotation and reported as percentages. More details on the annotation guideline can be found in Appendix D. Table 1 summarizes the results of human evaluation, with scores for coherence and fluency being averaged between the annotators. Meanwhile, for correctness and cultural relevance, we count the percentage of data perceived as correct or culturally relevant by both annotators. Inter-annotator agreement scores ranges from 0.4 to 0.7, as shown in Appendix C.

We observe that among the evaluated LLMs, both GPT-4o and Claude consistently demonstrate strong performance across all metrics. Notably, their cultural relevance scores are comparable to those of human-written texts. Applying localiza-

tion to the machine-translated data using GPT-4o (MT_{train}+GPT-4o) improves coherence and cultural relevance. Finally, while human post-editing ensures near-perfect scores in coherence, fluency, and correctness, achieving full cultural localization remains challenging, as not all content can be naturally adapted without compromising narrative plausibility.

4.3 Lexical Diversity

We analyze the lexical diversity of LLM-generated data for Sundanese and Javanese using key metrics such as vocabulary size, moving-average type-token ratio (MATTR) (Covington and McFall, 2010), and the proportion of loanwords. To measure loanword presence, we manually review the top 100 most frequent words for each model.

As shown in Table 2, GPT-4o achieves a high MATTR score, making it highly comparable to human-written data. Among the LLM-generated datasets, Mixtral has the largest vocabulary size but also introduced the highest proportion of loanwords, with 16% in Sundanese and 13% in Javanese, suggesting a significant reliance on non-native terms. In contrast, GPT-4o and Claude generate text entirely in Sundanese and Javanese without incorporating foreign words, highlighting their ability to produce better datasets.

Upon manual inspection, we find that LLMs frequently generate common Javanese names such as *Ayu*, *Dwi*, *Bayu*, *Eko*, and *Sari*. For Sundanese, commonly produced names include *Lia*, *Budi*, *Dewi*, and *Rina*. While these names are widely used across Indonesia, the variation in honorific terms is limited across all models, only *Pak* and *Bu*, along with their formal variants *Bapak* and *Ibu*, appear consistently. This suggests that, although some models demonstrate surface-level lexical diversity, deeper sociolinguistic features such as honorific variation remain underrepresented.

5 Experiments and Analysis

5.1 Classification

5.1.1 Setup

We adopt the classification accuracy metric, as proposed in both Mostafazadeh et al. (2016) and Koto et al. (2022), defined as the ratio of correctly predicted instances to the total number of test cases. For our experiments, we fine-tune several models: Qwen 2.5 7B (Qwen et al., 2025), Llama 3.1 8B (Grattafiori et al., 2024), Gemma 2 9B (Rivière

Model	Javanese					Sundanese				
	0-shot	MT _{Train}	MT _{Train} +GPT-4o	All_LLM	LLM_Filt	0-shot	MT _{Train}	MT _{Train} +GPT-4o	All_LLM	LLM_Filt
XML-R	NA	69.00	67.67	80.72	81.47	NA	75.42	50.34	75.93	72.73
Qwen 2.5	76.94	85.44	84.31	84.88	87.71	64.48	74.75	72.22	80.64	79.63
Llama 3.1	75.24	90.17	86.96	91.68	92.44	48.32	79.97	71.55	81.14	78.62
Gemma 2	85.07	93.95	95.46	95.46	95.27	51.52	86.20	89.23	87.88	85.02
SahabatAI Llama	77.13	95.46	94.14	97.16	97.73	34.51	87.88	87.21	91.25	92.42
SEA-LION Llama	69.19	96.60	94.71	93.76	95.27	25.93	88.55	83.67	82.15	77.44

Table 3: Accuracy of models on the human-written test set in Javanese and Sundanese across training sets.

Model	Javanese					Sundanese				
	0-shot	MT _{Train}	MT _{Train} +GPT-4o	All_LLM	LLM_Filt	0-shot	MT _{Train}	MT _{Train} +GPT-4o	All_LLM	LLM_Filt
XML-R	NA	69.40	70.20	66.80	62.60	NA	56.60	73.00	67.60	66.00
Qwen 2.5	68.00	80.00	75.00	75.80	75.80	63.60	78.80	74.20	76.60	77.60
Llama 3.1	47.60	86.00	70.40	77.40	73.40	48.60	83.40	74.00	75.00	76.00
Gemma 2	63.00	91.80	92.80	83.60	83.40	57.60	90.00	91.80	80.80	83.40
SahabatAI Llama	34.80	90.00	87.60	84.20	88.40	30.80	87.40	86.60	83.60	87.60
SEA-LION Llama	32.20	92.60	87.40	76.20	72.20	29.80	92.20	88.80	77.60	71.20

Table 4: Accuracy of models on the machine-translated test set in Javanese and Sundanese across training sets.

et al., 2024), SahabatAI Llama 8B (GoToCompany, 2024), SEA-LION Llama 8B (Ng et al., 2025), and XML-R (Conneau et al., 2019). For LLMs, we conduct instruction fine-tuning with a multiple-choice question framework using a LoRA adapter (Hu et al., 2022) on the combined Javanese and Sundanese training set. Full training details are provided in Appendix A. To ensure robustness, results are averaged over three runs. For comparison, we also report the zero-shot performance of each model prior to fine-tuning.

In addition to the zero-shot setting, we experiment with the following training data variations: (i) MT_{train} (machine-translated data), (ii) MT_{train}+GPT-4o (machine-translated data localized using GPT-4o), (iii) All LLM (the full set of LLM-generated samples), and (iv) LLM_Filt (a filtered subset comprising the top 10% of All LLM based on human evaluation). We evaluate each model on two test sets: (i) a human-written set and (ii) a machine-translated set.

5.1.2 Overall Performance

Table 3 and Table 4 present the classification accuracies of all models trained on different training sets, evaluated on the human-written and machine-translated test sets, respectively. In the zero-shot setting, model performance ranges from approximately 34% to 70% across both Javanese and Sundanese, underscoring the inherent challenges of cultural commonsense reasoning in these languages. Fine-tuning consistently improves model performance over the zero-shot baseline, with LLMs showing particularly strong gains. Notably, XML-R underperforms relative to the LLMs, suggesting that large generative models are more effective at

capturing cultural nuances.

We observe that models trained on LLM-generated data perform best when evaluated on the human-written test set (Table 3), while those trained on machine-translated data tend to perform better on the machine-translated test set (Table 4), indicating some sensitivity to data distribution alignment. Interestingly, localizing the machine-translated training data (MT_{train}+GPT-4o) does not consistently lead to improved model performance compared to using the original machine-translated data (MT_{train}).

5.1.3 Performance Across Different Topics

Figure 3 presents the topic-wise performance of SahabatAI on the human-written test set. The chart shows that models fine-tuned on both MT_{train} and LLM_{Filtered} consistently achieve higher accuracy across most categories compared to the zero-shot baseline. Interestingly, the zero-shot setting performs relatively well on the *Art* category. Fine-tuning on LLM_{Filtered} yields notable improvements in culturally rich topics such as *Wedding*, *Pregnancy*, and *Art*, outperforming models trained on MT_{train}.

5.2 Generation

5.2.1 Setup

Using the same set of LLMs from the classification experiments, we fine-tune the models to perform story continuation: given a four-sentence premise, the model is trained to generate a coherent fifth sentence in either Javanese or Sundanese. We apply supervised fine-tuning using QLoRA (Detrmers et al., 2023), with training details provided in appendix A. To evaluate generation quality, we use

Model	Javanese					Sundanese				
	0-shot	MT	MT _{Train} +GPT-4o	All_LLM	LLM_Filt	0-shot	MT _{Train}	MT _{Train} +GPT-4o	All_LLM	LLM_Filt
Qwen 2.5	72.5 / 21.8	71.7 / 19.2	72.0 / 19.5	72.4 / 21.7	71.9 / 19.5	69.2 / 15.4	70.3 / 15.6	70.3 / 16.5	70.5 / 16.7	69.2 / 14.6
Llama 3.1	62.4 / 8.3	72.7 / 21.5	72.4 / 21.1	72.7 / 22.9	72.7 / 22.2	59.4 / 5.6	70.0 / 16.1	70.3 / 16.23	70.6 / 17.9	68.9 / 15.5
Gemma 2	70.9 / 17.7	73.2 / 24.0	73.1 / 23.1	72.8 / 22.9	72.6 / 22.2	68.2 / 13.2	70.3 / 18.1	70.2 / 17.9	70.8 / 17.9	70.2 / 17.1
SahabatAI Llama	63.1 / 15.3	71.8 / 20.1	59.7 / 9.2	62.6 / 13.6	67.2 / 16.6	57.7 / 8.9	69.2 / 16.2	59.1 / 7.5	62.4 / 11.7	70.6 / 17.6
SEA-LION Llama	72.7 / 23.0	72.4 / 20.9	72.5 / 21.5	72.8 / 23.9	72.6 / 22.5	68.9 / 16.7	70.1 / 16.3	70.3 / 17.0	71.0 / 18.3	71.3 / 18.6

Table 5: BERTScore / ROUGE-L F1 of models on the human-written test set in Javanese and Sundanese across training sets.

Model	Javanese					Sundanese				
	0-shot	MT _{Train}	MT _{Train} +GPT-4o	All_LLM	LLM_Filt	0-shot	MT _{Train}	MT _{Train} +GPT-4o	All_LLM	LLM_Filt
Qwen 2.5	70.5 / 15.6	70.7 / 18.3	71.0 / 18.1	71.6 / 18.8	70.6 / 15.4	69.9 / 14.0	70.9 / 17.8	70.9 / 18.1	71.3 / 16.7	70.2 / 13.7
Llama 3.1	59.7 / 4.4	72.1 / 21.4	72.0 / 20.7	71.8 / 20.4	71.3 / 18.8	59.3 / 4.2	71.4 / 19.2	71.2 / 18.6	71.3 / 17.7	68.8 / 15.7
Gemma 2	69.7 / 14.5	72.3 / 22.5	72.1 / 21.5	71.9 / 20.9	71.4 / 19.7	69.4 / 14.1	72.4 / 21.3	72.1 / 20.7	71.9 / 19.0	70.4 / 17.3
SahabatAI Llama	59.2 / 9.3	72.1 / 22.2	60.2 / 8.9	62.5 / 12.4	64.6 / 12.8	58.1 / 7.9	71.5 / 20.5	59.9 / 8.0	62.7 / 10.9	70.4 / 16.6
SEA-LION Llama	69.7 / 16.9	72.4 / 21.3	72.0 / 20.5	71.9 / 20.7	71.6 / 19.6	69.7 / 15.4	72.1 / 19.5	71.5 / 18.0	71.5 / 18.0	71.1 / 18.5

Table 6: BERTScore / ROUGE-L F1 of models on the machine-translated test set in Javanese and Sundanese across training sets.

Language	Model	Coherence	Fluency	Correctness	Cultural Rel.
Javanese	Gemma 2	4.92	4.94	76	92
	SEA-LION Llama	4.98	4.98	84	92
Sundanese	Gemma 2	4.22	4.74	74	86
	SEA-LION Llama	4.40	4.92	78	94

Table 7: Human evaluation results for Javanese and Sundanese.

two automatic metrics: ROUGE-L (Lin, 2004) for lexical overlap and BERTScore (Zhang et al., 2020) for semantic similarity.

5.2.2 Overall Performance

Table 5 and Table 6 presents the automated evaluation metrics for different training sets across Sundanese and Javanese on both human-written and machine-translated test sets. Finetuning consistently improves performance over the 0-shot. Notably, on the human-written data that contains more cultural nuanced story, model fine-tuned with LLM-generated data gives higher improvement compared to others.

Among the models, SEA-LION Llama achieves the highest score across most test, then followed closely by Gemma 2. The LLM_Filt data often matches or outperforms the All_LLM settings that uses more samples. Similar to classification, in human-written test set, LLM-generated-training data tends to be better than in machine-translated test set.

5.2.3 Human Evaluation

We conducted a human evaluation to compare models between SEA-LION Llama and Gemma 2 fine-tuned on All LLM-generated data, the two models that showed strong performance in both classification and generation tasks (see Table 3, 4, 5, and 6).

Using the human-written test set, annotators were presented with a story premise and the generated ending sentence. They were asked to rate the outputs based on coherence, fluency, correctness, and cultural relevance, following the same guidelines as in the earlier manual evaluation. As shown in Table 7, both models perform well in Javanese and Sundanese, with SEA-LION Llama slightly outperforming Gemma 2 across most human evaluation criteria. However, this advantage is less evident when measured using automatic metrics.

6 Conclusion

We explored the potential and limitations of LLM-generated data for commonsense reasoning and story generation in Javanese and Sundanese, introducing the first cloze dataset for these languages with high-quality test sets. Our preliminary analysis in classification and generation settings shows that GPT-4o and Claude-3 Opus demonstrate strong capabilities in generating plausible short stories but face challenges in fluency and cultural accuracy. Despite these limitations, our findings suggest that LLM-assisted data generation is a practical and effective approach for constructing datasets in low-resource languages.

7 Limitations

This study acknowledges several limitations in terms of cultural nuance, language scope, and dialectal representation. While we carefully curated data across 12 cultural topics, our focus was limited to only two local languages—Javanese and Sundanese. Although these are the most widely spoken regional languages in Indonesia, they do not cap-

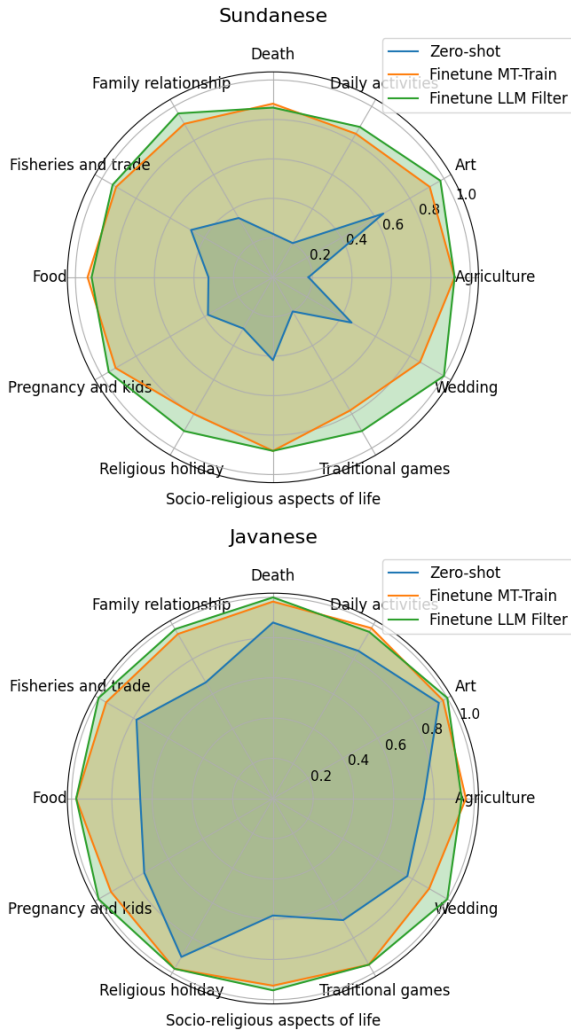


Figure 3: Topic-wise accuracy of SahabatAI (an Indonesian-centric LLM) on the human-written test set for Javanese and Sundanese, comparing zero-shot, and fine-tuning on MT_{train} fine-tuned, and LLM_{filtered}.

ture the full linguistic and cultural diversity present in the world. Moreover, our predefined topics and data sources may not comprehensively reflect the rich variation of cultural practices, dialects, and regional expressions within these languages.

Additionally, due to resource constraints and the primary focus on exploring the potential of LLM-generated data for commonsense reasoning and story generation, this research explored a limited range of LLM prompts and hyperparameter configurations. Future research could investigate a wider language scope, prompt variation, and other settings to identify configurations that maximize the performance of LLMs in generating culturally nuanced common sense reasoning in Javanese and Sundanese.

8 Ethical Considerations

All human-written datasets have been manually validated to ensure that harmful or offensive questions are not present in the dataset. We paid our expert workers fairly, based on the monthly minimum wage in Indonesia⁶. All workers were informed that their stories submitted would be used and distributed for research. Furthermore, no sensitive or personal information about the workers would be disclosed.

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⁶The average monthly minimum wage in Indonesia is approximately 3,000,000 IDR. The workload to complete all the tasks equates to roughly 8 days of full-time work. Each worker was paid 1,250,000 IDR accordingly

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A Training Configurations

For classification, we set the maximum token length for the pre-trained language model to 450 for the premise and 50 for the ending sentence. The model was trained over 20 epochs with early stopping (patience set to 5), using a batch size of 40, Adam optimizer, an initial learning rate of $5e-6$ for XLM-R, and a warm-up phase comprising 10% of the total training steps.

For training the text generation models, we use 4-bit quantization with a LoRA rank of 64 and a LoRA alpha of 128. The models are trained with a batch size of 8, gradient accumulation of 8, a learning rate of $2e-4$, and for a single epoch. We employ the Unsloth.ai framework for efficient fine-tuning (Daniel Han and team, 2023).

For training the classifier for data filtering, we fine-tune the XLM-R model with a maximum token length of 1024 for the premise and 128 for the ending sentence. The model was trained over 26 epochs, using a batch size of 16, Adam optimizer,

an initial learning rate of $1e-5$ for XLM-R, and a warm-up phase comprising 5% of the total training steps.

Figure 4 shows the prompt template used for in-context learning, guiding the LLM to generate new Javanese and Sundanese.

B Distribution of Filtered LLM-Generated Training Data

Initially, training data was generated using six different LLMs, with each model contributing approximately 16.67% of the total 10K samples (around 2K samples per model). However, after filtering the bad examples, the final dataset composition shifted. The data consist of 1,220 samples, the distribution is as follows: Claude (37.7%), GPT-4o (29.0%), LLama (8.6%), Cohere (4.3%), and Gemma-2 (1.7%).

Your task is to write several triplets of story premises consisting of four sentences, wrong ending, and correct ending in {language}. Include {language} cultural values in the story with the topic {topic}. Here are some examples of the story format:

```

Story: {premise_1}
Correct Ending: {correct_ending_1}
Incorrect Ending: {incorrect_ending_1}

...

Story: {premise_5}
Correct Ending: {correct_ending_5}
Incorrect Ending: {incorrect_ending_5}

```

Please generate several triplets, strictly following the format in the examples, do not add bullets or any additional response.

in-context samples

Figure 4: Prompt template instructing LLM to generate a new example for Javanese and Sundanese.

C Agreement Score

We measure the fluency and coherency agreement scores using Pearson’s correlation and computed the correctness and cultural relevance scores using Cohen’s kappa. They are summarized in Table 8.

Metric	Javanese	Sundanese
Fluency	0.73	0.76
Coherency	0.77	0.71
Correctness	0.74	0.50
Cultural Relevance	0.75	0.49

Table 8: Agreement Scores for Javanese and Sundanese

D Workers Scoring Guidelines

- **Fluency (0–5):** Each sentence should be grammatically correct and fluent.
 - **5:** All sentences are grammatically correct and fluent.
 - **0:** Sentences are grammatically incorrect and lack fluency.

- **Coherency (0–5):** The story should be coherent, with all sentences logically connected.
 - **5:** Story is highly coherent, with clear and logical flow between sentences.
 - **0:** Sentences are disconnected and lack a logical sequence.
- **Correctness (Binary):** The correct story closure should be valid, while the incorrect closure should clearly be wrong.
 - **1:** The correct ending is indeed correct, and the incorrect ending is clearly wrong.
 - **0:** Either the correct ending is not valid, or the incorrect ending is not clearly wrong.
- **Cultural Relevance (Binary):** The story should reflect appropriate cultural norms, values, or symbols relevant to the language.
 - **1:** The story contains relevant cultural norms, values, symbols for the corresponding language.
 - **0:** The story lacks cultural relevance or includes irrelevant cultural aspects.

Scoring Guidelines:

- **Coherency:** Ranges from 0 to 5, where 5 means each sentence is strongly connected and flows well with the previous and next sentence.
- **Fluency:** Ranges from 0 to 5, where 5 indicates all sentences are grammatically sound and highly fluent.
- **Correctness:** A binary score of 0 or 1 to ensure that the correct ending is truly valid and the incorrect ending is clearly wrong.
- **Cultural Relevance:** A binary score of 0 or 1 to ensure the whole story contains appropriate and relevant cultural symbols and norms for the language being used.

E Topic and Story-Writing Guidelines

We create a total of 300 native-authored stories as part of the Javanese and Sundanese Cloze Project. These stories are evenly distributed across 12 pre-defined topic categories, with 25 stories per topic. Each story must reflect traditional Javanese and Sundanese values and customs, with attention to

detail and coherence in the narrative. The topic categories and their subcategories follows IndoCulture (Koto et al., 2024). Each story must consist of 4 sentences and two endings: one correct and one incorrect. Ensure that all stories adhere to the topics and categories outlined in the taxonomy and reflect traditional values and cultural relevance.

F Machine Translation Evaluation

	Javanese	Sundanese
Google Translate	0.11 / 0.41 / 45.2	0.09 / 0.35 / 42.8
NLLB-200-3.3B	0.18 / 0.30 / 53.1	0.12 / 0.33 / 43.8

Table 9: BLEU F1 / METEOR / ChrF comparison of Google Translate and NLLB Dense Transformers Translation Model (Costa-Jussà et al., 2022) for Indonesian to Javanese / Sundanese translation on NusaX dataset (Winata et al., 2023)

Zero-Shot Cross-Lingual Transfer using Prefix-Based Adaptation

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Abstract

With the release of new large language models (LLMs) like Llama and Mistral, zero-shot cross-lingual transfer has become increasingly feasible due to their multilingual pretraining and strong generalization capabilities. However, adapting these decoder-only LLMs to new tasks across languages remains challenging. While parameter-efficient fine-tuning (PeFT) techniques like Low-Rank Adaptation (LoRA) are widely used, prefix-based techniques such as soft prompt tuning, prefix tuning, and Llama Adapter are less explored, especially for zero-shot transfer in decoder-only models. We present a comprehensive study of three prefix-based methods for zero-shot cross-lingual transfer from English to 35+ high- and low-resource languages. Our analysis further explores transfer across linguistic families and scripts, as well as the impact of scaling model sizes from 1B to 24B. With Llama 3.1 8B, prefix methods outperform LoRA-baselines by up to **6%** on the Belebele benchmark. Similar improvements were observed with Mistral v0.3 7B as well. Despite using only 1.23M learning parameters with prefix tuning, we achieve consistent improvements across diverse benchmarks. These findings highlight the potential of prefix-based techniques as an effective and scalable alternative to LoRA, particularly in low-resource multilingual settings.

1 Introduction

Large language models (LLMs) exhibit strong multilingual and zero-shot generalization abilities due to exposure to diverse pretraining data. Nonetheless, cross-lingual transfer remains challenging given the linguistic diversity and complexity of adapting large models efficiently without significant computational overhead.

To address the high computational and memory costs of full model finetuning, recent advances in parameter-efficient finetuning (PeFT)

techniques focus on updating only a small subset of model parameters while keeping the majority of the pretrained weights frozen. This design significantly reduces the adaptation cost and makes large-scale models more practical for multilingual and domain-specific applications. Methods such as Low-Rank Adaptation (LoRA) (Hu et al., 2022) and instruction-tuned adapters have shown promising results in efficiently tailoring models to new tasks without requiring extensive resources. Among the various PeFT techniques, prefix-based approaches like soft prompting (Lester et al., 2021; Liu et al., 2024a) and prefix tuning (Li and Liang, 2021) are particularly compelling because they introduce learnable components either at the input or within the transformer stack, enabling flexible task adaptation without altering the underlying architecture of the model.

While these prefix-based techniques have been shown to be effective in monolingual scenarios and task-specific settings, their potential in facilitating zero-shot cross-lingual transfer is under-explored. This is especially relevant for decoder-only LLMs, which are increasingly being deployed in multilingual environments. Unlike encoder-decoder models that have been more thoroughly studied for transfer across languages, decoder-only models present unique challenges due to their reliance on autoregressive decoding. Understanding whether prefix-based PeFT methods can enhance zero-shot cross-lingual performance in such models has not been previously studied in detail.

In this work, we provide the first systematic study of prefix-based PeFT methods for zero-shot cross-lingual transfer in *decoder-only LLMs*. Our contributions can be summarized as follows:

- We evaluate prefix-based adaptation on models ranging from 1B parameters to large-scale 24B models to show the effectiveness of prefix tuning in multilingual transfer across models

of varying sizes.

- Our study spans four well-recognized multilingual benchmarks – XQUAD, XNLI, Belebele and MGSM – to compare the performance of LoRA and prefix-based tuning.
- We provide a detailed comparison of prefix-based methods (soft prompts, prefix tuning, LLaMA-Adapter) against LoRA and full fine-tuning¹, systematically analyzing their strengths and limitations across tasks and 35+ high- and low-resource languages. Additionally, we investigate transfer patterns across linguistic families and scripts.

Together, our findings position prefix-based adaptation as a lightweight yet powerful strategy for cross-lingual and reasoning-oriented applications, particularly in resource-constrained multilingual settings.

2 Related Work

Cross-lingual transfer is a key challenge in multilingual NLP. It is traditionally tackled through full fine-tuning of multilingual models. However, with large decoder-only LLMs like Llama and Mistral, full fine-tuning is costly, leading to PeFT approaches. LoRA (Hu et al., 2022) introduces low-rank trainable matrices into frozen weights to reduce training overhead. Alternatively, prefix-based methods either add learnable tokens at the input layer (Lester et al., 2021; Liu et al., 2024a) or to attention keys and values at each layer (Li and Liang, 2021), enabling efficient task adaptation.

Soft prompt tuning has been extensively studied for cross-lingual transfer in encoder and encoder-decoder models, particularly in classification tasks. For instance, (Philippy et al., 2024) demonstrated that soft prompts can generalize better across languages with fewer parameters, following the “less is more” principle. Similarly, (Philippy et al., 2025) utilized multilingual verbalizers and contrastive label smoothing to further enhance cross-lingual classification. Recent work such as (Vykopal et al., 2025) introduced language-specific soft prompts specifically designed for transfer learning, showing that combining language-specific and task-specific prompts improves generalization. However, these prior works predominantly used multi-

lingual encoder-only and encoder-decoder models, and appended prefix tokens only to the input.

As soft prompts have several limitations in effectively adapting models to new tasks, prefix tuning emerged as a promising approach. Cross-lingual alignment through prompt-based pretraining, as proposed by (Tu et al., 2024), further improved intent classification and slot-filling performance but it is not a zero-shot setting (as in our work). A recent variant of prefix tuning is LLaMA Adapter (Dubey et al., 2024) that introduced zero-initialized attention mechanisms for efficient prefix training and achieved strong instruction-following capabilities; however, they did not evaluate on any multilingual benchmarks. A related line of work has focused on extending prefix tuning to instance-specific adaptation based on the input prompt for improved model performance (Liu et al., 2024c; Jiang et al., 2022; Liu et al., 2024b; Zhu et al., 2024).

Few comparative studies have examined parameter-efficient tuning for multilingual settings, and most have been restricted to encoder-only models or small decoder-only models with only a few million parameters. For instance, (Zhao and Schütze, 2021) systematically compared discrete prompting, soft prompting, and fine-tuning on the few-shot multilingual NLI task using XLM-RoBERTa-base. Similarly, (Tu et al., 2022) compared prompt tuning with fine-tuning across diverse NLU tasks on XLM-R and mBERT. (Tu et al., 2022) evaluate prefix tuning on the encoder-only XLM-R model and showed its effectiveness over full fine-tuning in zero-shot cross-lingual transfer. Tu et al. (2022) investigated a decoder-based multilingual model (XGLM), but their analysis was limited to a single small model. They showed that prompt tuning can sometimes surpass fine-tuning, particularly for low-resource languages, although performance remained highly sensitive to the underlying tokenization scheme. Our work significantly extends their analysis to large decoder-only LLMs and presents a comprehensive comparison of multiple prefix-based methods, including soft prompts, prefix tuning, and LLaMA Adapter.

3 Methodology

Low-Rank Adaptation (LoRA). LoRA (Hu et al., 2022) is a parametric fine-tuning technique that has become one of the most popular approaches to enable cross-lingual transfer in LLMs. It introduces trainable low-rank matrices, typically

¹Due to computational limitations, full fine-tuning is restricted to the SQuAD dataset on Llama 3.1 8B.

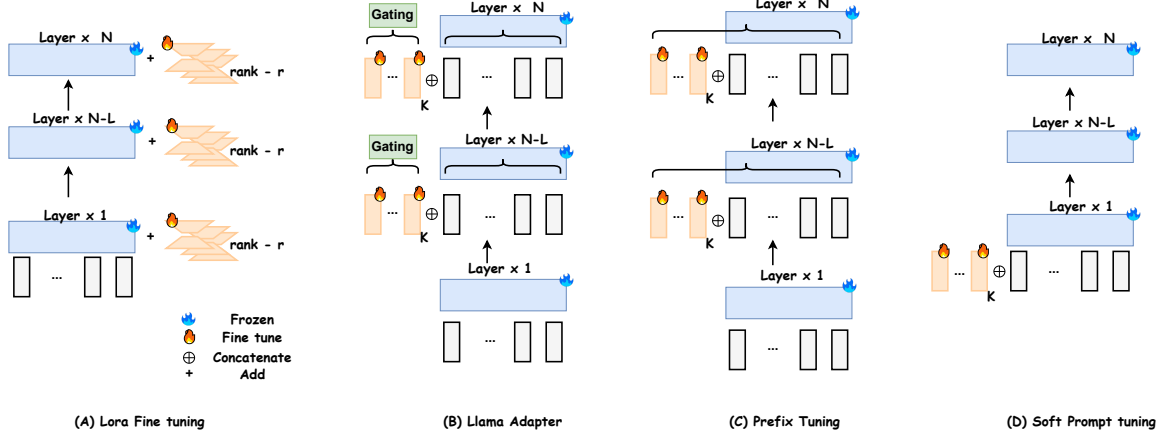


Figure 1: Schematic representation of: (A) LoRA fine-tuning and prefix-based methods, (B) Llama Adapter, (C) Prefix tuning, and (D) Soft prompt tuning.

in the query, key, and value projections, while keeping the base model frozen. These learned matrices are added to the original weights during inference. Unlike prefix-based methods, LoRA directly modifies the model parameters. A standard cross-lingual transfer setup involves fine-tuning the model using LoRA on task-specific English data and evaluating it on the target language of interest. Formally, let $W \in \mathbb{R}^{d \times k}$ be a pretrained weight matrix of a projection layer (e.g., W_q, W_k, W_v). Instead of updating W directly, LoRA parameterizes the weight update as a product of two low-rank matrices:

$$\Delta W = BA, \quad A \in \mathbb{R}^{r \times k}, B \in \mathbb{R}^{d \times r}, \quad (1)$$

where $r \ll \min(d, k)$ is the rank of the adaptation. The modified projection becomes:

$$W' = W + \Delta W = W + BA. \quad (2)$$

Given an input hidden state $h \in \mathbb{R}^k$, the output of the adapted projection layer is computed as:

$$y = W'h = Wh + BAh. \quad (3)$$

Here, only A and B are trainable, while W remains frozen. This formulation enables efficient fine-tuning by reducing the number of trainable parameters and allowing task-specific adaptation without updating the full weight matrices.

Prefix Tuning. Given an LLM, prefix tuning (Li and Liang, 2021) introduces a set of learnable prefix tokens to all layers of the transformer. In our implementation, we only append the learnable prefixes to the final L layers of the transformer. The

main intuition is that these prefix tokens act as additional context vectors that the model can attend to. These vectors guide the model toward task-specific behavior, while the pretrained parameters of the LLM remain frozen.

Formally, let $P_l \in \mathbb{R}^{K \times d}$ denote the learnable prefix tokens at layer l , where K is the number of prefix tokens and d is the embedding dimension. We consider the computation for the $(M+1)$ -th token, denoted by $t_l \in \mathbb{R}^{1 \times d}$. The layer's input hidden states (including the current token) are represented as $H_l \in \mathbb{R}^{(M+1) \times d}$. Each attention head operates on these hidden states using projection matrices $W_q, W_k, W_v \in \mathbb{R}^{d \times d}$.

The query vector corresponding to the current token t_l is computed using the frozen projection matrix W_q :

$$Q_l = t_l W_q \in \mathbb{R}^{1 \times d}$$

The keys and values corresponding to the input sequence (H_l) are also computed using the frozen projection matrices W_k and W_v :

$$K_l^H = H_l W_k, \quad V_l^H = H_l W_v$$

The key idea of prefix tuning is the concatenation of the learnable prefix parameters with keys and values derived from the input.

$$P_l^K = P_l W_k, \quad P_l^V = P_l W_v$$

$P_l^K \in \mathbb{R}^{K \times d}$ and $P_l^V \in \mathbb{R}^{K \times d}$ denote the learnable prefix keys and values of layer l , respectively. The final keys and values at layer l become:

$$K_l = [P_l^K; K_l^H], \quad V_l = [P_l^V; V_l^H]$$

Method	en	hi	el	vi	sw	bg	th	ar	de	es	fr	ru	tr	zh	ur	Avg
Base Model	53.8	48.0	51.0	49.7	45.9	52.0	48.0	48.6	50.4	51.8	49.6	50.8	50.0	50.1	48.7	49.9
LoRA ₄	90.3	70.1	74.5	77.5	<u>60.2</u>	73.0	72.4	71.5	77.8	79.2	80.2	73.6	73.2	77.9	65.0	74.4
Soft Prompts	84.3	67.9	54.2	72.7	51.4	51.4	66.1	63.2	52.3	57.2	59.0	59.4	58.4	41.4	62.6	60.1
Llama Adapter	93.4	74.5	79.8	79.2	59.6	<u>78.4</u>	76.0	76.5	83.8	83.7	<u>84.6</u>	79.6	75.9	81.2	71.8	78.5
Prefix Tuning	93.9	76.5	<u>79.4</u>	<u>79.1</u>	60.3	79.4	76.2	<u>75.7</u>	<u>83.5</u>	84.4	85.0	79.9	<u>75.5</u>	<u>79.9</u>	<u>71.7</u>	78.7

Table 1: LLaMA 3.1 8B performance (accuracy) on XNLI benchmark comparing LoRA and prefix based adaption methods. The best performance for each language is shown in **bold**, and the second-best is underlined.

Method	en	hi	el	vi	ar	de	es	ro	ru	th	tr	zh	Avg
Base Model	79.3	59.3	60.5	71.2	59.4	68.5	67.6	68.5	60.3	63.2	62.5	59.5	65.0
LoRA ₄	86.2	66.1	72.0	75.3	68.9	76.4	78.0	78.0	72.0	75.8	69.1	71.7	74.1
Soft Prompts	54.5	10.8	27.9	45.5	25.8	42.2	52.0	48.2	32.2	11.2	36.8	16.1	33.6
Llama Adapter	<u>89.4</u>	<u>75.1</u>	<u>76.9</u>	<u>79.8</u>	72.1	<u>82.4</u>	<u>83.2</u>	<u>82.6</u>	78.4	<u>71.6</u>	73.3	<u>72.3</u>	78.1
Prefix Tuning	90.2	75.7	78.4	79.3	<u>70.4</u>	82.8	84.2	83.5	<u>76.9</u>	70.9	<u>72.6</u>	72.5	78.1

Table 2: Llama 3.1 8B performance (F1 score) on XQUAD benchmark comparing LoRA and prefix based adaption methods. The best performance for each language is shown in **bold**, and the second-best is underlined.

K_l and V_l are expanded matrices encompassing both the learned prefixes and the input sequence.

The attention scores are obtained by comparing the query Q_l against the concatenated keys K_l :

$$S_l = \frac{Q_l K_l^T}{\sqrt{d}} \in \mathbb{R}^{1 \times (K+M+1)}. \quad (4)$$

The attention distribution is computed by applying the softmax function, which weights the contributions of both the prefix and the input tokens:

$$A_l = \text{softmax}(S_l) = [A_l^P, A_l^H] \in \mathbb{R}^{1 \times (K+M+1)},$$

where A_l^P represents the attention weights over the learned prefixes and A_l^H represents the weights over the input sequence.

Finally, as is typically done in transformer models, the attended output representation at layer l is computed as a weighted sum of the concatenated values V_l , followed by an output projection:

$$t_l^o = (A_l V_l) W_o \in \mathbb{R}^{1 \times d}, \quad (5)$$

where W_o is the output projection matrix. In this way, prefix tuning directly modifies the attention mechanism by injecting learned keys and values (P_l^K, P_l^V), steering the model’s representations without modifying the base model weights.

Llama Adapter. The Llama Adapter (Zhang et al., 2024) builds upon the principles of prefix tuning but introduces an important modification to stabilize training in large-scale LLMs. Specifically, it replaces the standard attention mechanism with a zero-initialized variant. This mitigates instabilities that often arise from randomly initialized prefix

tokens in the early stages of fine-tuning. To further enhance stability, a learnable gating mechanism is introduced, allowing the model to gradually scale the influence of prefix tokens during optimization. The gated attention scores are given by:

$$A_l^g = [\text{softmax}(S_l^K) \cdot \tanh(g_l), \text{softmax}(S_l^{M+1})] \quad (6)$$

where the attention scores can be split into contributions from the learnable prefix S_l^K and the original sequence S_l^{M+1} . g_l is a learnable scalar gating that adaptively controls the contribution of the prefix tokens. Finally, the output representation t_l^o is obtained using the same formulation in Equation 5. By weighting the prefix contributions using a learned gate, Llama Adapter ensures stable and effective adaptation of decoder-only LLMs.

Soft Prompts. Soft prompts (Lester et al., 2021; Liu et al., 2024a) involve prepending learnable continuous embeddings to the input, serving a similar goal as manual prompts. However, instead of manually selecting discrete prompts, soft prompting optimizes a continuous set of embeddings that serve as the prompt. This allows the model to learn how to best steer its behavior through gradient-based updates to the soft prompts.

Let $S \in \mathbb{R}^{K \times d}$ represent the learnable soft prompt embeddings, where K denotes the number of prompt tokens and d is the hidden dimension. Given an input sequence T , the modified input \tilde{T} is obtained by prepending the soft prompts:

$$\tilde{T} = [S; T] \quad (7)$$

where $[:]$ denotes concatenation. The sequence \tilde{T} is then passed through the transformer as usual,

Method	en	th	zh	sw	fr	bn	de	te	ja	es	ru	Avg
Base Model	50.4	23.2	<u>27.6</u>	13.2	28	16.4	26	12.4	16.8	34.8	30	25.34
LoRA ₄	36.8	16.8	27.6	7.6	25.2	4.8	22.8	0.8	19.2	24	27.2	19.34
Llama Adapter	53.6	18.4	32.4	8	<u>32.8</u>	9.6	<u>33.6</u>	2	<u>25.2</u>	<u>35.6</u>	<u>32</u>	<u>25.74</u>
Prefix Tuning	<u>52.8</u>	26	37.6	<u>10.8</u>	34	<u>12.8</u>	41.2	<u>6.4</u>	25.6	37.6	39.2	29.45

Table 3: Llama 3.1 8B performance (maj@1) on MGSM benchmark comparing LoRA and prefix based adaption methods. The best performance for each language is shown in **bold**, and the second-best is underlined.

with S updated via gradient-based optimization during fine-tuning. Unlike prefix tuning, which injects key-value pairs at every transformer layer, soft prompting only modifies the input embeddings.

4 Experiments

Models. All experiments are conducted on Llama 3.1 (8B) (Dubey et al., 2024) and Mistral v0.3 (7B) (Jiang et al., 2023). To study the effect of model scaling, we additionally evaluate smaller and larger variants - Llama 3.2 (1B) and Mistral Small (24B), respectively. The Llama 3.1 and 3.2 series, developed by Meta, comprise multilingual large language models. Mistral v0.3 (7B) is an updated release from Mistral AI with an extended vocabulary compared to Mistral v0.1. Notably, Mistral Small (24B) establishes a new benchmark in the “small” LLM category (under 70B) by offering improved multilingual capabilities and a larger vocabulary. We have limited our experiment to the base model variants only.

Datasets. We evaluate on three widely-used cross-lingual benchmarks, each targeting a distinct aspect of language understanding: XQUAD (Artetxe et al., 2019) for cross-lingual question answering, XNLI (Conneau et al., 2018) for cross-lingual natural language inference, and Belebele (Bandarkar et al., 2024) for cross-lingual machine reading comprehension. We also evaluate on the MGSM (Shi et al., 2023) benchmark to assess the reasoning capabilities of large language models in multilingual settings.

Training Details We fine-tune prefix-based adaptation methods and LoRA with rank 4 using the English SQuAD training set for XQUAD containing 87.6K samples and a subset of the English NLI training data containing 100K samples for XNLI evaluations. For Belebele, we use their suggested training set containing 67.5K English samples. Finally, we use the GSM8K English training dataset with 7.47K samples (Cobbe et al., 2021) and evalu-

ate on MGSM. All the datasets are publicly available; more training details are in Appendix A.

We experimented with learning rates (3e-3, 1e-3 and 3e-4), epochs (2,3,5), and weight decay (0.02,0.04,0.1), and report the best performance for each model. We used a learning rate of 3e-3, 2 epochs, and a weight decay of 0.02. For XNLI, we sampled 1,000 instances per language for evaluation due to computational constraints. Since XQUAD does not provide a separate test set, we evaluated on the full validation set, which includes approximately 1.19K samples per language. Finally for Belebele, we evaluated on 23 languages, where each language has 900 samples. All experiments were conducted on a single NVIDIA A100 80GB GPU.

5 Analysis and Ablations

Comparison with LoRA Fine-Tuning. Tables 1 and 2 (and Tables 14 and 15 in the Appendix) shows the performance of Llama 3.1 and Mistral v0.3 models across various tuning strategies, including LoRA, soft prompt tuning, prefix tuning, and Llama adapters on the XNLI and XQUAD datasets. To ensure fair comparisons, the number of trainable parameters in LoRA was matched with those of the prompt-based methods by setting $r = 4$ and $\alpha = 8$. The results show that prefix-based methods consistently outperform LoRA on both Llama 3.1 8B and Mistral v0.3 7B with English as the source language. This highlights the ability of prefix-based tuning for effective multilingual adaptation, even with as little as **1.23M** model parameters being trained.

We observe consistent improvements from prefix tuning across all benchmarks. Using Llama 3.1 (8B), prefix tuning achieves up to **28%** higher accuracy on XNLI, **13%** higher F1 on XQUAD, and **18%** higher accuracy on Belebele compared to the base model. Moreover, it provides additional gains of up to **4–6%** over LoRA, as shown in Tables 1, 2, 4a, and 4b. Similar trends are observed for Mistral, with consistent improvements reported in Tables,

Table 4: Overall Llama 3.1 8B performance (accuracy) on the Belebele benchmark, grouped by script and family. Best performance is in **bold**, second-best is underlined.

Script	Language	Base Model	LoRA ₄	Soft Prompt	Llama Adapter	Prefix tuning
Cyrillic	Kyrgyz	37.2	52.9	59.3	<u>60.5</u>	64.2
	Russian	50.4	81.0	86.1	<u>87.7</u>	88.1
	Serbian	48.7	71.7	81.1	81.9	<u>81.5</u>
Burmese	Burmese	30.9	36.2	43.3	<u>45.1</u>	48.4
	Shan	31.1	28.0	30.0	29.0	33.0
Latin	Swati	30.2	<u>34.3</u>	33.4	<u>34.3</u>	34.5
	Sundanese	35.3	47.1	52.3	<u>56.4</u>	57.8
	Bambara	28.4	34.3	<u>33.1</u>	32.2	32.2
Arabic	Sindhi	36.9	46.4	51.1	<u>53.3</u>	55.8
	Egyptian Arabic	40.1	57.6	65.2	<u>68.4</u>	68.7
	Western Persian	47.5	72.9	79.6	<u>81.4</u>	82.2
Ethiopic	Amharic	30.5	34.7	<u>37</u>	34.9	37.8
	Tigrinya	24	29.2	<u>29.7</u>	28.1	29.8

(a) Grouped by language **script**.

Family	Language	Base Model	LoRA ₄	Soft Prompting	Llama Adapter	Prefix tuning
Turkic	Kazakh	38	53.8	61.8	<u>63.9</u>	64.2
	Kyrgyz	37.2	52.9	59.3	<u>60.5</u>	64.2
	North Azerbaijani	39.9	58.4	65.4	<u>68.3</u>	68.5
Dravidian	Kannada	35.2	46.0	59.3	<u>59.5</u>	61.1
	Malayalam	35.5	49.3	56.9	<u>60.0</u>	63.9
	Tamil	36.9	52.3	60.1	<u>60.8</u>	65.3
Afro-Asiatic	Amharic	30.5	34.7	<u>37.0</u>	34.9	37.8
	Tigrinya	24	29.2	<u>29.7</u>	28.1	29.8
	Tsonga	32.7	36.3	<u>37.3</u>	36.1	39
Indo-Aryan	Sindhi	36.9	46.4	51.1	<u>53.3</u>	55.9
	Odia	33.1	38.2	54.7	<u>55.3</u>	59.1
	Sinhala	34.2	47.8	<u>54.8</u>	53.8	60.8
Balto-Slavic	Russian	50.4	81.0	86.1	<u>87.7</u>	88.1
	Serbian	48.7	71.7	81.1	81.9	<u>81.5</u>
	Slovak	46.5	73.8	80.6	<u>83.5</u>	84.3

(b) Grouped by language **family**.

16 and 17 in Appendix D.

Effectiveness of prefix-based methods across high and low-resource languages. We further evaluate the effectiveness of prefix-based methods on languages categorised as high and low resource. Since XNLI and XQUAD benchmarks primarily span high-resource languages, we rely on the Belebele benchmark to assess performance on low-resource languages. We select 23 languages for our analysis, of which 19 are considered low-resource and 4 high-resource, as per the FLORES dataset classification. Across both the Mistral and Llama architectures, prefix-based adaptation methods yield significant performance gains while requiring only **1.23M** parameters to be tuned. Among low-resource languages, absolute improvements range from a minimum of **2%** for Shan to a maximum of **37%** for Western Persian using Llama 3.1 8B.

Prefix tuning and LLaMA adapters typically yield better cross-lingual transfer than soft prompts, likely due to more tunable parameters. However, in low-resource scenarios like those in the Belebele benchmark, soft prompting performs comparably or better as shown in Tables 4 and Tables 16, 17 in Appendix D. This is likely due to their lightweight design that helps preserve pretrained multilingual knowledge. Overall, prefix based methods appear to leverage inherent language knowledge better than LoRA.

Influence of script and language family. From Tables 4a and 4b, we observe that while both script-wise and family-wise groupings reveal performance gains with prefix-based methods, language family appears to be a reliable indicator of

Method	Params	Acc.
Full Fine-tuning	$\sim 8B$	37.74
LoRA ₄	75.50M	75.99
Llama Adapter	1.23M	78.09
Prefix tuning	1.23M	78.11

Table 5: Comparison of full fine-tuning and parameter-efficient methods on the XQUAD dataset using LLaMA 3.1 8B, reported in terms of average F1 score across all languages.

adaptation success. Languages within the same family tend to benefit similarly. Script-based trends show more variability, likely influenced by resource availability and linguistic diversity within a script group. The languages in our analysis span a diverse range of families such as Turkic, Dravidian, Afro-Asiatic, Balto-Slavic, and Indo-Aryan. The scripts span Cyrillic, Burmese, Arabic, Ethiopic, and Latin. Many of these languages are typologically and morphologically distant from our source language English. Prefix-based methods show strong cross-lingual performance even across distant languages, suggesting that typological similarity to English is not essential for effective adaptation. Similar trends are observed with Mistral as well, as shown in Table 16 and 17 in Appendix D.

Prefix-based adaptation vs. full fine-tuning. Table 5 presents a comparison of LoRA, prefix-based methods, and full fine-tuning. Detailed language-wise results are provided in Table 11 in Appendix D. We observe that while full fine-tuning leads to improvements in English, it negatively impacts the performance of target languages when applied to decoder-only models such as Llama-3.1 8B. Due to computational constraints, we were unable to extensively tune hyperparameters to achieve

Method	LLaMA 3.2 1B	Mistral v0.3 7B	LLaMA 3.1 8B	Mistral 24B
Base Model	27.51	56.1	65.0	72.57
LoRA ₄	56.80	59.12	74.1	70.19
Llama Adapter	64.26	65.1	78.1	79.70
Prefix Tuning	64.46	67.2	78.1	79.94

Table 6: Average Performance across all languages on XQUAD (F1 score) benchmark across all models comparing LoRA and prefix based adaption methods. The best performance for each language is shown in **bold**, and the second-best is underlined.

the best possible results. Overall, our findings indicate that LoRA and prefix-based methods are more effective and efficient choices for zero-shot cross-lingual transfer compared to full fine-tuning. We hypothesize that this could primarily be due to full-finetuning (on English data) leading to catastrophic forgetting in other languages.

Effect of model size on prefix-based adaptation vs. LoRA. In Figures 2b and 2a, we compare the performance of prefix-based methods against LoRA on XQUAD for Spanish and Hindi across different model sizes. We observe that both prefix tuning and LLaMA Adapter consistently outperform LoRA across all model size variations in both languages. Table 6 shows that prefix-based adaptations scale more effectively with model size, maintaining their advantage even as the underlying model grows larger. In particular, prefix tuning yields consistent improvements, thus highlighting the robustness of prefix-based approaches for multilingual transfer.

Effectiveness of prefix-based methods on MGSM. Table 3 presents results on the MGSM benchmark with Llama-3.1 8B. LLaMA Adapter and prefix tuning consistently outperform LoRA, with prefix tuning achieving the best average score (+4% over the base model). However, performance degraded for very low-resource languages like Swahili, Telugu, and Bengali. This suggests that while effective, prefix-tuning may not transfer well for complex reasoning and generation tasks without some language-specific data.

Varying temperature/top-p during prefix-tuning. For XQUAD, we have calculated both EM (Exact match) and F1 score. From figure 3, we find that while higher temperatures and top-p values can improve F1 scores on XQUAD, they often lead to a noticeable drop in EM. This highlights a trade-off between generating more diverse predictions

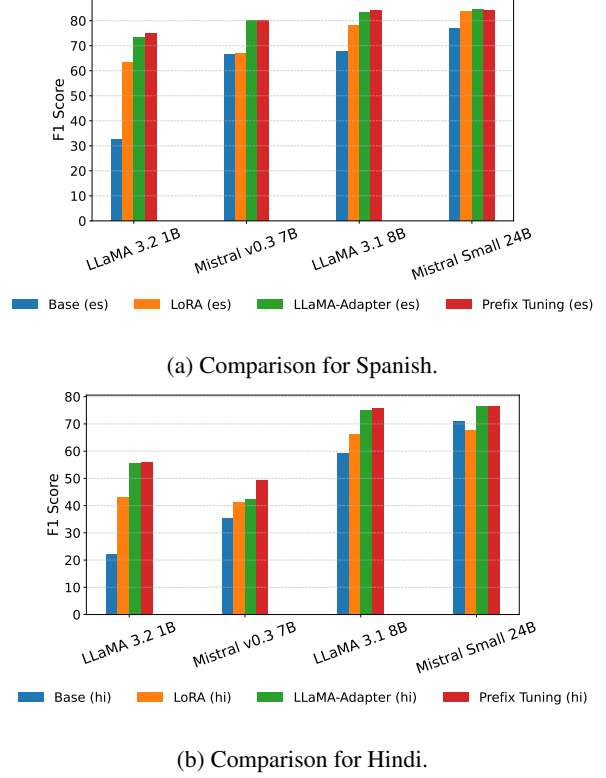


Figure 2: Comparison of prefix-based methods across model sizes against LoRA fine-tuning on XQUAD (F1 score).

Method	Params	XNLI Acc.	XQUAD F1 Score
LoRA ₄	2.36M	74.4	74.1
LoRA ₁₂₈	75.50M	76.7	76.0
Llama Adapter	1.23M	78.5	78.1
Prefix tuning	1.23M	78.7	78.1

Table 7: Higher Lora rank vs prefix based methods performance on XNLI and XQUAD for Llama 3.1 8B

(captured by F1) and producing exact matches (captured by EM). The best overall trade-off is obtained at our chosen setting of temperature=0.1 and top-p=0.75.

Performance comparison of LoRA₄, LoRA_{r128} with prefix tuning and Llama Adapters. Table 7 provides a comparative analysis of LoRA fine-tuning under two rank configurations, $r = 4$ and $r = 128$, against prefix tuning and Llama adapters. While increasing the LoRA rank from 4 to 128 substantially increases the number of trainable parameters, the resulting performance improvements are relatively modest. More importantly, our results show that parameter-efficient prefix-based approaches namely prefix tuning and Llama adapters consistently outperform LoRA, even at higher ranks. This trend is evident in both the XNLI and XQUAD benchmarks, emphasizing the

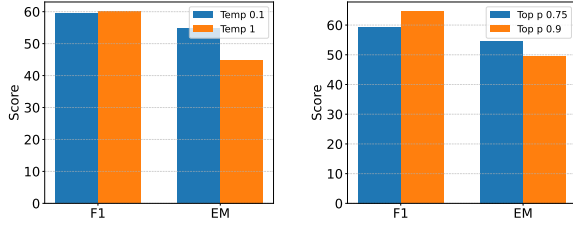


Figure 3: Varying temperature (left) and top-p (right) values using Llama 3.2 (1B) on the XQUAD task.

effectiveness of prefix-based adaptation for cross-lingual transfer. These findings suggest that simply scaling LoRA with larger ranks does not necessarily close the performance gap with prefix-based methods, and the latter remains a more efficient choice for multilingual scenarios.

Impact of hyperparameter tuning on prefix-based adaptation. Prefix-based approaches are governed by two critical hyperparameters: the prefix length and the number of transformer layers in which the prefixes are inserted. In soft prompt tuning, the adaptation is constrained to the input layer, whereas in prefix tuning, prefixes can be injected across multiple layers of the model. To better understand the effect of these design choices, we systematically varied both hyperparameters. Our experiments reveal that adapting 30 out of 32 layers with a prefix length of 10 tokens provides the strongest gains across benchmarks, as summarized in Tables 8 and 9. These results highlight the sensitivity of prefix-based methods to hyperparameter configurations, and emphasize the importance of carefully selecting the number of adapted layers and prefix length to maximize performance. (For results on other models, refer to Appendix C.)

6 Conclusion

We show that prefix-based adaptation methods are a practical and efficient mechanism for cross-lingual transfer in decoder-only LLMs. Methods like soft prompting, prefix-tuning, and Llama adapters introduce learnable prefixes at different layers, while using relatively small numbers of trainable parameters. This leads to highly efficient, task-specific cross-lingual learning.

Crucially, this performance was achieved using only English training data. We hypothesize this success stems from learning language-agnostic behaviors. By adding context vectors while keeping the base model frozen, these methods preserve the

Layers	Params	Acc.
20	0.82M	74.5
30	1.23M	78.7
32	1.31M	78.0

Table 8: XNLI performance accuracy by varying number of Llama 3.1 8B layers in which prefixes are inserted.

Tokens	Params	Acc.
5	0.61M	77.8
10	1.23M	78.7
20	2.46M	76.0

Table 9: XNLI performance accuracy by varying number of prefix tokens in 30 Llama 3.1 8B layers.

LLM’s inherent multilingual capabilities. In contrast, methods that alter full model weights (e.g., full fine-tuning and LoRA) suffer from catastrophic forgetting when adapted monolingually, degrading performance in unseen languages. These findings advocate for prefix-based adaptation as a robust strategy for zero-shot cross-lingual transfer.

Limitations

Our study shows that prefix-based methods yield strong zero-shot cross-lingual performance, but it has several limitations. First, due to computational constraints, our experiments were limited to 24B models; extending to larger models is a promising direction for future work. Second, our evaluations used only English as the source language. Analyzing other source languages could offer deeper insights into the methods’ cross-lingual capabilities. Finally, due to computational constraints, we were unable to perform an extensive hyperparameter search for full fine-tuning. We would like to emphasize this limitation more explicitly and clarify that our intention is not to claim full fine-tuning is inherently weaker, but rather to highlight that parameter-efficient methods provide strong alternatives under realistic computational constraints. In future work, we plan to explore improving response generation for low-resource languages as seen in the MGSM benchmark and also explore more diverse response generation tasks (e.g. summarization and translation). We also plan to investigate why prefix-tuning is effective through attention visualization and representation probing.

Acknowledgments

We are grateful to the anonymous reviewers for their insightful feedback. The last author gratefully acknowledges the generous support provided by the joint AI/ML initiative of Amazon and the Indian Institute of Technology Bombay.

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A Prompt Templates

Training and inference prompts for all the three benchmarks we have evaluated. For MGSM, we use the 8-shot chain-of-thought prompt as in (Wei et al., 2022) (maj@1) to evaluate.

XQUAD

Below is an instruction that describes a task, paired with an input that provides further context. Write a response that appropriately completes the request.

Instruction:

You will answer reading comprehension questions using information from a provided passage. Extract the exact answer from the passage without modification and present it in the following structured format:

```
{ 'answer' : <Extracted Answer> }
```

Input:

Context:

<context>

Question:

<question>

Response:

```
{ 'answer' :
```

Belebele

Below is an instruction that describes a task, paired with an input that provides further context. Write a response that appropriately completes the request.

Instruction:

The task is to perform a reading comprehension task. Given the following passage, question, and answer choices, output the number corresponding to the correct answer only.

Input:

Passage:

<passage>

Question:

<question>

Choices:

<choices>

Response: The correct choice number is

Benchmark	Languages
XNLI	en, hi, el, vi, sw, bg, th, ar, ar, de, es, fr, ru, tr, zh, ur
XQUAD	en, hi, el, vi, ar, de, es, ro, ru, th, tr, zh

Table 10: Languages used in the XNLI and XQUAD benchmarks.

XNLI
Below is an instruction that describes a task, paired with an input that provides further context. Write a response that appropriately completes the request.
Instruction:
The task is to solve Natural Language Inference (NLI) problems. NLI is the task of determining whether the inference relation between the second sentence (Hypothesis) with respect to the first sentence (Premise) is one of the following:
1. Entailment
2. Neutral
3. Contradiction
Output the relation number only.
Input:
Premise:
<premise>
Hypothesis:
<hypothesis>
Response: The relation number is

B Languages details

Evaluation language details included in the benchmarks are given in Tables 10, 12 and 13.

C Hyperparameter details

We insert 10 prefix tokens across 30 layers for LLaMA 3.1 8B, Mistral 7B, and Mistral 24B, while for LLaMA 3.2 1B, the tokens are inserted across all layers as it is small. For full fine-tuning, we used a batch size of 8, a learning rate of 1e-5 with a cosine learning rate scheduler, a warm-up ratio of 0.1, and trained the model for 2 epochs. Finally for LoRA fine tuning, we applied it to the Q, K, and V projection matrices across all layers.

D Complete elaborated experiment results

Language	F1	EM
ar	14.43	9.83
de	61.95	43.36
el	22.63	17.98
en	84.69	72.10
es	62.08	41.34
hi	15.23	11.76
ro	58.57	40.76
ru	18.65	10.42
th	16.13	12.35
tr	42.38	26.72
vi	43.47	25.88
zh	12.66	9.50
Avg	37.74	26.83

Table 11: Full fine tuning performance of Llama 3.1 8B on XQUAD

Language	Family
Kazakh	Turkic
Kyrgyz	Turkic
North Azerbaijani	Turkic
Kannada	Dravidian
Malayalam	Dravidian
Tamil	Dravidian
Amharic	Afro-Asiatic
Tigrinya	Afro-Asiatic
Tsonga	Afro-Asiatic
Sindhi	Indo-Aryan
Odia	Indo-Aryan
Sinhala	Indo-Aryan
Russian	Balto-Slavic
Serbian	Balto-Slavic
Slovak	Balto-Slavic

Table 12: Languages grouped by family included in Belebele

Language	Script
Kyrgyz	Cyrillic
Russian	Cyrillic
Serbian	Cyrillic
Burmese	Burmese
Shan	Burmese
Swati	Latin
Sundanese	Latin
Bambara	Latin
Sindhi	Arabic
Egyptian Arabic	Arabic
Western Persian	Arabic
Amharic	Ethiopic
Tigrinya	Ethiopic

Table 13: Languages grouped by script included in Belebele

Method	en	hi	el	vi	sw	bg	th	ar	de	es	fr	ru	tr	zh	ur	Avg
Base Model	34.3	34.7	33.8	33.6	33.4	33.8	32.8	33.6	34.1	33.8	33.5	33.6	34.2	33.9	33.6	33.8
LoRA ₄	47.3	42.2	42.1	44.8	43.5	47.3	44.0	45.0	41.6	42.1	40.0	48.3	40.0	43.9	40.6	43.5
Soft Prompts	79.4	41.8	46.7	67.6	44	70.5	48.8	56.5	73.2	75.3	75.9	67.0	60.9	69.4	49.5	61.7
Llama Adapter	92.0	58.1	64.8	69.3	46.9	<u>73.9</u>	<u>61.3</u>	61.7	79.0	<u>79.3</u>	80.6	<u>76.0</u>	<u>65.2</u>	<u>76.7</u>	55.6	69.4
Prefix Tuning	<u>90.8</u>	<u>56.7</u>	<u>61.9</u>	69.3	<u>43.4</u>	75.7	62.8	<u>61.5</u>	<u>78.8</u>	80.3	<u>79.5</u>	76.7	63.9	78.3	<u>54.5</u>	<u>69.0</u>

Table 14: Mistral v0.3 7B performance (accuracy) on XNLI benchmark comparing LoRA and prefix based adaption methods. The best performance for each language is shown in **bold**, and the second-best is underlined.

Method	en	hi	el	vi	ar	de	es	ro	ru	th	tr	zh	Avg
Base Model	77.7	35.4	47.9	62.7	46.9	65.4	66.4	64.3	53.8	<u>47.4</u>	48.0	57.8	56.1
LoRA ₄	82.5	41.37	<u>53.52</u>	48.0	<u>54.1</u>	67.1	68.2	66.7	58.8	53.2	51.1	64.9	59.12
Soft Prompts	72.1	1.6	19.4	42.2	18.4	61.6	62.3	59.6	49.3	10.1	48.1	18.4	38.6
Llama Adapter	88.5	<u>42.5</u>	53.4	<u>69.1</u>	51.1	<u>75.9</u>	<u>80.0</u>	78.6	72.3	41.3	<u>58.3</u>	71.0	<u>65.1</u>
Prefix Tuning	<u>88.4</u>	49.3	60.4	69.5	55.4	77.4	80.0	<u>78.2</u>	<u>71.7</u>	46.1	60.9	<u>69.1</u>	67.2

Table 15: Mistral v0.3 7B performance (F1 score) on XQUAD benchmark comparing LoRA and prefix based adaption methods. The best performance for each language is shown in **bold**, and the second-best is underlined.

Script	Language	Base Model	LoRA ₄	Soft Prompt	Llama Adapter	Prefix tuning
Cyrillic	Kyrgyz	31.7	29.2	35.8	<u>34.1</u>	35.5
	Russian	57.3	62.2	<u>83.1</u>	83.8	82.3
	Serbian	55.5	60.2	<u>79.0</u>	79.8	76.5
Burmese	Burmese	28.3	23.0	33.0	<u>30.8</u>	30.7
	Shan	26.0	21.5	<u>26.1</u>	25.3	27.0
Latin	Swati	28.6	27.3	29.6	<u>30.0</u>	32.0
	Sundanese	32.1	30.5	37.4	<u>35.7</u>	35.4
	Bambara	29.3	28.3	<u>31.3</u>	31.2	32.8
Arabic	Sindhi	31.3	24.3	31.4	29.2	30.8
	Egyptian Arabic	39.3	35.0	48.6	<u>45.1</u>	43.7
	Western Persian	41.2	35.1	55.4	49.8	<u>52.5</u>
Ethiopic	Amharic	29.3	22.7	31.1	29.2	<u>30.7</u>
	Tigrinya	28.3	23.0	25.7	26.1	27.0

Table 16: Performance (accuracy) of Mistral v0.3 7B on the Belebele benchmark, grouped by language **script**, comparing LoRA and prefix-based adaptation methods. The best performance for each language is shown in **bold**, and the second-best is underlined.

Family	Language	Base Model	LoRA ₄	Soft Prompting	Llama Adapter	Prefix tuning
Turkic	Kazakh	33.7	29.4	38.0	34.3	<u>35.6</u>
	Kyrgyz	31.7	29.2	35.8	34.1	<u>35.5</u>
	North Azerbaijani	34.7	35.2	45.5	<u>42.3</u>	42
Dravidian	Kannada	34.3	25.7	38.1	34.2	<u>36</u>
	Malayalam	31.8	25.7	36.7	<u>31.8</u>	31.4
	Tamil	34.1	29.0	<u>39.8</u>	36.5	40.0
Afro-Asiatic	Amharic	29.3	22.7	31.1	29.2	<u>30.7</u>
	Tigrinya	28.3	23.0	25.7	26.1	27.0
	Tsonga	28.4	28.5	34.7	33.3	<u>33.8</u>
Indo-Aryan	Sindhi	31.3	24.3	31.4	29.2	30.8
	Odia	30.5	23.6	30.3	30.7	<u>30.5</u>
	Sinhala	32.2	27.1	34.5	29.4	34.5
Balto-Slavic	Russian	57.3	62.2	<u>83.1</u>	83.8	82.3
	Serbian	55.5	60.2	<u>79.0</u>	79.8	76.5
	Slovak	52.9	58.2	73.1	<u>72.8</u>	72.3

Table 17: Performance (accuracy) of Mistral v0.3 7B on the Belebele benchmark, grouped by language **family**, comparing LoRA and prefix-based adaptation methods. The best performance for each language is shown in **bold**, and the second-best is underlined.

Exploring the Role of Transliteration in In-Context Learning for Low-resource Languages Written in Non-Latin Scripts

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Abstract

Decoder-only large language models (LLMs) excel in high-resource languages across various tasks through few-shot or even zero-shot in-context learning (ICL). However, their performance often does not transfer well to low-resource languages, especially those written in non-Latin scripts. Inspired by recent work that leverages transliteration in encoder-only models, we investigate whether transliteration¹ is also effective in improving LLMs’ performance for low-resource languages written in non-Latin scripts. To this end, we propose three prompt templates, where the target-language text is represented in (1) its original script ($\text{SCRIPT}_{\{\text{Orig}\}}$), (2) Latin script ($\text{SCRIPT}_{\{\text{Latn}\}}$), or (3) both ($\text{SCRIPT}_{\{\text{Combined}\}}$). We apply these methods to several representative LLMs of different sizes on various tasks including text classification and sequential labeling. Our findings show that the effectiveness of transliteration varies by task type and model size. For instance, all models benefit from transliterations for sequential labeling (with increases of up to 25%). We make our code publicly available.

1 Introduction

Decoder-only LLMs, such as LLaMA (Touvron et al., 2023), Mixtral (Jiang et al., 2024), XGLM (Lin et al., 2022), and BLOOM (Scao et al., 2023), have shown impressive capability across a wide range of tasks for high-resource languages, particularly through few-shot ICL (Brown et al., 2020). However, they often underperform in low-resource languages, especially those written in underrepresented scripts. Multiple reasons exist, such as the scarcity of low-resource languages in the training data (Team et al., 2022; Üstün et al., 2024), insufficient crosslingual alignment during pretraining (Hämmerl et al., 2024), as well as English being the only language in the instruction tuning phase

¹We consider a special type of transliteration that converts non-Latin scripts into Latin script (also called romanization).

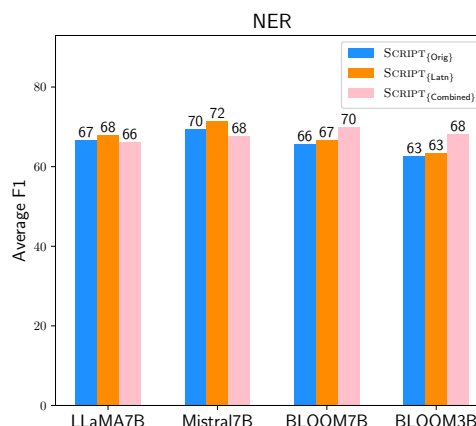
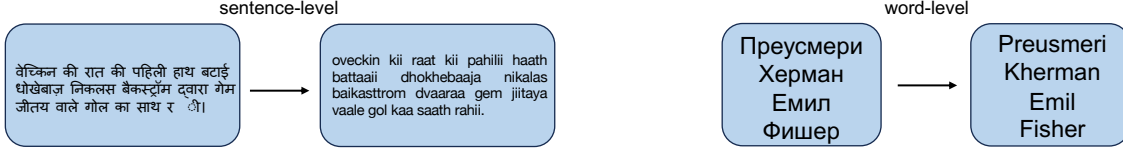


Figure 1: Results of LLaMA7B, Mistral7B, BLOOM7B and BLOOM3B on NER task. By leveraging transliteration, $\text{SCRIPT}_{\{\text{Latn}\}}$ or $\text{SCRIPT}_{\{\text{Combined}\}}$ consistently improve the performance on NER across all models.

(Chen et al., 2024). The mainstream methodology attempts to address this issue by translating the texts written in languages other than English into English using either external machine translation systems (Artetxe et al., 2023) or self-translate, i.e., translation by leveraging the few-shot translation capabilities of the model itself (Etxaniz et al., 2023). However, the quality of translations is constrained by the quality of the external systems or the LLM itself. Additionally, this type of approach is infeasible for truly low-resource languages.

Recent studies have demonstrated that leveraging transliteration into a common-script effectively improves the crosslingual transfer performance of encoder-only models on low-resource languages of non-Latin scripts (Liu et al., 2024a). This is because a common script facilitates the model to transfer knowledge through increased *lexical overlap* (Dhamecha et al., 2021; Purkayastha et al., 2023; Moosa et al., 2023). Inspired by this line of work, a natural research question is to explore whether transliteration is also effective for decoder-only LLMs, especially through their ICL capability

Step 1: Transliteration with Uroman



Step 2: Prompt formalization

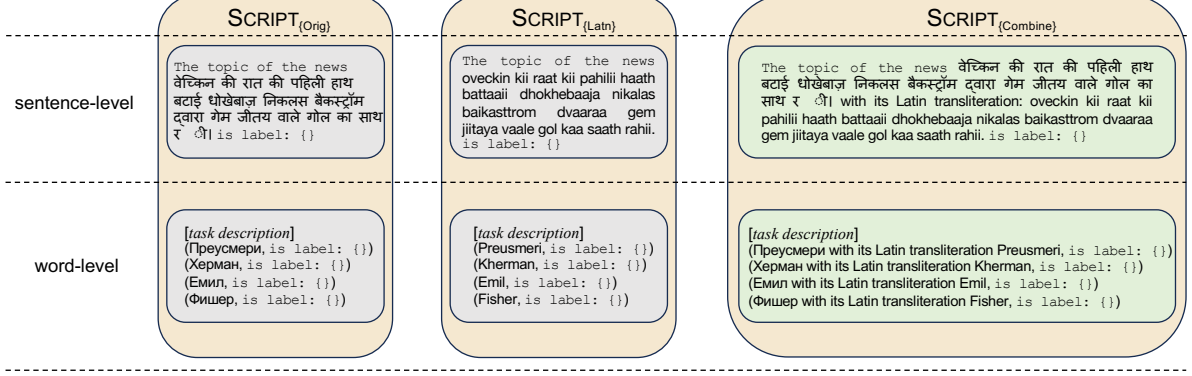


Figure 2: Illustration of our framework. We use Uroman (Hermjakob et al., 2018) to transliterate non-Latin texts (sentence-level for text classification, and word-level for sequential labeling). We propose three prompts: $\text{SCRIPT}_{\text{Orig}}$ (the original text is used), $\text{SCRIPT}_{\text{Latn}}$ (the Latin-script transliteration is used), and $\text{SCRIPT}_{\text{Combined}}$ (transliteration is used as an augmentation to the original text).

which does not require any parameter updates.

To this end, the paper investigates the above research question and proposes three types of prompt templates where the non-Latin target-language text is represented in (1) its original script ($\text{SCRIPT}_{\text{Orig}}$), (2) Latin script ($\text{SCRIPT}_{\text{Latn}}$), or (3) both ($\text{SCRIPT}_{\text{Combined}}$). Given that texts in different scripts convey the same semantics, the knowledge encoded in one script should complement the other. A capable model, therefore, should leverage this complementarity: when a word or an entire sentence in the original script is not well understood, the model should refer to its transliteration, and vice versa. We apply our methods to several LLMs on various tasks and observe that the effectiveness of transliteration varies by task type and model size. Transliteration is particularly helpful for sequential labeling. On other tasks, however, transliteration-augmented prompts are less effective, indicating models might have limited capacity to exploit complementary information.

Our contributions are as follows: (i) We conduct the first investigation towards the effectiveness of transliteration in ICL for decoder-only LLMs. (ii) We propose transliteration-augmented prompts that are specifically for low-resource languages in non-Latin scripts; (iii) We offer insights on when and how transliteration can enhance ICL performance.

2 Experimental Settings

Models. We experiment with six models: LLaMA2-7B (Touvron et al., 2023), Mistral-7B-Instruct (Jiang et al., 2024), and the 7B, 3B, 1B, and 560M variants of the BLOOM model (Scao et al., 2023). LLaMA2 is a model trained on 28 languages and 5 scripts (Cyrillic, Latin, Hang, Hani and Japanese). Mistral is an English-centric model trained on five languages in Latin script, while BLOOM is a multilingual LLM covering a wide range of languages in 11 scripts.² We select these models to compare the effectiveness of transliteration-augmented ICL on **model type** (English-centric vs multilingual models) and **model size** (different variants of BLOOM).

Methods. To investigate how transliteration impacts the ICL performance for low-resource languages in non-Latin scripts, we propose three prompt methods: (1) $\text{SCRIPT}_{\text{Orig}}$, where we feed the model with text in its original script, (2) $\text{SCRIPT}_{\text{Latn}}$, where we first transliterate the text into Latin script and only feed the transliteration into the model, and (3) $\text{SCRIPT}_{\text{Combined}}$, where we combine the text in its original script and its

²We check languages covered in each model’s training data and consider the dominant script of each language as a script supported by the model.

Model	Size	Method	NER	SIB200	Taxi1500
LLaMA2	7B	SCRIPT _{Orig}	<u>66.8</u>	<u>37.2</u>	<u>44.8</u>
		SCRIPT _{Latn}	67.9	21.6	46.7
		SCRIPT _{Combined}	66.3	48.5	46.7
Mistral	7B	SCRIPT _{Orig}	<u>69.5</u>	50.6	54.6
		SCRIPT _{Latn}	71.5	33.2	51.1
		SCRIPT _{Combined}	67.7	<u>48.6</u>	<u>54.3</u>
BLOOM	7B	SCRIPT _{Orig}	65.6	53.5	48.1
		SCRIPT _{Latn}	<u>66.7</u>	24.3	45.7
		SCRIPT _{Combined}	70.0	<u>53.2</u>	<u>47.4</u>
	3B	SCRIPT _{Orig}	62.6	48.1	48.0
		SCRIPT _{Latn}	<u>63.4</u>	29.3	46.5
		SCRIPT _{Combined}	68.2	<u>39.1</u>	<u>47.8</u>
	1B	SCRIPT _{Orig}	51.6	42.4	50.3
		SCRIPT _{Latn}	<u>56.5</u>	22.0	50.4
		SCRIPT _{Combined}	64.0	43.8	50.4
	560M	SCRIPT _{Orig}	52.9	41.5	<u>46.1</u>
		SCRIPT _{Latn}	56.7	20.4	45.8
		SCRIPT _{Combined}	<u>56.1</u>	<u>39.1</u>	46.5

Table 1: Task performance of three prompts (SCRIPT_{Orig}, SCRIPT_{Latn}, and SCRIPT_{Combined}) for different decoder-only LLMs of various sizes, averaged by languages. Transliteration shows strong effectiveness for NER task but not for other tasks. **Bold** (underlined): best (second-best) result for each model in each task.

transliteration and feed both together into the model to solve the task. The methods are illustrated in Figure 2. For transliteration, we use Uroman (Her-mjakob et al., 2018), a tool for universal romanization, which can be applied to any underrepresented scripts with high efficiency. Note that the task description (in English) is the same across all prompt templates. The target-language texts used for few-shot demonstrations are also transliterated in SCRIPT_{Latn} and SCRIPT_{Combined}.

Evaluation. We consider the following tasks for evaluation: named entity recognition (NER), a sequence labeling task using WikiANN (Pan et al., 2017); SIB200 (Adelani et al., 2024), a multilingual classification task covering 205 languages; and Taxi1500 (Ma et al., 2024), a multilingual 6-class text classification dataset contains more than 1,500 languages. For each task, we only consider a subset of languages that are written in non-Latin scripts (details are shown in §A). For Taxi1500, we perform a 3-shot prompt and follow the method in Lin et al. (2024), calculating the average of word embeddings in layer 8 of the Glot500 model (Imani-Googhari et al., 2023) to retrieve semantically similar ICL samples. For NER, we perform a 3-shot prompt, since each sentence contains multiple tokens to predict and we find that 3 random demonstrations can usually cover most NER categories. We perform a 7-shot prompt for SIB200 to ensure the demonstrations cover most classes. Details of

selecting the ICL demonstrations are in §B.

3 Results and Discussion

We report the average performance across all languages in Table 1 (per-language performance is in §C). In addition, we show the performance on NER averaged by script group in Table 3.

Transliteration benefits sequential labeling.

Across all models, we can observe that either SCRIPT_{Latn} or SCRIPT_{Combined} outperforms SCRIPT_{Orig} on NER. For instance, SCRIPT_{Combined} increases by 12.4 compared to SCRIPT_{Orig} on BLOOM-1B, which is more than 24% improvement. This demonstrates that models can make better predictions by leveraging the knowledge encoded in the Latin-script transliterations. This can be explained by the fact that NER data contains many (proper) nouns shared across languages. Transliteration enables the model to better exploit such shared vocabularies for inference.

The impact of transliteration on text classification varies across models.

SCRIPT_{Latn} almost always performs the worst across all models compared with its counterparts, indicating that the transliteration alone is not enough for the model to understand the sentence-level semantics. Besides, SCRIPT_{Combined} performs suboptimal compared to SCRIPT_{Orig} on the English-centric (Mistral) model and models trained on many multilingual

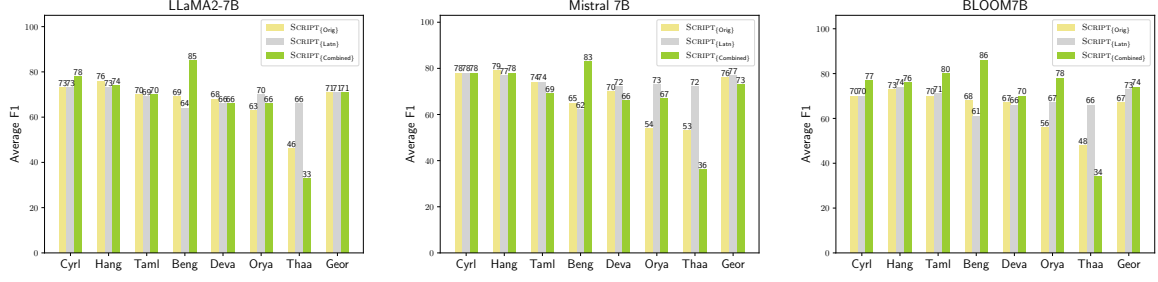


Figure 3: Performance on NER task averaged by languages of the same script. Transliterations are generally effective in improving the ICL across all models and scripts: $\text{SCRIPT}_{\{\text{Latn}\}}$ or $\text{SCRIPT}_{\{\text{Combined}\}}$ outperforms $\text{SCRIPT}_{\{\text{Orig}\}}$.

data (BLOOM), which suggests these models cannot well leverage complementary information. Instead, such information confuses the models. However, transliteration can be a good auxiliary input for good Latin-dominant models such as LLaMA ($\text{SCRIPT}_{\{\text{Combined}\}}$ achieves more than 29% and 4% on SIB200 and Taxi1500 respectively), as the model can leverage transliteration when it cannot fully understand the text in the original script.

Model performance varies by different scripts.

Figure 3 shows the average macro-F1 of ten scripts on the NER task of LLaMA2-7B, Mistral-7B, and BLOOM-7B. For BLOOM-7B, $\text{SCRIPT}_{\{\text{Combined}\}}$ outperforms $\text{SCRIPT}_{\{\text{Orig}\}}$ and $\text{SCRIPT}_{\{\text{Latn}\}}$ on most scripts except Thaana, a script not seen by BLOOM-7B. Moreover, for scripts covered in the pretraining data (Tamil, Bengali, and Odia), $\text{SCRIPT}_{\{\text{Combined}\}}$ obtains the largest improvement. On the English-centric Mistral-7B, prompts containing transliteration ($\text{SCRIPT}_{\{\text{Latn}\}}$ or $\text{SCRIPT}_{\{\text{Combined}\}}$) beats $\text{SCRIPT}_{\{\text{Orig}\}}$ on 5 out of 8 scripts. For LLaMA, combining both the original text and transliteration is effective: $\text{SCRIPT}_{\{\text{Combined}\}}$ achieves the best performance on most scripts, indicating a strong ICL capability of leveraging complementary information.

Model size plays an important role. Scaling up the model size usually indicates a stronger capacity from which the ICL can benefit (Zhao et al., 2023). Indeed, we observe that the performance generally increases for the BLOOM family when the model size scales up for all three prompt types across different tasks except for Taxi1500. We hypothesize this is because Taxi1500 is a relatively easy task and its data builds up on the Bible, which is part of the training data of these LLMs. In addition, the sentences in Taxi1500 contain many proper nouns whose transliterations the LLMs can easily exploit

for making predictions. Therefore, we also observe good performance for $\text{SCRIPT}_{\{\text{Latn}\}}$ (comparable to the other prompts) in Taxi1500, but not in SIB200.

4 Related Work

Positive effects of transliterating data into a common script have been demonstrated in various recent works for encoder-only models (Dhamecha et al., 2021; Purkayastha et al., 2023; Moosa et al., 2023; Liu et al., 2024b). Additionally, leveraging transliteration as an auxiliary input at fine-tuning stage improves the cross-script performance (Liu et al., 2024a). To improve ICL performance for low-resource languages, demonstrations play an important role. One line of approaches replaces the target-language texts with English translations (Artetxe et al., 2023; Shi et al., 2023; Etzaniz et al., 2023). Another type of research augments the ICL demonstrations, e.g., by retrieving the most similar English texts to the target-language text (Nie et al., 2023; Li et al., 2023; Wang et al., 2023)

5 Conclusion

This study explores the effectiveness of transliteration in enhancing the ICL performance of decoder-only LLMs, focusing on low-resource languages written in non-Latin scripts. By proposing three prompt templates – using original script, Latin script, and a combination of both – we evaluate their impact across various tasks on several representative LLMs. Our findings indicate that transliteration is particularly effective for sequential labeling but its benefits for text classification tasks are less consistent. We also observe a mixed effect of transliteration related to the model type and model size. Our results highlight the potential of transliteration as a possible way to enhance LLMs’ performance for low-resource languages.

Limitations

There are mainly two limitations in our work. First, we only consider models with up to 7 billion parameters due to constraints in our computing resources. Second, the evaluation data is limited in terms of the types of tasks. The major reason is the limited availability of evaluation datasets containing a variety of scripts. Nevertheless, as a pioneer study in exploring the effectiveness of transliteration for ICL involving low-resource languages in non-Latin scripts, we hope future research can leverage larger models and more datasets to explore this direction.

Acknowledgements

This research was supported by DFG (grant SCHU 2246/14-1) and The European Research Council (NonSequeToR, grant #740516).

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A Task Data Information

The basic information of each task dataset is shown in Table 3. The number of languages of script groups for each downstream task is shown in Table 2. We introduce the detailed hyperparameters settings for each task in the following.

For Named Entity Recognition (NER), we employ a 3-shot prompting strategy. Given that each sentence comprises multiple tokens requiring prediction, we have determined that three randomly

Task	Method	Prompt
NER	SCRIPT _{Orig}	Named Entity Recognition involves identifying and classifying named entities in a text into predefined categories such as person names, organizations, locations, and others. You will need to use the tags defined below: O means the word doesn't correspond to any entity. B-PER/I-PER means the word corresponds to the beginning of/is inside a person entity. B-ORG/I-ORG means the word corresponds to the beginning of/is inside an organization entity. B-LOC/I-LOC means the word corresponds to the beginning of/is inside a location entity. Do not try to answer the question! Just tag each token in the sentence. {{'Светислав'}} {{labels}}
	SCRIPT _{Latn}	Named Entity Recognition involves identifying and classifying named entities in a text into predefined categories such as person names, organizations, locations, and others. You will need to use the tags defined below: O means the word doesn't correspond to any entity. B-PER/I-PER means the word corresponds to the beginning of/is inside a person entity. B-ORG/I-ORG means the word corresponds to the beginning of/is inside an organization entity. B-LOC/I-LOC means the word corresponds to the beginning of/is inside a location entity. Do not try to answer the question! Just tag each token in the sentence. {{'Svetislav'}} {{labels}}
	SCRIPT _{Combined}	Named Entity Recognition involves identifying and classifying named entities in a text into predefined categories such as person names, organizations, locations, and others. You will need to use the tags defined below: O means the word doesn't correspond to any entity. B-PER/I-PER means the word corresponds to the beginning of/is inside a person entity. B-ORG/I-ORG means the word corresponds to the beginning of/is inside an organization entity. B-LOC/I-LOC means the word corresponds to the beginning of/is inside a location entity. Do not try to answer the question! Just tag each token in the sentence. {{'Светислав' with its Latin transliteration Svetislav'}} {{labels}}
SIB200	SCRIPT _{Orig}	The topic of the news {አዚአቶም ብጣ/ኦሚ ቀለልቴ ኣይኮነን፣ ስለዝኮነ ኣውን ኣሰሩ ብትልሙ ክመጽእ ብትራክቲካዊ ጎሳታት ዙርያ ነዊሕ ዙሪት ወሲዱ.} is label: { }
	SCRIPT _{Latn}	The topic of the news {eziaatome betaa/omi qalaleti aayekonune, selazekona aawene aasaru betelemu kematsee beteraaketikaawi gobotaate zureyaa nawihhe zurate wasidu.} is label: { }
	SCRIPT _{Combined}	The topic of the news {አዚአቶም ብጣ/ኦሚ ቀለልቴ ኣይኮነን፣ ስለዝኮነ ኣውን ኣሰሩ ብትልሙ ክመጽእ ብትራክቲካዊ ጎሳታት ዙርያ ነዊሕ ዙሪት ወሲዱ.} with its Latin transliteration: eziaatome betaa/omi qalaleti aayekonune, selazekona aawene aasaru betelemu kematsee beteraaketikaawi gobotaate zureyaa nawihhe zurate wasidu.} is label: { }
Taxi1500	SCRIPT _{Orig}	The topic of the verse {既然 你們 要 按使 人 自由 的 律法 受 審判 , 就 應該 按 律法 行事 為 人。} is label: { }
	SCRIPT _{Latn}	The topic of the verse {jiran nimen yao anshi ren ziyou de lufa shou shenpan , jiu yinggai an lufa xingshi weiren.} is label: { }
	SCRIPT _{Combined}	The topic of the verse {既然 你們 要 按使 人 自由 的 律法 受 審判 , 就 應該 按 律法 行事 為 人。 with its Latin transliteration: jiran nimen yao anshi ren ziyou de lufa shou shenpan , jiu yinggai an lufa xingshi weiren.} is label: { }

Figure 4: Three types of prompt templates (SCRIPT_{Orig}, SCRIPT_{Latn} and SCRIPT_{Combined}) that are used for each task. We follow the prompt templates in (Lin et al., 2024) for the SCRIPT_{Orig}, where the target-language text is represented in the original script. We use Latin-script transliterations obtained by Uroman (Hermjakob et al., 2018) for SCRIPT_{Latn}. SCRIPT_{Combined} leverages both the original script and its Latin transliteration.

Task	llanl							
NER	Cyrl	Arab	Hani	Deva	Geor	Hebr	Beng	other all
	17	10	5	5	2	2	2	19 62
SIB200	Arab	Deva	Cyrl	Mymr	Beng	Tibt	Hebr	
	15	9	8	2	2	2	2	22 62
Taxi1500	Cyrl	Arab	Deva	Hani	Mymr	Beng	Orya	
	24	9	7	3	2	2	2	15 64

Table 2: The number of languages in each script group for each downstream task.

selected demonstrations typically encompass the majority of NER categories. For SIB200, we do a 7-shot prompt. The 7 demonstrations are manually selected to cover the 7 classes of the task. For Taxi1500, we use a 3-shot prompt and adhere to the methodology outlined in Lin et al. (2024). Specifically, we calculate the average of contextualized word embeddings from layer 8 of the Glot500 model (ImaniGooghari et al., 2023) to identify 10 most semantically similar samples, and randomly select 3 samples as the demonstrations.

	llanl	lrowsl	#class	measure (%)
NER	62	119	7	F1 score
SIB200	62	1140	7	Accuracy
Taxi1500	64	666	6	Accuracy

Table 3: Information of evaluation tasks. llanl: languages we select as subset to evaluate; #class: the number of the categories if it is a sequence-level or token-level classification task.

B Prompt Templates

We follow the prompt templates in (Lin et al., 2024) for SCRIPT_{Orig}, where the demonstrations and the query are in the original script of the target language. We employ Uroman (Hermjakob et al., 2018) to transliterate the target-language demonstrations and the target-language query into Latin script. SCRIPT_{Latn} only uses the transliteration, while SCRIPT_{Combined} leverage both the original script and its Latin transliteration.

C Full Results for All Scripts/Languages

We report the complete results for all tasks and language-scripts in Table 4 and Table 5 (NER),

Table 6 and Table 7 (**SIB200**), and Table 8 and Table 9 (**Taxi1500**).

Language	SCRIPT _{Orig}	SCRIPT _{Latn}	SCRIPT _{Combined}	Language	SCRIPT _{Orig}	SCRIPT _{Latn}	SCRIPT _{Combined}	Language	SCRIPT _{Orig}	SCRIPT _{Latn}	SCRIPT _{Combined}
ara_Arab	60.4	<u>56.0</u>	41.1	ara_Arab	<u>63.2</u>	59.4	82.3	ara_Arab	<u>69.8</u>	63.8	84.4
arz_Arab	62.4	<u>58.3</u>	40.7	arz_Arab	<u>64.1</u>	62.4	77.9	arz_Arab	<u>69.9</u>	65.9	81.0
ckb_Arab	<u>61.7</u>	56.7	73.6	ckb_Arab	<u>58.7</u>	57.9	77.7	ckb_Arab	<u>61.6</u>	60.4	84.1
fas_Arab	61.9	<u>59.7</u>	59.4	fas_Arab	<u>62.8</u>	61.8	82.6	fas_Arab	<u>66.3</u>	63.7	85.1
mzn_Arab	72.8	<u>68.6</u>	64.2	mzn_Arab	<u>67.2</u>	<u>70.0</u>	82.3	mzn_Arab	<u>78.4</u>	74.0	87.1
pnb_Arab	53.5	58.3	<u>58.2</u>	pnb_Arab	57.1	<u>57.5</u>	81.0	pnb_Arab	<u>66.4</u>	65.8	87.3
pus_Arab	47.2	<u>41.2</u>	30.4	pus_Arab	42.4	<u>39.5</u>	28.3	pus_Arab	49.3	<u>48.7</u>	30.2
snd_Arab	47.7	<u>41.5</u>	18.3	snd_Arab	<u>44.0</u>	45.4	19.3	snd_Arab	<u>49.7</u>	52.9	19.8
uig_Arab	49.0	<u>49.4</u>	50.3	uig_Arab	49.1	<u>50.6</u>	56.0	uig_Arab	55.5	<u>55.6</u>	58.7
urd_Arab	<u>53.8</u>	62.6	39.3	urd_Arab	48.4	<u>65.0</u>	71.2	urd_Arab	47.2	<u>69.3</u>	83.8
hye_Armn	47.7	<u>57.8</u>	71.3	hye_Armn	47.3	<u>57.4</u>	71.6	hye_Armn	64.1	<u>64.5</u>	78.6
asm_Beng	<u>51.7</u>	49.3	60.4	asm_Beng	43.4	<u>53.6</u>	70.7	asm_Beng	<u>59.3</u>	55.1	79.8
ben_Beng	<u>57.6</u>	56.7	66.5	ben_Beng	<u>60.9</u>	57.3	86.0	ben_Beng	<u>66.9</u>	60.2	87.0
bak_Cyrl	64.2	69.1	<u>64.6</u>	bak_Cyrl	<u>65.5</u>	63.2	69.1	bak_Cyrl	71.3	<u>72.2</u>	73.6
bel_Cyrl	55.3	<u>58.2</u>	68.7	bel_Cyrl	<u>56.2</u>	55.6	76.0	bel_Cyrl	<u>66.7</u>	64.9	75.3
bul_Cyrl	58.5	<u>62.7</u>	68.6	bul_Cyrl	58.6	<u>61.4</u>	73.7	bul_Cyrl	69.1	<u>70.3</u>	73.6
che_Cyrl	<u>57.2</u>	58.8	42.5	che_Cyrl	59.6	61.5	48.4	che_Cyrl	<u>68.9</u>	70.0	52.0
chv_Cyrl	57.8	<u>62.3</u>	75.6	chv_Cyrl	56.6	<u>61.8</u>	80.2	chv_Cyrl	<u>69.6</u>	68.1	85.3
kaz_Cyrl	59.9	<u>64.6</u>	69.3	kaz_Cyrl	58.7	<u>61.3</u>	70.8	kaz_Cyrl	72.5	<u>72.5</u>	75.7
kir_Cyrl	53.5	65.7	<u>62.3</u>	kir_Cyrl	56.5	<u>60.1</u>	65.1	kir_Cyrl	<u>70.5</u>	72.1	69.7
mhr_Cyrl	54.4	<u>55.7</u>	65.1	mhr_Cyrl	51.6	<u>54.5</u>	72.3	mhr_Cyrl	62.8	<u>65.0</u>	75.9
mkd_Cyrl	<u>58.4</u>	63.6	54.7	mkd_Cyrl	<u>59.3</u>	61.9	59.2	mkd_Cyrl	<u>69.4</u>	69.6	60.1
mon_Cyrl	50.6	<u>51.4</u>	70.8	mon_Cyrl	53.9	<u>54.6</u>	77.8	mon_Cyrl	<u>63.1</u>	59.4	81.7
oss_Cyrl	56.2	<u>59.6</u>	69.6	oss_Cyrl	57.8	<u>60.3</u>	71.4	oss_Cyrl	<u>68.3</u>	68.0	75.7
rus_Cyrl	51.6	<u>58.3</u>	71.2	rus_Cyrl	<u>55.3</u>	55.0	75.2	rus_Cyrl	<u>66.1</u>	65.4	79.3
sah_Cyrl	60.3	<u>68.3</u>	76.5	sah_Cyrl	59.0	<u>63.8</u>	79.8	sah_Cyrl	70.5	<u>71.6</u>	82.2
srp_Cyrl	55.4	<u>56.6</u>	69.5	srp_Cyrl	50.3	<u>55.1</u>	73.4	srp_Cyrl	<u>64.0</u>	62.0	77.2
tat_Cyrl	58.3	<u>61.5</u>	70.7	tat_Cyrl	57.3	<u>60.0</u>	73.5	tat_Cyrl	70.9	69.8	78.0
tgk_Cyrl	50.6	<u>54.7</u>	65.2	tgk_Cyrl	51.7	<u>52.6</u>	71.7	tgk_Cyrl	58.6	<u>60.1</u>	74.9
ukr_Cyrl	53.8	<u>60.1</u>	67.2	ukr_Cyrl	54.8	<u>58.3</u>	72.6	ukr_Cyrl	64.7	<u>67.3</u>	74.1
bih_Deva	47.0	44.6	49.6	bih_Deva	45.0	45.6	54.0	bih_Deva	56.1	49.4	55.8
hin_Deva	54.0	55.6	64.1	hin_Deva	52.1	56.2	79.6	hin_Deva	<u>62.8</u>	60.7	82.0
mar_Deva	56.1	61.6	52.4	mar_Deva	47.6	59.1	70.3	mar_Deva	61.6	65.9	77.7
nep_Deva	50.4	52.0	49.1	nep_Deva	47.2	55.7	67.5	nep_Deva	62.2	62.0	71.5
san_Deva	52.0	56.8	40.7	san_Deva	49.7	58.5	50.6	san_Deva	69.5	70.7	55.7
amh_Ethi	41.4	54.9	72.3	amh_Ethi	54.2	60.0	77.4	amh_Ethi	63.5	63.6	81.2
kat_Geor	57.0	<u>67.3</u>	69.9	kat_Geor	58.1	63.8	65.9	kat_Geor	68.0	<u>72.3</u>	73.7
xmf_Geor	54.8	<u>61.3</u>	67.8	xmf_Geor	55.2	<u>57.7</u>	69.6	xmf_Geor	63.4	<u>68.1</u>	72.1
ell_Grek	58.0	62.6	59.2	ell_Grek	61.8	60.4	66.4	ell_Grek	70.0	69.6	65.1
guj_Gujr	<u>51.4</u>	70.4	24.7	guj_Gujr	31.6	64.8	37.8	guj_Gujr	<u>73.3</u>	76.3	47.9
pan_Guru	43.9	57.6	46.2	pan_Guru	33.8	58.0	70.3	pan_Guru	55.9	63.2	78.5
kor_Hang	60.7	<u>63.6</u>	66.3	kor_Hang	58.5	60.5	70.6	kor_Hang	69.6	<u>70.1</u>	72.4
gan_Hani	54.7	54.1	72.6	gan_Hani	59.3	58.7	76.4	gan_Hani	57.2	<u>60.3</u>	72.3
lzh_Hani	58.4	<u>57.8</u>	41.3	lzh_Hani	<u>60.9</u>	62.4	50.3	lzh_Hani	70.4	71.7	52.1
wuu_Hani	51.5	<u>55.0</u>	71.7	wuu_Hani	55.8	55.6	75.6	wuu_Hani	<u>56.1</u>	52.6	72.8
yue_Hani	47.2	43.2	44.1	yue_Hani	47.7	44.1	39.7	yue_Hani	57.2	<u>53.2</u>	50.0
zho_Hani	44.8	38.1	37.7	zho_Hani	43.2	<u>39.0</u>	34.2	zho_Hani	51.4	<u>47.2</u>	40.0
heb_Hebr	62.7	60.1	67.5	heb_Hebr	61.6	59.9	66.0	heb_Hebr	<u>69.6</u>	67.9	72.2
yid_Hebr	<u>66.0</u>	59.6	67.3	yid_Hebr	61.9	57.7	69.1	yid_Hebr	<u>68.2</u>	65.5	71.2
jpn_Jpan	<u>33.6</u>	34.9	20.0	jpn_Jpan	38.8	<u>35.0</u>	20.0	jpn_Jpan	45.4	45.0	25.2
khm_Khmr	47.6	46.2	55.9	khm_Khmr	48.1	<u>52.4</u>	55.1	khm_Khmr	51.9	<u>56.7</u>	57.7
kan_Knda	52.8	71.6	34.2	kan_Knda	37.4	65.7	61.0	kan_Knda	74.4	<u>75.4</u>	76.1
mal_Mlym	<u>54.3</u>	65.9	53.7	mal_Mlym	47.7	61.6	70.1	mal_Mlym	68.8	68.9	76.9
mya_Mymr	32.3	52.5	37.8	mya_Mymr	32.4	51.4	30.7	mya_Mymr	49.3	59.1	36.3
ori_Orya	35.8	57.3	43.4	ori_Orya	28.4	<u>56.3</u>	64.9	ori_Orya	54.8	<u>66.8</u>	73.9
sin_Sinh	44.4	56.8	61.7	sin_Sinh	46.5	59.1	61.5	sin_Sinh	62.9	<u>64.6</u>	66.1
arc_Syrc	47.4	<u>51.9</u>	64.8	arc_Syrc	<u>51.3</u>	50.9	65.0	arc_Syrc	53.1	<u>54.8</u>	69.2
tam_Taml	62.1	<u>64.0</u>	65.9	tam_Taml	57.1	<u>62.5</u>	73.8	tam_Taml	69.6	69.2	80.2
tel_Telu	59.4	70.7	61.1	tel_Telu	47.5	67.8	67.6	tel_Telu	73.8	<u>75.2</u>	78.8
div_Thaa	<u>32.8</u>	46.6	31.0	div_Thaa	31.4	52.6	31.0	div_Thaa	<u>39.9</u>	58.0	33.8
tha_Thai	<u>17.7</u>	18.3	0.7	tha_Thai	<u>12.6</u>	21.7	0.4	tha_Thai	<u>17.5</u>	25.7	0.6
bod_Tibt	<u>61.5</u>	53.1	77.8	bod_Tibt	<u>60.5</u>	49.9	79.3	bod_Tibt	<u>59.8</u>	51.0	76.1

Table 4: Macro-F1 score of NER task on BLOOM 560m, BLOOM 1B and BLOOM3B (from left to right).

Language	SCRIPT _{Orig}	SCRIPT _{Latn}	SCRIPT _{Combined}	Language	SCRIPT _{Orig}	SCRIPT _{Latn}	SCRIPT _{Combined}	Language	SCRIPT _{Orig}	SCRIPT _{Latn}	SCRIPT _{Combined}
ara_Arab	70.6	65.7	86.9	ara_Arab	69.8	65.5	86.0	ara_Arab	74.0	69.2	85.9
arz_Arab	69.8	67.7	81.3	arz_Arab	73.6	67.0	70.1	arz_Arab	78.0	73.1	78.7
ckb_Arab	64.0	63.0	84.7	ckb_Arab	65.5	64.2	82.0	ckb_Arab	64.3	62.2	83.7
fas_Arab	70.5	67.3	87.2	fas_Arab	73.1	68.2	85.9	fas_Arab	70.8	67.8	84.5
mzn_Arab	80.4	79.4	87.7	mzn_Arab	79.7	77.9	82.3	mzn_Arab	81.9	81.3	83.9
pnb_Arab	68.5	68.7	86.9	pnb_Arab	72.5	71.1	90.2	pnb_Arab	74.0	71.7	90.9
pus_Arab	51.1	52.9	31.7	pus_Arab	53.0	58.6	33.9	pus_Arab	55.5	57.1	29.4
snd_Arab	52.2	57.5	21.6	snd_Arab	48.8	59.7	25.1	snd_Arab	48.7	59.3	18.7
uig_Arab	57.8	60.6	62.1	uig_Arab	58.3	58.5	55.5	uig_Arab	62.3	64.2	60.9
urd_Arab	62.7	71.8	83.4	urd_Arab	74.0	70.3	90.4	urd_Arab	74.9	70.0	89.6
hye_Armn	67.5	66.6	81.6	hye_Armn	72.1	71.5	80.8	hye_Armn	71.8	73.2	81.1
asm_Beng	64.9	60.4	83.3	asm_Beng	65.9	62.0	81.0	asm_Beng	62.5	61.2	78.5
ben_Beng	72.0	62.6	88.5	ben_Beng	71.4	65.5	88.7	ben_Beng	66.7	62.3	87.0
bak_Cyrl	75.2	73.6	73.2	bak_Cyrl	76.1	75.9	71.9	bak_Cyrl	83.0	83.3	73.8
bel_Cyrl	70.1	67.4	79.7	bel_Cyrl	74.8	72.8	81.1	bel_Cyrl	77.6	78.3	82.8
bul_Cyrl	71.6	73.9	78.7	bul_Cyrl	76.2	74.7	81.6	bul_Cyrl	81.3	82.1	81.2
che_Cyrl	69.4	73.2	53.9	che_Cyrl	73.8	75.3	51.9	che_Cyrl	76.7	74.9	55.3
chv_Cyrl	70.0	68.8	86.0	chv_Cyrl	75.9	76.5	84.8	chv_Cyrl	79.6	80.3	87.5
kaz_Cyrl	73.3	74.2	77.1	kaz_Cyrl	77.9	76.8	79.3	kaz_Cyrl	80.9	80.2	79.9
kir_Cyrl	73.4	74.2	70.2	kir_Cyrl	73.1	74.6	69.7	kir_Cyrl	78.5	79.3	69.5
mhr_Cyrl	67.2	67.7	83.0	mhr_Cyrl	69.5	73.8	85.3	mhr_Cyrl	79.4	78.3	84.9
mkd_Cyrl	71.7	73.0	61.2	mkd_Cyrl	75.7	73.6	65.1	mkd_Cyrl	78.4	79.0	62.9
mon_Cyrl	66.1	66.8	85.2	mon_Cyrl	69.0	66.7	83.1	mon_Cyrl	73.9	73.3	81.3
oss_Cyrl	70.5	70.1	81.2	oss_Cyrl	73.5	72.4	80.2	oss_Cyrl	76.5	74.7	80.5
rus_Cyrl	69.0	68.8	80.7	rus_Cyrl	71.9	72.8	83.4	rus_Cyrl	78.2	76.6	83.4
sah_Cyrl	69.9	69.2	82.9	sah_Cyrl	74.7	72.5	81.7	sah_Cyrl	81.3	80.7	83.9
srp_Cyrl	66.5	68.7	79.3	srp_Cyrl	70.1	69.7	82.6	srp_Cyrl	77.2	76.8	82.6
tat_Cyrl	72.4	73.3	79.7	tat_Cyrl	76.9	74.5	82.6	tat_Cyrl	81.2	79.7	81.1
tgk_Cyrl	63.3	61.8	76.3	tgk_Cyrl	65.0	65.3	74.8	tgk_Cyrl	70.6	71.3	78.8
ukr_Cyrl	66.7	71.3	78.0	ukr_Cyrl	72.7	73.1	82.5	ukr_Cyrl	77.9	78.8	80.6
bih_Deva	63.5	60.7	62.3	bih_Deva	65.0	64.6	69.0	bih_Deva	64.9	68.9	57.3
hin_Deva	66.4	65.1	82.9	hin_Deva	69.8	65.8	86.0	hin_Deva	71.2	69.7	83.2
mar_Deva	62.3	68.1	77.0	mar_Deva	71.0	70.1	78.6	mar_Deva	76.1	75.1	76.8
nep_Deva	70.6	68.9	74.5	nep_Deva	72.3	64.5	60.1	nep_Deva	72.8	70.7	62.7
san_Deva	71.9	68.8	51.5	san_Deva	59.4	65.9	38.6	san_Deva	58.7	71.4	42.4
amh_Ethi	69.0	68.2	83.5	amh_Ethi	66.1	63.6	76.7	amh_Ethi	69.7	69.4	80.4
kat_Geor	69.7	76.2	74.8	kat_Geor	73.0	73.5	70.1	kat_Geor	77.2	79.1	75.0
xmf_Geor	64.7	69.2	72.9	xmf_Geor	68.2	68.9	71.8	xmf_Geor	73.8	75.3	72.0
ell_Grek	72.0	74.3	68.5	ell_Grek	74.7	74.4	66.6	ell_Grek	78.7	80.8	63.0
guj_Gujr	73.5	77.1	47.9	guj_Gujr	38.8	72.5	15.9	guj_Gujr	47.2	77.1	19.0
pan_Guru	58.7	64.8	81.3	pan_Guru	67.5	68.7	82.5	pan_Guru	65.3	67.4	79.5
kor_Hang	72.8	73.9	75.9	kor_Hang	75.5	72.7	73.9	kor_Hang	78.6	77.2	78.0
gan_Hani	65.3	65.1	78.0	gan_Hani	75.0	75.8	85.0	gan_Hani	68.7	72.1	84.5
lzh_Hani	75.0	76.0	52.5	lzh_Hani	76.1	71.5	45.2	lzh_Hani	78.6	79.5	51.4
wuu_Hani	68.7	62.4	83.4	wuu_Hani	73.3	61.4	82.2	wuu_Hani	69.3	66.6	87.6
yue_Hani	63.6	58.6	43.1	yue_Hani	64.7	61.2	43.7	yue_Hani	68.5	62.5	42.1
zho_Hani	55.6	51.5	40.5	zho_Hani	58.9	53.1	39.2	zho_Hani	62.5	55.5	40.6
heb_Hebr	71.1	69.8	70.5	heb_Hebr	72.5	71.5	71.7	heb_Hebr	77.8	74.5	69.8
yid_Hebr	67.2	66.3	73.0	yid_Hebr	73.4	71.2	69.2	yid_Hebr	72.6	72.1	71.4
jpn_Jpan	49.7	48.6	25.1	jpn_Jpan	51.9	50.1	21.5	jpn_Jpan	55.9	51.2	26.0
khm_Khmr	59.9	62.1	65.7	khm_Khmr	52.1	62.0	49.1	khm_Khmr	62.3	71.4	64.1
kan_Knda	72.0	76.8	74.7	kan_Knda	53.0	76.1	25.7	kan_Knda	71.6	78.8	55.8
mal_Mlym	66.9	70.3	78.4	mal_Mlym	71.0	70.0	61.3	mal_Mlym	53.1	73.3	34.8
mya_Mymr	50.3	62.8	37.9	mya_Mymr	50.6	54.1	42.7	mya_Mymr	56.8	64.0	39.8
ori_Orya	56.4	67.4	77.9	ori_Orya	63.4	70.2	66.1	ori_Orya	54.4	73.2	67.0
sin_Sinh	64.6	66.1	65.8	sin_Sinh	65.1	67.9	61.8	sin_Sinh	66.6	71.7	65.5
arc_Syrc	59.1	61.7	77.2	arc_Syrc	62.0	65.5	73.7	arc_Syrc	62.0	66.5	79.4
tam_Taml	70.3	70.7	80.0	tam_Taml	69.6	68.6	69.7	tam_Taml	74.1	73.7	68.9
tel_Telu	72.3	78.1	77.2	tel_Telu	56.2	74.9	22.6	tel_Telu	71.2	78.7	49.7
div_Thaa	48.1	66.3	33.8	div_Thaa	46.0	65.9	32.6	div_Thaa	53.2	71.6	36.1
tha_Thai	18.0	27.0	0.7	tha_Thai	21.8	24.7	0.8	tha_Thai	22.0	26.1	0.7
bod_Tibt	61.7	53.9	81.4	bod_Tibt	62.0	66.7	84.7	bod_Tibt	56.1	70.6	87.6

Table 5: Macro-F1 score of NER task on NER task on BLOOM 7B, LLaMA2-7B and Mistral 7B (from left to right)

Language	SCRIPT _(Orig)	SCRIPT _(Latn)	SCRIPT _(Combined)	Language	SCRIPT _(Orig)	SCRIPT _(Latn)	SCRIPT _(Combined)	Language	SCRIPT _(Orig)	SCRIPT _(Latn)	SCRIPT _(Combined)
ace_Arab	18.1	18.6	20.6	ace_Arab	16.7	16.7	21.6	ace_Arab	27.5	19.6	20.6
acm_Arab	63.7	16.7	66.7	acm_Arab	67.6	18.1	70.1	acm_Arab	77.9	19.1	66.7
acq_Arab	63.7	16.7	64.7	acq_Arab	69.1	17.2	72.1	acq_Arab	77.9	21.1	64.7
aeb_Arab	63.2	17.6	56.9	aeb_Arab	62.7	17.2	67.2	aeb_Arab	74.0	18.6	56.9
ajp_Arab	68.6	18.1	67.2	ajp_Arab	71.1	18.1	74.5	ajp_Arab	75.0	25.5	67.2
apc_Arab	70.1	19.1	71.1	apc_Arab	74.5	17.2	75.0	apc_Arab	77.9	26.5	71.1
ars_Arab	65.7	15.7	65.7	ars_Arab	67.6	16.7	72.1	ars_Arab	76.5	19.6	65.7
ary_Arab	63.7	16.7	61.3	ary_Arab	60.8	16.7	72.1	ary_Arab	76.0	20.1	61.3
azb_Arab	36.3	17.6	32.4	azb_Arab	32.8	17.6	35.8	azb_Arab	34.3	22.5	32.4
ckb_Arab	21.1	19.1	19.6	ckb_Arab	19.6	17.2	20.6	ckb_Arab	25.5	24.0	19.6
knc_Arab	23.5	19.1	24.0	knc_Arab	20.6	19.6	23.0	knc_Arab	18.6	28.9	24.0
pbt_Arab	38.7	20.6	32.4	pbt_Arab	34.8	24.0	35.3	pbt_Arab	48.0	28.9	32.4
pes_Arab	39.7	19.1	44.1	pes_Arab	48.0	21.6	52.0	pes_Arab	52.0	28.4	44.1
prs_Arab	42.2	15.2	36.8	prs_Arab	45.6	20.1	51.5	prs_Arab	52.0	25.0	36.8
uig_Arab	20.1	16.7	16.7	uig_Arab	19.1	17.2	20.6	uig_Arab	21.6	24.5	16.7
hye_Armn	16.7	25.0	18.6	hye_Armn	15.7	32.4	15.7	hye_Armn	21.1	36.3	18.6
asm_Beng	58.3	12.3	42.6	asm_Beng	43.6	17.6	42.6	asm_Beng	72.1	23.5	42.6
ben_Beng	73.5	16.7	69.1	ben_Beng	72.5	16.2	69.6	ben_Beng	77.5	27.5	69.1
bak_Cyrl	19.6	39.2	24.5	bak_Cyrl	26.0	39.2	31.9	bak_Cyrl	37.7	50.5	24.5
kaz_Cyrl	23.0	30.4	22.1	kaz_Cyrl	29.9	35.3	31.4	kaz_Cyrl	37.3	43.1	22.1
kir_Cyrl	26.5	34.3	22.1	kir_Cyrl	28.9	38.7	34.8	kir_Cyrl	34.3	50.0	22.1
mkd_Cyrl	21.1	33.8	24.0	mkd_Cyrl	24.0	38.2	28.4	mkd_Cyrl	34.8	51.5	24.0
rus_Cyrl	24.0	37.3	26.0	rus_Cyrl	43.6	41.2	43.6	rus_Cyrl	57.8	51.5	26.0
srp_Cyrl	25.5	37.3	25.5	srp_Cyrl	25.5	35.8	29.4	srp_Cyrl	32.4	54.4	25.5
tgk_Cyrl	20.6	25.0	20.6	tgk_Cyrl	22.1	29.4	28.4	tgk_Cyrl	27.0	45.1	20.6
ukr_Cyrl	21.1	39.7	24.5	ukr_Cyrl	28.4	41.2	31.9	ukr_Cyrl	40.7	51.0	24.5
awa_Deva	63.7	17.6	59.8	awa_Deva	68.6	18.1	66.2	awa_Deva	73.5	26.5	59.8
bho_Deva	69.6	17.6	63.7	bho_Deva	64.7	19.1	66.2	bho_Deva	72.5	28.4	63.7
hin_Deva	65.7	14.7	63.2	hin_Deva	71.1	16.7	72.5	hin_Deva	74.5	22.5	63.2
hne_Deva	63.2	15.2	57.8	hne_Deva	65.2	18.1	64.2	hne_Deva	73.5	22.1	57.8
kas_Deva	43.6	23.5	46.1	kas_Deva	50.0	21.1	51.5	kas_Deva	49.5	35.3	46.1
mag_Deva	66.2	15.2	62.3	mag_Deva	67.6	17.2	67.2	mag_Deva	75.5	22.5	62.3
mai_Deva	64.2	15.7	59.8	mai_Deva	63.7	18.1	62.3	mai_Deva	73.5	24.5	59.8
npi_Deva	65.7	17.6	58.8	npi_Deva	71.6	20.1	68.6	npi_Deva	65.2	27.0	58.8
san_Deva	57.8	14.2	53.4	san_Deva	53.4	20.6	56.9	san_Deva	59.8	24.0	53.4
amh_Ethi	17.6	18.1	15.2	amh_Ethi	14.7	16.2	17.2	amh_Ethi	15.7	27.9	15.2
tir_Ethi	20.1	18.1	15.7	tir_Ethi	15.2	16.2	16.2	tir_Ethi	16.7	27.9	15.7
kat_Geor	21.1	30.4	23.5	kat_Geor	17.6	36.3	25.5	kat_Geor	14.7	41.7	23.5
ell_Grek	19.6	27.9	17.6	ell_Grek	16.7	33.8	25.0	ell_Grek	24.0	45.6	17.6
pan_Guru	57.4	17.2	54.9	pan_Guru	54.4	16.7	56.4	pan_Guru	69.6	20.6	54.9
zho_Hans	70.1	20.1	68.6	zho_Hans	75.5	17.6	73.0	zho_Hans	73.5	23.5	68.6
yue_Hant	68.6	18.1	67.2	yue_Hant	72.1	21.1	71.6	yue_Hant	74.5	25.5	67.2
zho_Hant	74.0	12.7	71.1	zho_Hant	76.0	19.1	74.0	zho_Hant	76.5	25.0	71.1
heb_Hebr	21.1	16.7	18.1	heb_Hebr	15.2	16.7	18.6	heb_Hebr	21.6	20.6	18.1
ydd_Hebr	21.1	18.6	15.2	ydd_Hebr	21.6	17.6	20.6	ydd_Hebr	16.2	22.5	15.2
jpn_Jpan	63.7	21.1	57.8	jpn_Jpan	67.2	18.1	66.2	jpn_Jpan	75.0	26.0	57.8
khm_Khmr	21.6	26.0	16.7	khm_Khmr	20.6	28.9	21.1	khm_Khmr	29.9	37.7	16.7
kan_Knda	57.8	16.2	55.4	kan_Knda	64.7	16.7	66.2	kan_Knda	66.7	27.0	55.4
lao_Lao	22.5	24.0	22.1	lao_Lao	28.9	27.0	31.9	lao_Lao	28.9	37.3	22.1
mal_Mlym	68.1	16.7	49.0	mal_Mlym	67.6	18.6	70.6	mal_Mlym	71.6	21.1	49.0
mya_Mymr	17.6	20.6	18.1	mya_Mymr	12.7	18.1	15.7	mya_Mymr	19.1	28.4	18.1
shn_Mymr	21.1	22.1	18.1	shn_Mymr	27.9	31.9	25.0	shn_Mymr	26.5	40.2	18.1
nqo_Nkoo	17.2	16.7	17.6	nqo_Nkoo	13.2	18.1	14.2	nqo_Nkoo	14.2	27.0	17.6
sat_Olck	18.1	18.6	20.1	sat_Olck	16.7	14.7	15.7	sat_Olck	22.5	22.5	20.1
ory_Orya	58.8	19.1	58.8	ory_Orya	67.6	20.6	63.7	ory_Orya	65.7	31.4	58.8
sin_Sinh	17.2	16.2	17.6	sin_Sinh	13.2	18.6	14.7	sin_Sinh	15.2	21.6	17.6
tam_Taml	76.5	17.2	64.7	tam_Taml	75.0	17.2	71.1	tam_Taml	74.5	23.5	64.7
tel_Telu	62.3	15.7	53.4	tel_Telu	67.2	22.1	58.3	tel_Telu	66.2	25.0	53.4
tzm_Tfng	14.2	16.2	13.7	tzm_Tfng	14.2	16.7	12.3	tzm_Tfng	15.2	24.0	13.7
bod_Tibt	19.1	14.7	14.7	bod_Tibt	13.2	17.2	15.7	bod_Tibt	21.6	25.0	14.7
dzo_Tibt	17.2	19.1	14.2	dzo_Tibt	13.2	16.2	9.3	dzo_Tibt	14.2	18.1	14.2

Table 6: Accuracy of SIB200 task on BLOOM 560m, BLOOM 1B and BLOOM3B (from left to right).

Language	SCRIPT _(Orig)	SCRIPT _(Latn)	SCRIPT _(Combined)	Language	SCRIPT _(Orig)	SCRIPT _(Latn)	SCRIPT _(Combined)	Language	SCRIPT _(Orig)	SCRIPT _(Latn)	SCRIPT _(Combined)
ace_Arab	22.1	17.6	24.5	ace_Arab	17.6	11.8	19.6	ace_Arab	29.4	16.7	29.9
acm_Arab	79.9	10.3	81.4	acm_Arab	63.7	22.5	70.1	acm_Arab	77.0	22.5	73.0
acq_Arab	78.9	12.7	81.9	acq_Arab	62.3	15.2	67.2	acq_Arab	77.0	21.1	74.0
aeb_Arab	76.5	12.3	74.5	aeb_Arab	58.8	17.6	65.7	aeb_Arab	72.1	20.1	69.6
ajp_Arab	82.4	19.1	76.5	ajp_Arab	60.3	17.2	65.7	ajp_Arab	72.5	26.0	70.1
apc_Arab	79.9	17.6	81.9	apc_Arab	56.9	16.2	65.2	apc_Arab	75.5	24.0	73.5
ars_Arab	78.4	10.8	78.9	ars_Arab	61.3	15.2	71.1	ars_Arab	77.5	20.1	75.0
ary_Arab	77.0	13.2	77.5	ary_Arab	53.9	16.7	62.7	ary_Arab	75.0	19.6	71.1
azb_Arab	42.6	17.6	41.2	azb_Arab	29.9	17.2	43.1	azb_Arab	56.4	22.5	52.0
ckb_Arab	23.5	20.6	27.0	ckb_Arab	16.7	18.1	22.1	ckb_Arab	30.9	26.5	34.8
knc_Arab	24.5	21.1	20.1	knc_Arab	16.7	18.6	20.6	knc_Arab	23.0	24.5	25.0
pbt_Arab	56.9	30.9	50.5	pbt_Arab	25.5	22.5	29.9	pbt_Arab	54.9	32.8	50.5
pes_Arab	68.1	25.0	64.7	pes_Arab	53.4	21.1	64.7	pes_Arab	73.5	32.8	70.1
prs_Arab	66.7	21.1	62.3	prs_Arab	54.4	20.1	62.3	prs_Arab	73.5	32.8	67.6
uig_Arab	23.0	17.6	20.6	uig_Arab	17.2	17.2	22.1	uig_Arab	35.8	30.9	39.2
hye_Armn	20.1	31.4	28.4	hye_Armn	17.2	26.0	22.1	hye_Armn	40.2	40.2	44.1
asm_Beng	77.9	16.2	78.4	asm_Beng	26.0	25.5	38.2	asm_Beng	49.5	40.2	45.1
ben_Beng	75.0	17.6	80.4	ben_Beng	37.7	27.9	50.5	ben_Beng	62.7	38.2	54.4
bak_Cyrl	49.0	51.0	44.1	bak_Cyrl	41.7	42.2	46.1	bak_Cyrl	59.8	57.8	61.3
kaz_Cyrl	45.6	49.0	44.1	kaz_Cyrl	32.8	43.1	35.3	kaz_Cyrl	58.8	53.4	57.8
kir_Cyrl	45.6	48.5	44.6	kir_Cyrl	38.7	41.2	41.2	kir_Cyrl	63.7	56.4	62.3
mkd_Cyrl	45.1	49.0	48.5	mkd_Cyrl	64.7	59.8	66.2	mkd_Cyrl	76.0	68.1	76.0
rus_Cyrl	66.7	57.4	70.6	rus_Cyrl	73.5	66.2	77.5	rus_Cyrl	83.8	77.5	80.9
srp_Cyrl	43.1	51.5	49.0	srp_Cyrl	70.1	69.6	74.0	srp_Cyrl	83.3	80.9	82.4
tgk_Cyrl	33.3	40.2	35.8	tgk_Cyrl	25.0	31.9	28.9	tgk_Cyrl	49.5	52.0	49.5
ukr_Cyrl	52.5	50.0	53.9	ukr_Cyrl	74.0	55.4	75.5	ukr_Cyrl	80.4	71.6	81.4
awa_Deva	77.9	15.7	77.0	awa_Deva	52.0	34.8	62.3	awa_Deva	64.2	45.6	61.3
bho_Deva	76.0	17.2	75.5	bho_Deva	41.7	32.8	49.5	bho_Deva	59.3	45.6	57.4
hin_Deva	79.9	19.6	78.9	hin_Deva	52.9	41.7	62.3	hin_Deva	67.6	56.9	66.7
hne_Deva	75.5	17.2	74.5	hne_Deva	44.6	29.9	54.4	hne_Deva	60.8	42.2	61.3
kas_Deva	59.8	25.5	57.4	kas_Deva	31.4	24.0	36.8	kas_Deva	50.0	34.3	48.5
mag_Deva	77.9	15.2	78.9	mag_Deva	45.1	29.4	56.4	mag_Deva	59.3	42.6	55.9
mai_Deva	77.0	15.2	77.9	mai_Deva	45.1	34.8	56.9	mai_Deva	60.3	39.2	59.8
npi_Deva	78.4	22.1	79.4	npi_Deva	50.5	33.8	52.5	npi_Deva	62.7	49.5	55.9
san_Deva	70.1	16.7	64.7	san_Deva	39.2	33.8	46.1	san_Deva	52.0	46.1	50.5
amh_Ethi	17.2	18.6	14.7	amh_Ethi	14.7	17.6	16.2	amh_Ethi	21.6	27.5	25.0
tir_Ethi	18.1	19.6	14.7	tir_Ethi	14.7	16.7	15.7	tir_Ethi	21.1	23.0	23.5
kat_Geor	25.0	46.6	35.3	kat_Geor	23.5	39.7	28.9	kat_Geor	49.5	52.0	56.9
ell_Grek	32.8	49.5	31.4	ell_Grek	53.9	39.7	63.2	ell_Grek	74.0	60.8	69.6
pan_Guru	78.9	10.8	79.4	pan_Guru	16.7	19.1	20.6	pan_Guru	27.5	31.9	27.0
zho_Hans	80.9	21.6	83.8	zho_Hans	72.1	15.7	78.4	zho_Hans	81.4	31.4	80.9
yue_Hant	78.9	16.2	81.4	yue_Hant	70.1	14.7	76.0	yue_Hant	77.5	24.5	78.4
zho_Hant	82.8	14.7	83.8	zho_Hant	72.5	11.8	76.0	zho_Hant	80.4	27.9	81.4
heb_Hebr	27.5	20.1	23.0	heb_Hebr	40.7	13.2	47.5	heb_Hebr	65.2	16.2	60.8
ydd_Hebr	23.0	23.0	21.6	ydd_Hebr	20.6	18.6	24.5	ydd_Hebr	32.8	23.0	28.4
jpn_Jpan	78.9	17.6	77.5	jpn_Jpan	66.7	14.7	76.5	jpn_Jpan	81.4	25.0	77.5
khm_Khmr	38.7	37.3	33.3	khm_Khmr	23.0	23.5	24.0	khm_Khmr	42.2	32.8	39.2
kan_Knda	74.5	20.6	77.5	kan_Knda	21.1	26.0	25.0	kan_Knda	41.7	38.2	42.2
lao_Lao	33.8	43.1	30.4	lao_Lao	20.6	26.0	25.0	lao_Lao	36.3	32.8	34.8
mal_Mlym	76.5	16.7	80.9	mal_Mlym	19.6	20.1	24.5	mal_Mlym	28.4	32.4	27.0
mya_Mymr	18.6	25.0	17.6	mya_Mymr	20.1	19.1	18.6	mya_Mymr	27.9	22.1	24.0
shn_Mymr	31.9	39.2	29.4	shn_Mymr	32.4	31.4	27.9	shn_Mymr	35.3	39.2	38.7
nqo_Nkoo	15.7	15.7	12.3	nqo_Nkoo	16.7	14.2	16.7	nqo_Nkoo	15.2	18.6	17.2
sat_Olck	15.2	20.6	12.7	sat_Olck	14.7	13.2	17.2	sat_Olck	9.8	13.2	11.3
ory_Orya	78.4	19.1	77.0	ory_Orya	17.2	26.0	20.6	ory_Orya	22.1	44.1	30.9
sin_Sinh	18.6	15.7	15.7	sin_Sinh	18.1	26.0	23.5	sin_Sinh	26.5	35.8	28.4
tam_Taml	77.9	16.2	77.9	tam_Taml	20.1	14.7	33.8	tam_Taml	37.3	23.0	32.8
tel_Telu	75.0	20.6	76.5	tel_Telu	18.1	27.5	23.0	tel_Telu	30.9	45.6	37.7
tzm_Tfng	20.6	16.2	16.7	tzm_Tfng	13.7	14.2	16.2	tzm_Tfng	15.7	18.6	19.1
bod_Tibt	20.1	15.7	19.1	bod_Tibt	16.2	18.1	16.7	bod_Tibt	22.5	17.2	23.0
dzo_Tibt	15.7	12.7	16.7	dzo_Tibt	15.2	16.2	15.7	dzo_Tibt	20.6	14.7	19.1

Table 7: Accuracy of SIB200 task on BLOOM 7B, LLaMA2-7B and Mistral 7B (from left to right)

Language	SCRIPT _{Orig}	SCRIPT _{Latn}	SCRIPT _{Combined}	Language	SCRIPT _{Orig}	SCRIPT _{Latn}	SCRIPT _{Combined}	Language	SCRIPT _{Orig}	SCRIPT _{Latn}	SCRIPT _{Combined}
arb_Arab	45.9	45.9	46.8	arb_Arab	53.2	54.1	53.2	arb_Arab	49.5	46.8	55.0
ary_Arab	34.2	41.4	36.9	ary_Arab	43.2	45.0	45.9	ary_Arab	36.0	35.1	44.1
arz_Arab	35.1	35.1	36.9	arz_Arab	44.1	45.9	45.9	arz_Arab	40.5	36.9	41.4
azb_Arab	43.2	42.3	39.6	azb_Arab	46.8	50.5	48.6	azb_Arab	41.4	41.4	43.2
ckb_Arab	45.0	46.8	47.7	ckb_Arab	46.8	48.6	48.6	ckb_Arab	43.2	44.1	43.2
fas_Arab	53.2	49.5	53.2	fas_Arab	53.2	55.0	55.0	fas_Arab	49.5	49.5	49.5
pes_Arab	53.6	46.4	55.5	pes_Arab	50.0	51.8	55.5	pes_Arab	49.1	48.2	50.0
prs_Arab	56.8	54.1	55.9	prs_Arab	60.4	59.5	59.5	prs_Arab	56.8	53.2	57.7
snd_Arab	54.1	53.2	53.2	snd_Arab	55.9	54.1	55.9	snd_Arab	48.6	49.5	49.5
hye_Armn	45.9	47.7	45.9	hye_Armn	52.3	58.6	53.2	hye_Armn	52.3	52.3	55.9
asm_Beng	36.0	37.8	36.9	asm_Beng	45.0	36.9	38.7	asm_Beng	48.6	36.0	46.8
ben_Beng	40.5	37.8	40.5	ben_Beng	47.7	45.0	43.2	ben_Beng	47.7	42.3	45.0
alt_Cyrl	48.6	48.6	45.9	alt_Cyrl	53.2	52.3	46.8	alt_Cyrl	47.7	46.8	45.9
bak_Cyrl	45.0	45.0	43.2	bak_Cyrl	51.4	55.9	51.4	bak_Cyrl	46.8	51.4	46.8
bel_Cyrl	45.9	43.2	45.0	bel_Cyrl	51.4	55.0	52.3	bel_Cyrl	45.0	45.9	45.0
bul_Cyrl	41.4	36.9	37.8	bul_Cyrl	44.1	42.3	41.4	bul_Cyrl	46.8	44.1	44.1
che_Cyrl	36.0	36.0	36.0	che_Cyrl	40.5	44.1	41.4	che_Cyrl	33.3	34.2	35.1
chv_Cyrl	46.8	48.6	47.7	chv_Cyrl	50.5	52.3	51.4	chv_Cyrl	42.3	41.4	45.9
crh_Cyrl	47.7	48.6	46.8	crh_Cyrl	48.6	47.7	49.5	crh_Cyrl	51.4	45.9	48.6
kaz_Cyrl	45.0	44.1	48.6	kaz_Cyrl	50.5	52.3	46.8	kaz_Cyrl	55.0	53.2	52.3
kir_Cyrl	62.2	61.3	59.5	kir_Cyrl	62.2	64.0	63.1	kir_Cyrl	56.8	59.5	58.6
kjh_Cyrl	42.3	44.1	44.1	kjh_Cyrl	49.5	50.5	49.5	kjh_Cyrl	42.3	47.7	45.0
kmr_Cyrl	38.7	37.8	38.7	kmr_Cyrl	44.1	45.0	45.0	kmr_Cyrl	43.2	43.2	39.6
krc_Cyrl	45.0	41.4	42.3	krc_Cyrl	49.5	55.9	51.4	krc_Cyrl	45.9	45.9	45.0
mhr_Cyrl	48.2	50.9	51.8	mhr_Cyrl	50.0	49.1	44.5	mhr_Cyrl	50.9	44.5	49.1
mkd_Cyrl	54.1	57.7	55.9	mkd_Cyrl	61.3	61.3	57.7	mkd_Cyrl	56.8	53.2	55.0
myv_Cyrl	36.0	38.7	38.7	myv_Cyrl	46.8	44.1	46.8	myv_Cyrl	45.0	45.0	40.5
oss_Cyrl	47.7	48.6	48.6	oss_Cyrl	52.3	53.2	52.3	oss_Cyrl	46.8	48.6	47.7
rus_Cyrl	43.2	44.1	45.9	rus_Cyrl	46.8	48.6	48.6	rus_Cyrl	45.0	45.0	42.3
sah_Cyrl	48.6	49.5	48.6	sah_Cyrl	48.6	56.8	53.2	sah_Cyrl	45.9	46.8	50.5
tat_Cyrl	43.2	45.0	43.2	tat_Cyrl	53.2	49.5	51.4	tat_Cyrl	47.7	47.7	50.5
tgk_Cyrl	45.9	48.6	44.1	tgk_Cyrl	54.1	50.5	50.5	tgk_Cyrl	47.7	47.7	46.8
tyv_Cyrl	36.0	39.6	39.6	tyv_Cyrl	45.0	47.7	45.0	tyv_Cyrl	47.7	45.9	43.2
udm_Cyrl	42.3	44.1	43.2	udm_Cyrl	45.0	43.2	48.6	udm_Cyrl	43.2	44.1	41.4
ukr_Cyrl	50.5	49.5	50.5	ukr_Cyrl	49.5	55.9	53.2	ukr_Cyrl	48.6	50.5	48.6
uzn_Cyrl	43.2	46.8	43.2	uzn_Cyrl	48.6	49.5	50.5	uzn_Cyrl	43.2	50.5	41.4
hin_Deva	55.0	45.9	51.4	hin_Deva	47.7	47.7	50.5	hin_Deva	46.8	50.5	47.7
hne_Deva	55.9	55.0	52.3	hne_Deva	61.3	58.6	58.6	hne_Deva	57.7	55.9	55.9
mai_Deva	45.0	45.0	44.1	mai_Deva	52.3	55.0	53.2	mai_Deva	49.5	45.9	51.4
mar_Deva	49.5	44.1	48.6	mar_Deva	48.6	49.5	51.4	mar_Deva	49.5	42.3	48.6
nep_Deva	51.4	45.9	50.5	nep_Deva	57.7	55.9	58.6	nep_Deva	54.1	45.9	48.6
npi_Deva	55.9	50.5	55.9	npi_Deva	55.0	54.1	57.7	npi_Deva	59.5	49.5	52.3
suz_Deva	42.3	45.0	42.3	suz_Deva	47.7	46.8	49.5	suz_Deva	45.0	47.7	47.7
mdy_Ethi	46.8	48.6	47.7	mdy_Ethi	45.9	49.5	47.7	mdy_Ethi	45.0	45.9	42.3
tir_Ethi	37.8	35.1	38.7	tir_Ethi	41.4	42.3	38.7	tir_Ethi	31.5	34.2	28.8
kat_Geor	43.2	42.3	45.0	kat_Geor	45.0	50.5	46.8	kat_Geor	43.2	45.9	49.5
ell_Grek	44.1	44.1	45.0	ell_Grek	48.6	52.3	46.8	ell_Grek	49.5	48.6	45.9
guj_Gujr	45.9	45.9	45.0	guj_Gujr	47.7	55.9	52.3	guj_Gujr	51.4	44.1	49.5
pan_Guru	44.1	40.5	45.0	pan_Guru	46.8	42.3	44.1	pan_Guru	46.8	41.4	45.9
kor_Hang	48.6	49.5	49.5	kor_Hang	51.4	55.9	53.2	kor_Hang	52.3	56.8	53.2
cmn_Hani	44.1	40.5	49.5	cmn_Hani	54.1	49.5	54.1	cmn_Hani	54.1	43.2	55.0
lzh_Hani	51.4	55.9	53.2	lzh_Hani	55.9	48.6	56.8	lzh_Hani	53.2	49.5	56.8
yue_Hani	45.9	43.2	52.3	yue_Hani	54.1	41.4	51.4	yue_Hani	53.2	48.6	52.3
khm_Khmr	52.3	55.9	54.1	khm_Khmr	55.9	56.8	59.5	khm_Khmr	52.3	53.2	52.3
lao_Lao	47.7	51.4	49.5	lao_Lao	51.4	48.6	53.2	lao_Lao	56.8	56.8	56.8
ksw_Mymr	39.6	40.5	37.8	ksw_Mymr	49.5	43.2	39.6	ksw_Mymr	42.3	40.5	40.5
mya_Mymr	51.4	47.7	48.6	mya_Mymr	53.2	50.5	51.4	mya_Mymr	41.4	41.4	43.2
ori_Orya	51.4	51.4	47.7	ori_Orya	55.9	51.4	49.5	ori_Orya	54.1	45.0	52.3
ory_Orya	53.2	49.5	52.3	ory_Orya	51.4	49.5	55.9	ory_Orya	59.5	52.3	58.6
sin_Sinh	41.4	43.2	45.0	sin_Sinh	46.8	54.1	45.0	sin_Sinh	42.3	45.0	44.1
tam_Taml	55.0	56.8	55.9	tam_Taml	55.0	54.1	61.3	tam_Taml	60.4	55.0	57.7
tel_Telu	38.7	36.0	41.4	tel_Telu	52.3	46.8	48.6	tel_Telu	51.4	41.4	49.5
tha_Thai	45.0	45.0	45.9	tha_Thai	46.8	46.8	48.6	tha_Thai	41.4	39.6	42.3
dzo_Tibt	42.3	41.4	45.9	dzo_Tibt	41.4	40.5	44.1	dzo_Tibt	43.2	43.2	39.6

Table 8: Accuracy of Taxi1500 task on BLOOM 560m, BLOOM 1B and BLOOM3B (from left to right).

Language	SCRIPT _{Orig}	SCRIPT _{Latn}	SCRIPT _{Combined}	Language	SCRIPT _{Orig}	SCRIPT _{Latn}	SCRIPT _{Combined}	Language	SCRIPT _{Orig}	SCRIPT _{Latn}	SCRIPT _{Combined}
arb_Arab	49.5	45.9	51.4	arb_Arab	43.2	45.9	45.9	arb_Arab	62.2	48.6	61.3
ary_Arab	38.7	30.6	38.7	ary_Arab	32.4	35.1	29.7	ary_Arab	55.9	38.7	50.5
arz_Arab	45.0	35.1	41.4	arz_Arab	31.5	39.6	34.2	arz_Arab	54.1	47.7	58.6
azb_Arab	47.7	43.2	48.6	azb_Arab	39.6	42.3	42.3	azb_Arab	51.4	42.3	55.9
ckb_Arab	45.0	47.7	42.3	ckb_Arab	44.1	45.0	42.3	ckb_Arab	47.7	44.1	46.8
fas_Arab	57.7	51.4	49.5	fas_Arab	49.5	50.5	53.2	fas_Arab	66.7	46.8	63.1
pes_Arab	59.1	51.8	56.4	pes_Arab	50.9	49.1	56.4	pes_Arab	64.5	49.1	62.7
prs_Arab	55.9	55.9	52.3	prs_Arab	50.5	55.0	55.9	prs_Arab	65.8	59.5	64.0
snd_Arab	56.8	50.5	52.3	snd_Arab	44.1	46.8	45.0	snd_Arab	62.2	51.4	62.2
hye_Armn	45.9	46.8	45.9	hye_Armn	45.9	50.5	53.2	hye_Armn	55.0	53.2	53.2
asm_Beng	55.0	43.2	55.9	asm_Beng	45.9	44.1	49.5	asm_Beng	55.9	50.5	53.2
ben_Beng	52.3	45.0	52.3	ben_Beng	40.5	45.9	45.0	ben_Beng	57.7	48.6	56.8
alt_Cyrl	45.0	46.8	44.1	alt_Cyrl	44.1	43.2	48.6	alt_Cyrl	45.9	48.6	45.9
bak_Cyrl	49.5	49.5	50.5	bak_Cyrl	45.0	47.7	46.8	bak_Cyrl	48.6	52.3	47.7
bel_Cyrl	48.6	39.6	45.9	bel_Cyrl	47.7	44.1	42.3	bel_Cyrl	55.9	58.6	58.6
bul_Cyrl	48.6	45.0	43.2	bul_Cyrl	45.0	45.0	44.1	bul_Cyrl	61.3	57.7	64.0
che_Cyrl	36.9	36.9	35.1	che_Cyrl	37.8	42.3	41.4	che_Cyrl	42.3	36.9	40.5
chv_Cyrl	45.0	45.9	45.0	chv_Cyrl	43.2	43.2	44.1	chv_Cyrl	45.0	50.5	51.4
crh_Cyrl	47.7	49.5	51.4	crh_Cyrl	49.5	47.7	49.5	crh_Cyrl	56.8	59.5	55.9
kaz_Cyrl	51.4	50.5	48.6	kaz_Cyrl	49.5	53.2	47.7	kaz_Cyrl	55.0	53.2	51.4
kir_Cyrl	47.7	53.2	46.8	kir_Cyrl	51.4	53.2	56.8	kir_Cyrl	53.2	57.7	60.4
kjh_Cyrl	45.0	43.2	41.4	kjh_Cyrl	44.1	42.3	43.2	kjh_Cyrl	47.7	49.5	51.4
kmr_Cyrl	45.0	46.8	40.5	kmr_Cyrl	39.6	40.5	38.7	kmr_Cyrl	39.6	41.4	39.6
krc_Cyrl	48.6	47.7	49.5	krc_Cyrl	45.9	44.1	45.0	krc_Cyrl	55.0	52.3	50.5
mhr_Cyrl	45.5	45.5	46.4	mhr_Cyrl	47.3	51.8	50.0	mhr_Cyrl	45.5	46.4	50.0
mkd_Cyrl	56.8	55.0	55.9	mkd_Cyrl	52.3	51.4	53.2	mkd_Cyrl	66.7	72.1	67.6
myv_Cyrl	40.5	44.1	38.7	myv_Cyrl	39.6	36.9	41.4	myv_Cyrl	45.0	47.7	45.9
oss_Cyrl	49.5	45.9	45.0	oss_Cyrl	49.5	45.9	48.6	oss_Cyrl	47.7	49.5	45.0
rus_Cyrl	50.5	52.3	50.5	rus_Cyrl	49.5	47.7	48.6	rus_Cyrl	57.7	64.9	64.0
sah_Cyrl	44.1	43.2	40.5	sah_Cyrl	40.5	41.4	41.4	sah_Cyrl	45.9	44.1	47.7
tat_Cyrl	45.9	46.8	45.9	tat_Cyrl	47.7	50.5	47.7	tat_Cyrl	53.2	47.7	51.4
tgk_Cyrl	48.6	49.5	48.6	tgk_Cyrl	42.3	44.1	46.8	tgk_Cyrl	55.9	58.6	54.1
tyv_Cyrl	43.2	44.1	45.9	tyv_Cyrl	38.7	45.0	43.2	tyv_Cyrl	47.7	46.8	46.8
udm_Cyrl	42.3	45.0	41.4	udm_Cyrl	36.9	40.5	38.7	udm_Cyrl	41.4	47.7	43.2
ukr_Cyrl	51.4	49.5	48.6	ukr_Cyrl	52.3	50.5	48.6	ukr_Cyrl	63.1	64.0	62.2
uzn_Cyrl	45.0	51.4	42.3	uzn_Cyrl	45.9	43.2	44.1	uzn_Cyrl	59.5	55.9	55.9
hin_Deva	49.5	44.1	50.5	hin_Deva	51.4	53.2	54.1	hin_Deva	64.9	59.5	64.0
hne_Deva	54.1	52.3	56.8	hne_Deva	55.9	56.8	55.0	hne_Deva	61.3	57.7	61.3
mai_Deva	49.5	46.8	48.6	mai_Deva	45.0	51.4	47.7	mai_Deva	62.2	51.4	58.6
mar_Deva	53.2	40.5	53.2	mar_Deva	49.5	51.4	51.4	mar_Deva	55.9	54.1	59.5
nep_Deva	63.1	49.5	57.7	nep_Deva	45.0	45.9	46.8	nep_Deva	66.7	61.3	64.9
npi_Deva	55.9	49.5	62.2	npi_Deva	51.4	50.5	51.4	npi_Deva	66.7	60.4	65.8
suz_Deva	42.3	42.3	41.4	suz_Deva	46.8	48.6	44.1	suz_Deva	43.2	49.5	48.6
mdy_Ethi	43.2	38.7	42.3	mdy_Ethi	39.6	45.9	44.1	mdy_Ethi	55.0	52.3	57.7
tir_Ethi	27.9	31.5	30.6	tir_Ethi	29.7	36.9	36.9	tir_Ethi	39.6	29.7	36.0
kat_Geor	42.3	41.4	41.4	kat_Geor	41.4	44.1	41.4	kat_Geor	45.0	46.8	45.9
ell_Grek	49.5	43.2	43.2	ell_Grek	49.5	43.2	52.3	ell_Grek	57.7	62.2	59.5
guj_Gujr	52.3	45.0	52.3	guj_Gujr	45.9	43.2	49.5	guj_Gujr	52.3	55.9	55.0
pan_Guru	46.8	39.6	48.6	pan_Guru	41.4	45.0	47.7	pan_Guru	45.9	50.5	49.5
kor_Hang	49.5	48.6	51.4	kor_Hang	48.6	50.5	55.9	kor_Hang	72.1	50.5	69.4
cmn_Hani	53.2	45.0	50.5	cmn_Hani	48.6	45.0	48.6	cmn_Hani	61.3	50.5	64.0
lzh_Hani	54.1	45.0	52.3	lzh_Hani	55.0	48.6	52.3	lzh_Hani	65.8	51.4	59.5
yue_Hani	53.2	45.0	50.5	yue_Hani	43.2	52.3	53.2	yue_Hani	63.1	48.6	65.8
khn_Khmr	48.6	47.7	54.1	khn_Khmr	52.3	53.2	53.2	khn_Khmr	55.9	50.5	53.2
lao_Lao	46.8	49.5	46.8	lao_Lao	45.0	49.5	51.4	lao_Lao	45.0	46.8	46.8
ksw_Mymr	42.3	40.5	40.5	ksw_Mymr	44.1	47.7	45.0	ksw_Mymr	44.1	48.6	49.5
mya_Mymr	44.1	47.7	43.2	mya_Mymr	45.0	51.4	47.7	mya_Mymr	51.4	45.9	49.5
ori_Orya	51.4	46.8	50.5	ori_Orya	43.2	43.2	44.1	ori_Orya	50.5	58.6	47.7
ory_Orya	49.5	47.7	54.1	ory_Orya	44.1	48.6	52.3	ory_Orya	57.7	55.0	57.7
sin_Sinh	39.6	41.4	40.5	sin_Sinh	39.6	52.3	38.7	sin_Sinh	37.8	49.5	45.0
tam_Taml	50.5	51.4	58.6	tam_Taml	44.1	49.5	45.9	tam_Taml	60.4	50.5	55.9
tel_Telu	59.5	40.5	53.2	tel_Telu	33.3	43.2	36.9	tel_Telu	54.1	41.4	52.3
tha_Thai	43.2	43.2	39.6	tha_Thai	43.2	40.5	39.6	tha_Thai	57.7	43.2	52.3
dzo_Tibt	41.4	44.1	41.4	dzo_Tibt	45.0	49.5	47.7	dzo_Tibt	45.0	44.1	43.2

Table 9: Accuracy of Taxi1500 task on BLOOM 7B, LLaMA2-7B and Mistral 7B (from left to right).

Type and Complexity Signals in Multilingual Question Representations

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Abstract

This work investigates how a multilingual transformer model represents morphosyntactic properties of questions. We introduce the Question Type and Complexity (QTC) dataset with sentences across seven languages, annotated with type information and complexity metrics including dependency length, tree depth, and lexical density. Our evaluation extends probing methods to regression labels with selectivity controls to quantify gains in generalizability. We compare layer-wise probes on frozen Glot500-m (Imani et al., 2023) representations against subword TF-IDF baselines, and a fine-tuned model. Results show that statistical features classify questions effectively in languages with explicit marking, while neural probes capture fine-grained structural complexity patterns better. We use these results to evaluate when contextual representations outperform statistical baselines and whether parameter updates reduce availability of pre-trained linguistic information.

1 Introduction

Multilingual contextual embeddings show promise for accessing fine-grained morphosyntactic properties across hundreds of languages. Probing how transformer models encode certain linguistic properties has practical implications for language typology research, where systematic comparison of structural features often relies on automated analysis. Additionally, evaluations targeting specific linguistic phenomena can test common architectural assumptions about transformer models. Examples include the often discussed layer-wise specialization from syntactic to semantic processing (Tenney et al., 2019a) and the ability of shared embedding spaces to effectively capture cross-linguistic patterns.

Researchers rely on these assumptions in order to describe the internals of the models when testing on benchmarks (Conneau et al., 2020; Şahin

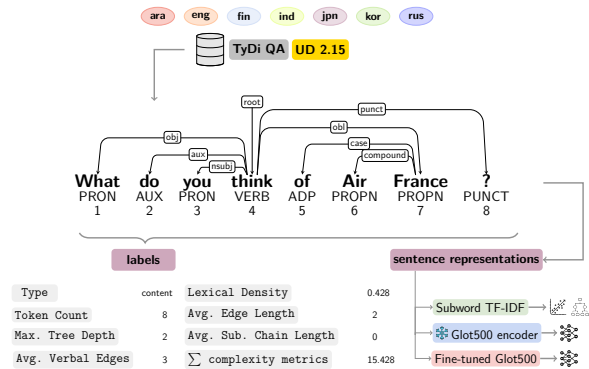


Figure 1: Experimental pipeline from multilingual datasets: TyDi QA (Clark et al., 2020), UD 2.15 (Zeman et al., 2024), through annotation of question types and complexity metrics to extraction of three representation types used for model training.

et al., 2020), but also when evaluating their general linguistic capabilities outside of specific tasks (Brunato et al., 2020). However, comparisons with appropriate baselines are often left out. Without those, we cannot determine whether observed linguistic capabilities reflect genuine structural processing or are the result of patterns that simpler statistical methods capture equally well.

This presents a challenge when investigating universal sentence-level phenomena where the relationship between surface form and underlying structure varies extensively (Tenney et al., 2019b; Ravishankar et al., 2019). We focus specifically on *interrogative sentences*, which illustrate this variation particularly well. For example, Arabic uses explicit particles like “هل” for polar (yes/no) questions and overt subordinating conjunctions for complex clauses. Alternatively, Japanese relies on contextual cues for question interpretation and implicit hierarchical embedding through case-marking for structural complexity. The differences in how languages encode both categorical distinctions and continuous complexity metrics create a natural setup for evaluating whether contextual rep-

representations capture structural patterns better than surface-level statistical correlations obtained by, for example, TF-IDF features.

We explore this question through controlled comparisons of neural representations with statistical baselines across seven typologically diverse languages. Our framework extends probing methods to continuous linguistic properties, including token count, lexical density, dependency length, tree depth, verbal arity, and subordination patterns. [Figure 1](#) illustrates our method: we start with existing multilingual datasets, process and annotate these for categorical (interrogative types) and continuous labels, and we finally evaluate three representation types (subword TF-IDF features, contextual embeddings, and a fine-tuned model) using our annotated data in Arabic, English, Finnish, Indonesian, Japanese, Korean, and Russian.

We present three key findings:

- Contextual embeddings outperform statistical baselines for question type classification, particularly in languages requiring contextual integration (Japanese, Korean, English, Finnish).
- Regression performance varies significantly across metrics, with distinct layer-wise profiles emerging for different structural properties.
- Fine-tuning compensates for unstable neural encoding patterns but degrades performance on metrics with stable layer-wise representations, revealing a trade-off between adaptation and preservation of pre-trained linguistic knowledge.

These results provide practical guidance for model selection based on typological properties and suggest that frozen representations may be preferable for certain analytical tasks. Additionally, our regression-based probing framework with selectivity controls opens new avenues for investigating continuous linguistic properties in neural representations.

2 Related Work

Probing methods assess what linguistic knowledge is encoded in neural representations by training classifiers to predict specific properties in word embeddings ([Adi et al., 2017](#); [Conneau et al., 2018](#)). Early work demonstrated that contextualized and static representations encode syntactic information like part-of-speech categories, dependency rela-

tions, and word order variation ([Köhn, 2015](#); [Shi et al., 2016](#)).

Most probing studies focus on token-level properties, with fewer approaches looking at variation in sentence-level regularities. [Şahin et al. \(2020\)](#); [Waldis et al. \(2024\)](#) introduce comprehensive evaluation frameworks for sentence level probing tasks. These reveal how models encode structural linguistic properties such as morphological case marking, agreement patterns, and syntactic hierarchies, as well as functional properties including semantic roles, discourse relations, and pragmatic features. Question type classification represents a natural extension of this work, as it requires models to integrate both formal markers (interrogative particles, auxiliary inversion) and functional understanding (information-seeking intent, presupposition structure).

Two assumptions motivate current probing approaches. First, the layer-wise specialization hypothesis suggests lower layers encode syntax while higher layers capture semantics ([Tenney et al., 2019a](#)). This informs decisions about which layers to probe for different linguistic tasks. Second, multilingual models develop shared embedding spaces that capture cross-linguistic patterns ([Conneau et al., 2020](#)), enabling efficient transfer across languages.

Probes mainly target categorical properties through classification tasks ([Tenney et al., 2019b](#); [Jawahar et al., 2019](#)). However, [Pimentel et al. \(2020\)](#) argue that complex linguistic phenomena require more sophisticated probing architectures that can approximate a wider range of information content. Regression-based probing is a simple approach that investigates linguistic properties like syntactic complexity, processing difficulty, and structural density. Complexity measures derived through dependency parsing allow us to generate target labels that reveal how models encode syntactic structure along continuous and discrete dimensions. We investigate these to assess how accessible structural features are from learned embeddings.

Determining whether probes capture genuine structural encoding requires appropriate baselines. [Hewitt and Liang \(2019\)](#) introduced selectivity controls comparing performance on real versus shuffled labels to distinguish linguistic encoding from spurious correlations. Most studies, however, evaluate neural representations without statistical baselines, making it difficult to assess whether contextual embeddings offer genuine advantages over

Language	#	% Polar	% Content	Avg. Score
Arabic	1,116	48.3	51.7	0.42
English	1,374	50.0	50.0	0.38
Finnish	1,368	49.9	50.1	0.34
Indonesian	1,136	48.2	51.8	0.39
Japanese	1,329	50.8	49.2	0.41
Korean	921	46.9	53.1	0.39
Russian	1,376	50.0	50.0	0.41
Total	8,620	50.6	49.4	0.39

Table 1: QTC dataset statistics by language. # shows total annotated sentences per language. Polar/Content percentages reflect question type distribution. Average Complexity represents normalized composite scores of individual complexity metrics (see Appendix A for details).

frequency-based methods.

Similarly, while probing typically uses frozen representations extracted from a specific layer of the encoder, the relationship between pre-trained knowledge and task-specific optimization remains underexplored. Understanding when end-to-end optimization preserves or degrades pre-trained linguistic knowledge requires direct comparison of frozen probes and fine-tuned models, particularly for structural properties that may be disrupted by task-specific adaptation.

3 Dataset

We introduce the Question Type and Complexity (QTC) dataset containing $\sim 9,000$ annotated questions across seven languages: Arabic, English, Finnish, Indonesian, Japanese, Korean, and Russian. QTC combines TyDiQA-GoldP training data (Clark et al., 2020) with Universal Dependency treebank test data (Nivre et al., 2020; Zeman et al., 2024) to balance natural language variation with standardized syntactic annotation, with approximately 70% of sentences drawn from TyDiQA and 30% from UD treebanks. The choice of languages was informed by different question formation strategies. Languages using explicit interrogative marking include Arabic with “هل”, Finnish with suffix “-ko/-kö”, and Russian with particle “ли”. Languages using implicit strategies like context or prosody include Japanese, Indonesian, and Korean. Lastly, auxiliary inversion in English can be seen as a mixed strategy.

Categorical and continuous labels were created using parallel annotation pipelines. For question type classification, TyDiQA data already contained human annotations from three independent annotators. We adopted annotations where all three an-

notators agreed and manually resolved disagreements. UD treebank sentences were annotated for question type using language-specific rule-based systems targeting morphosyntactic patterns: interrogative particles, wh-phrase positioning, and auxiliary structures. We label polar questions as ‘1’ and content questions as ‘0’.

For complexity metrics, we used UDPipe 2.0 (Straka, 2018) to parse all sentences, then applied the Profiling-UD framework (Brunato et al., 2020) to extract six raw complexity features capturing processing difficulty (see Appendix A for details). We validated complexity metrics through statistical outlier detection and (partial) manual verification of parse quality.¹

4 Probing Tasks

4.1 Question Type Classification

Classifying questions as polar (yes-no) or content (wh-) is an interesting test case for comparing neural representations against statistical baselines. As mentioned, languages with explicit marking strategies use dedicated particles or consistent transformations, like English auxiliary inversion (Dryer, 2013a). This makes classes identifiable through surface patterns that frequency features can capture.

Languages with implicit strategies prove challenging because they rely on context and prosody. Japanese polar questions like “Ashita kimasu ka?” [Tomorrow come-polite Q] and content questions “Itsu kimasu ka?” [When come-polite Q] have identical sentence-final particles, differing only in the presence of wh-words that often appear in non-initial positions (Dryer, 2013b). This variation allows us to test when contextual embeddings provide genuine advantages over frequency-based approaches for capturing structural patterns that go beyond readily available surface cues.

4.2 Linguistic Complexity Prediction

In addition to question type classification, we also use *continuous* labels and predict complexity scores derived from morphosyntactic properties. This operationalizes the idea that structural density increases processing difficulty (Hawkins, 2007). We formulate this as a regression task, targeting six normalized complexity metrics: token count, lexical

¹The QTC dataset and code are available at hf.co/rokot/question-type-and-complexity and github.com/rokot/qtype-eval.

density, average dependency length, maximum tree depth, verbal arity, and subordinate chain length. This tests whether different representations capture quantitative aspects of linguistic structure. We also evaluate performance on a combined complexity score calculated as the normalized sum of all six individual metrics, providing an abstract measure of structural density.

Statistical models can effectively capture surface-level complexity indicators. Token count correlates with question length from simple “Who left?” to complex “What did the committee decide about the proposal?”, while subordination patterns manifest through explicit conjunctions that TF-IDF features can detect. However, hierarchical syntactic properties present greater challenges. A question like “Who ate the cake that Alice brought?” shares the same interrogative markers as the simple example, but involves multiple dependency levels and clauses that increase syntactic complexity.

Unlike categorical properties typically studied in probing, continuous dimensions allow us to isolate aspects of linguistic structure most effectively captured by different representation approaches. This allows us to test competing hypotheses about how neural and statistical models encode structural information. If contextual representations truly capture abstract syntactic hierarchies, they should outperform frequency-based methods on metrics like tree depth and subordination complexity, which require understanding of long-distance dependencies and recursive structures. Conversely, if neural advantages primarily reflect sophisticated pattern matching, we expect statistical baselines to remain competitive across all complexity dimensions.

4.3 Experimental Setup

Our setup addresses the core methodological challenge of distinguishing genuine linguistic encoding from pattern memorization when comparing neural and statistical approaches. Following [Hewitt and Liang \(2019\)](#), we create three shuffled-label control variants per task that preserve label distributions while destroying text-label relationships. We define selectivity as normalized performance differences:

$$\begin{aligned} S_{cls} &= \frac{\text{acc}_{\text{real}} - \text{acc}_{\text{control}}}{\text{acc}_{\text{control}}} \\ S_{reg} &= \frac{\text{mse}_{\text{control}} - \text{mse}_{\text{real}}}{\text{mse}_{\text{control}}} \end{aligned} \quad (1)$$

with (acc)uracy for the classification task and

mean squared error (mse) for regression task.

This approach enables direct comparison of representational quality. Selectivity measures how much better a model performs when linguistic structure is present versus absent. Higher values (e.g., > 0.5) mean the model exploits “genuine” linguistic patterns, while low selectivity suggests the model performs similarly regardless of whether input-label relationships are meaningful or random. Strong selectivity shows when models capture information rather than surface correlations.

5 Experiments

The experiments were carried out on Glot500-m ([Imani et al., 2023](#)), a multilingual encoder-only transformer. Glot500-m was created by extending the XLM-R-base architecture ([Conneau et al., 2020](#)) using continued pre-training on a custom multilingual corpus and expanding the vocabulary from 250K to 401K tokens to cover 511 languages, including all seven languages in our dataset.

5.1 Subword TF-IDF Baselines

First, we establish baselines using linear and nonlinear predictors trained on TF-IDF features and corresponding sentence labels. We use the Glot-500-m tokenizer to generate TF-IDF representations for a fair comparison.

We establish baselines using linear models (logistic regression for classification, ridge regression for complexity prediction) and XGBoost ([Chen and Guestrin, 2016](#)) for nonlinear feature interactions. XGBoost provides an upper bound for statistical baseline performance while maintaining interpretability through feature importance scores. Dummy baselines using majority class and mean value prediction set floor performance.

5.2 Probes on Frozen Representations

We extract sentence-level embeddings from each of the 12 layers of the frozen encoder using mean pooling across token representations, resulting in a fixed-size 768-dimensional vector for each sentence. For every sentence embedding at every layer we train neural probes to predict the target label. This allows us to track where different kinds of linguistic information are most accessible to the probe.

We designed our probe architectures to capture complex patterns while maintaining training efficiency. Classification probes use two-layer MLPs

Language	TF-IDF Linear	\bar{S}	TF-IDF XGBoost	\bar{S}	Glott500 Best Probe	\bar{S}	Layer	Glott500 Fine-tuned
ara Arabic	90.9	0.92	97.4	0.83	85.7	0.20	2	74.1
eng English	83.6	0.55	80.9	0.56	97.3	0.95	5	91.8
fin Finnish	84.5	0.85	87.2	0.91	94.5	0.89	5	92.3
ind Indonesian	67.3	0.41	65.5	0.23	80.9	0.62	6	73.6
jpn Japanese	64.1	0.25	64.1	0.28	82.6	1.07	10	88.0
kor Korean	66.3	0.43	73.6	0.48	76.4	0.53	9	91.1
rus Russian	86.4	0.85	77.2	0.5	97.3	0.95	11	96.4

Table 2: Question type classification accuracy (%) and mean selectivity (\bar{S}) across approaches. Bold values indicate the highest accuracy and selectivity scores achieved for each language. Layer denotes the index of the encoder layer at which the probe achieved highest accuracy.

with 384 hidden units optimized using binary cross-entropy loss. Regression probes use three-layer MLPs with 128 hidden units and minimize the mean squared error loss. All probes are trained separately for each layer and task combination using 70/15/15 train/validation/test splits. While expressive enough to capture complex patterns, this setup ensures that performance differences reflect representational properties rather than probe capacity (Pimentel et al., 2020; Waldis et al., 2024).

5.3 Fine-tuned Model

To determine whether parameter updates preserve pre-trained linguistic information, we train the complete Glott500 model end-to-end on each task. The fine-tuned model uses identical task-specific heads as our probes but allows model updates (i.e., not frozen).

We employ two-layer MLPs with binary cross-entropy loss for classification and three-layer heads with MSE loss for regression.

This configuration enables direct comparison with frozen probes. If fine-tuning enhances linguistic representations, the updated model should consistently outperform probes across all metrics.

Conversely, degraded performance indicates that task-specific optimization disrupts structural knowledge encoded during pre-training.

We only report main task performance metrics for fine-tuned models because selectivity controls are less meaningful when the entire network adapts to the specific label distribution, potentially reflecting task-specific overfitting.

6 Results

Our statistical baselines employ logistic regression for classification and ridge regression for complexity prediction, with XGBoost capturing nonlinear feature interactions.

Results across the two tasks reveal trade-offs in the ability of our models to capture different kinds of linguistic information. For question type classification, neural probes consistently perform the best, with the majority of highest accuracy and selectivity scores. Regression results show more variety, with different representation types leading on different complexity metrics.

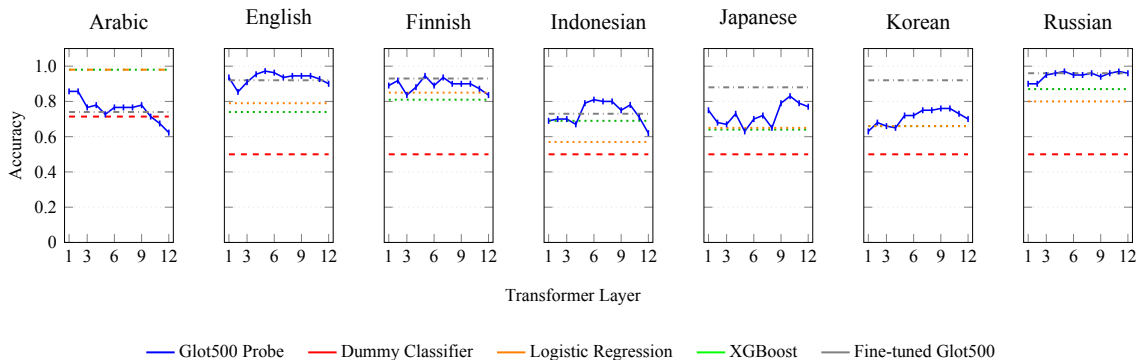


Figure 2: Question type classification across languages and methods. Probing results per layer of Glott500-m.





























Submetric	TF-IDF Ridge	\bar{S}	TF-IDF XGBoost	\bar{S}	Glott500 Best Probe	\bar{S}	Layer	Glott500 Fine-tuned
Token Count	0.042	0.46 	0.032	0.60 	0.004	0.68 	5	0.006 
Max. Tree Depth	0.013	0.60 	0.013	0.58 	0.002	0.57 	2	0.017 
Avg. Dependency Length	0.007	0.36 	0.007	0.73 	0.013	0.29 	4	0.002 
Avg. Subordinate Chain Length	0.015	0.52 	0.055	0.29 	0.053	0.47 	6	0.019 
Avg. Verbal Edges	0.042	0.35 	0.066	0.32 	0.070	0.40 	6	0.030 
Lexical Density	0.033	0.48 	0.082	0.27 	0.036	0.21 	3	0.023 
Combined Complexity	0.032	0.48 	0.017	0.60 	0.016	0.78 	4	0.020 

Table 3: Complexity submetric regression errors (mse) and mean selectivity (\bar{S}) across approaches. Language codes are shown next to every \bar{S} value to indicate the corresponding language.

6.1 Surface Markers and Contextual Classification Cues

Table 2 shows the classification accuracy and selectivity scores across all languages and predictors. Probes achieve the highest accuracy in four out of seven languages and the best selectivity scores in six. Arabic is the exception with XGBoost reaching 97.4% accuracy (0.83 selectivity) compared to 85.7% accuracy (0.20 selectivity) with the best performing probe. Linear models perform similarly well (90.9% accuracy, 0.92 selectivity).

Figure 2 tracks how probes perform when trained on representations from different encoder layers, compared to baseline predictors and the fine-tuned model. English, Finnish and Russian show similar trends, with both probes and fine-tuning achieving accuracies > 90%, although at different depths (layer 5 for English and Finnish, layer 11 for Russian).

Indonesian probes perform poorly until layer 5, after which they consistently exceed all baseline methods, dipping only at the final layer. Japanese and Korean show oscillating scores across layers, with fine-tuning achieving notably higher accuracy.

The benefits of contextual representations are clearest in English, Japanese, and Korean, where the performance gap between statistical baselines and Glott500-m probes/fine-tuning ranges from 10 to 20 percentage points increases. Finnish shows a more moderate contextual advantage of less than 10 percentage points, while Arabic, Indonesian, and Russian exhibit much smaller gaps between representation types.

6.2 Continuous Complexity Probing

Table 3 presents regression errors across six complexity sub-metrics plus the combined complexity score, limited to results for languages that achieved the best performance on each metric.

Glott500-m probes achieve the lowest error rates on three metrics: token count (0.004 MSE, 0.68 selectivity), tree depth (0.002 MSE, 0.57 selectivity), and combined complexity (0.016 MSE, 0.78 selectivity). Fine-tuning leads on three others: dependency length (0.002 MSE), verbal edges (0.030 MSE), and lexical density (0.023 MSE). Ridge regression achieves the best performance on subordinate chain length (0.015 MSE, 0.52 selectivity).

In terms of selectivity, statistical approaches are surprisingly competitive, with TF-IDF methods achieving the highest selectivity on four out of seven metrics. This contrasts with classification results where probes consistently outperformed our baselines.

Layer-wise regression patterns come in three distinct profiles. Most combinations show flat performance curves where all approaches converge around similar values, with the difference between highest and lowest error remaining below 0.01. Cases with moderate layer-to-layer variation (error differences between 0.01 and 0.03) suggest partial encoding of relevant information across the model’s depth. More pronounced oscillations, where error differences exceed 0.03, are usually coupled with low probe performance and point to failures of the contextual embeddings to encode the targeted information.

Fine-tuning achieves the lowest error rates on three metrics: dependency length, verbal edges, lexical density. These advantages appear concentrated on metrics that show relatively flat layer-wise profiles, suggesting that the linguistic properties may be better captured through end-to-end optimization rather than frozen representations. Conversely, metrics where probes excel (token count, tree depth, combined complexity) tend to show more pronounced layer preferences, with fine-tuning performing relatively poorly.

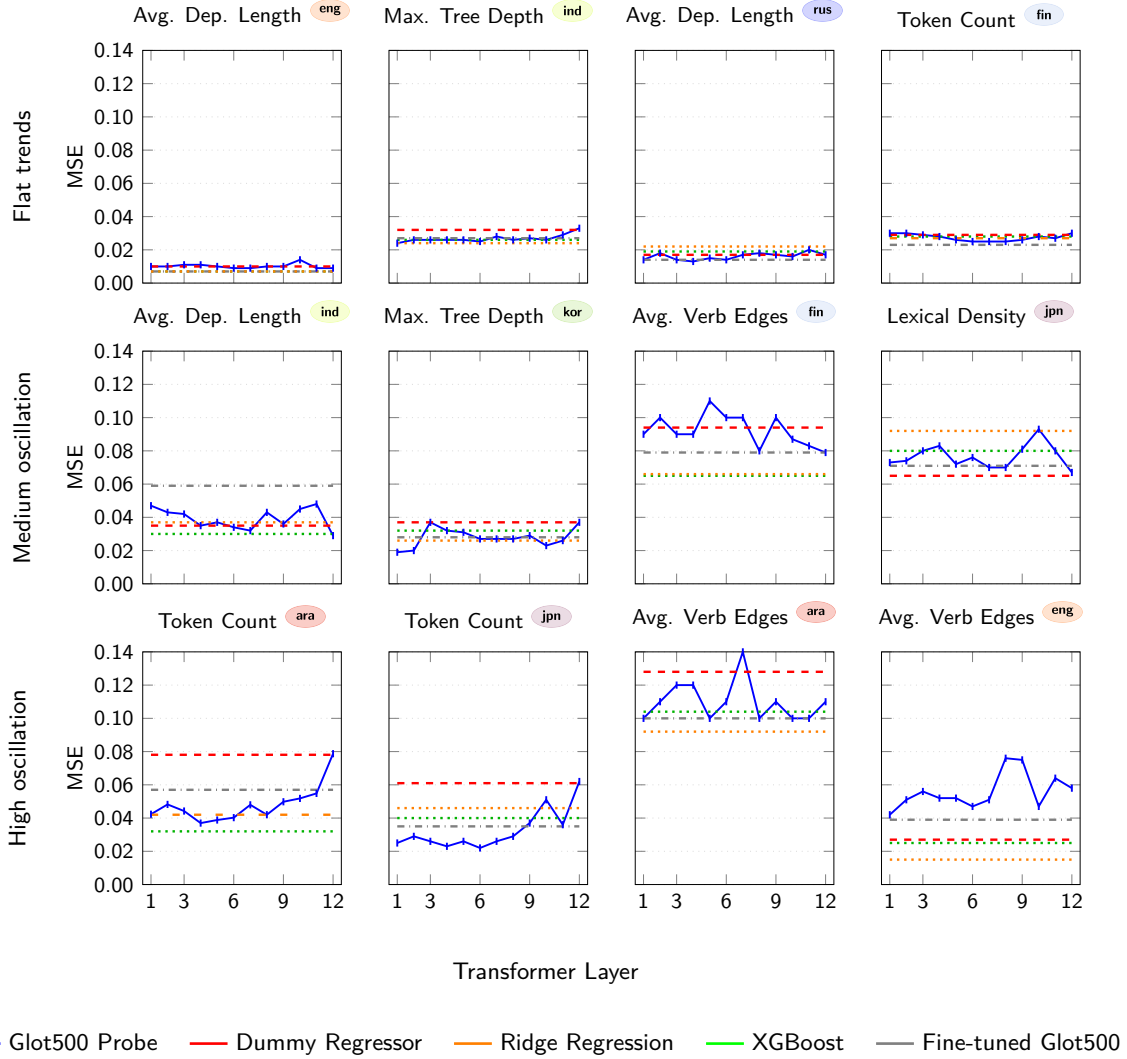


Figure 3: Layer-wise regression trends show three distinct encoding profiles.

7 Discussion

7.1 Classification Performance Analysis

Classification results show that neural approaches generally perform better than statistical baselines. Arabic is the only exception, possibly reflecting the widespread and unambiguous use of question particles. However, explicit marking does not uniformly favor TF-IDF features. For example, Russian uses particles which follow similar transformations, yet benefit more from Glot500 embeddings. This confirms that the nature of marking strategy matters more than its presence or absence.

English and Finnish further confirm this pattern. English auxiliary inversion (“Is it raining?” / “It is raining”) and Finnish suffixes (“-ko/-kö”) represent complex morphosyntactic transformations rather than simple particles, yet both show strong neural advantages (97.3% and 94.5% respectively) over

statistical baselines. This suggests that transformational marking strategies require contextual processing to identify the relevant structural changes, even when the markers themselves are explicit.

Selectivity scores reveal that these representation types capture distinct aspects of question formation. Statistical methods excel when surface distributions provide reliable cues, while neural representations become necessary when question identification requires integration of distributed contextual information that goes beyond simple frequency patterns.

Differences in processing stability across languages can be seen in Figure 2. These patterns appear related to how question type information is distributed through the transformer architecture. Arabic exhibits the highest variability with 0.25 accuracy difference between layers following its overall lower neural performance. Russian has the opposite tendency with minimal variation (< 0.1)

while maintaining consistently high performance. English, Korean, and Finnish show moderate variability (0.1), while Indonesian and Japanese display higher fluctuations (> 0.2) that correspond with the oscillations visible in their layer-wise profiles.

7.2 Regression Profiles

Despite Glot500 representations achieving consistently low errors in complexity regression tasks, TF-IDF approaches show higher selectivity scores on tree depth, dependency length, subordinate chain length, and lexical density metrics. Table 3 shows the variety in the ability of transformers to encode different morphosyntactic properties.

Regression probes have a clear advantage on token count and combined complexity, but they do not consistently outperform our baselines on most of the metrics. Selectivity scores reveal that statistical methods lead on four of seven complexity metrics, demonstrating that frequency features can distinguish meaningful structural patterns from spurious correlations more reliably than contextual representations.

Figure 3 shows a selection of layer-wise error trends highlighting the three most common performance profiles. Flat probe trends were observed most often, meaning that certain structural properties are tied to surface features and that contextual processing rarely provides additional benefit. High probe oscillations and poor performance are more interesting. They imply that rather than building increasingly sophisticated representations of structural complexity, the transformer may be losing and regaining access to relevant information as we move through successive layers.

The differences between fine-tuning and frozen probes point towards a trade-off between the two neural approaches. Fine-tuning performs well almost exclusively on metrics characterized by high oscillations and unstable layer-wise trends, suggesting that parameter updates may compensate for inconsistencies. On the other hand, low performance on metrics with flat profiles demonstrates that task-specific training may prevent access to or even destroy pre-trained information. In other words, when structural information is clearly encoded at specific layers, the parameter updates required for task optimization appear to interfere with these patterns.

However, the success of fine-tuning on predicting dependency length, verbal edges, and lexical density suggests that some properties are not read-

ily available in frozen transformer representations, requiring parameter updates to achieve reliable performance on these metrics.

8 Conclusion

We investigated how multilingual transformers encode question patterns by comparing contextual embeddings against statistical baselines across seven typologically diverse languages. Glot500 probes show advantages in question type classification, particularly for languages requiring contextual integration (Japanese, Korean, English, Finnish), while Arabic’s unambiguous particles favor statistical methods. For complexity regression, statistical baselines show better selectivity on most individual metrics, though neural methods excel at token count and verbal arity.

Different complexity metrics exhibit distinct layer-wise encoding patterns. Fine-tuning compensates for unstable neural encoding (high oscillations) but struggles on metrics with otherwise stable layer-wise representations, suggesting task-specific optimization can disrupt pre-trained knowledge.

Our QTC dataset and regression-based probing setup using selectivity controls provide tools for investigating continuous linguistic properties. We find that understanding when and why neural models capture linguistic structure requires careful comparison with principled baselines. Future work should examine applications to other architectures, investigate why certain complexity metrics resist neural encoding, and develop training procedures that preserve linguistic information while improving task performance.

Limitations

This study is limited to seven languages for which high-quality treebanks and interrogative sentence data were available. Our dataset focuses exclusively on questions, so the findings do not generalize to other clause types. While we carefully selected the languages to cover different interrogative patterns, we do not cover all typological variation between target languages. Complexity metrics are computed from automatic dependency parses, which can introduce parser-specific biases and reduce comparability. However, the cross-linguistic consistency of our findings suggests that genuine structural differences emerge despite potential parsing noise.

Ethics Statement

All source texts used in the dataset were collected from materials in the public domain or under licenses allowing redistribution for research purposes. No personally identifiable information is included. Although our analysis is diagnostic and does not inform system deployment, findings on cross-linguistic performance could be misused to justify reduced attention to underrepresented languages.

Acknowledgements

This paper is based on the first author’s Master’s thesis completed at KU Leuven (Kokot, 2025). We thank Miryam de Lhoneux for guidance throughout this research, and Kushal Jayesh Tatariya and Vincent Vandeghinste for their valuable feedback on the thesis work. We also thank the anonymous reviewers for constructive comments.

WP is funded by a KU Leuven Bijzonder Onderzoeksfonds C1 project with reference C14/23/096. The resources and services used in this work were provided by the VSC (Flemish Supercomputer Center), funded by the Research Foundation - Flanders (FWO) and the Flemish Government.

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A Metric Definitions

Token Count is a straightforward way to measure sentence complexity. It refers to the number of processed segments in a sentence, $|T|$. In languages like English, tokens are words and punctuation marks. In Japanese or Korean, which do not use spaces between words, tokens are aligned with grammatical morphemes rather than orthographic words. Generally, the more tokens a sentence has, the more likely it is to require greater processing efforts (Iavarone et al., 2021).

Lexical density is the ratio of content words (nouns, verbs, adjectives, adverbs) to the total number of tokens excluding punctuation. This metric captures the information density of a sentence and often serves as evidence of register difficulty due to its variation across domains.

$$LD = \frac{|\text{content words}|}{|T| - |\text{punct}|} = \frac{3}{7} = 0.428 \quad (2)$$

Average Dependency Length is the linear distance between words and their syntactic heads, across all dependency links in a sentence. This measure directly reflects cognitive processing load, as longer dependencies require holding more information during processing. Futrell et al. (2015) provide compelling evidence in 37 languages, showing that all human languages maintain shorter dependency lengths than would occur by random chance.

$$ADL = \frac{1}{N-1} \sum_{\text{token}(i)}^{N-1} |\text{dep}(i) - \text{head}(i)| = \frac{12}{6} = 2 \quad (3)$$

Where N is the number of tokens (i.e., words) without any punctuation and excluding the root of the sentence ($N - 1$).

Maximum Tree Depth measures the longest path from root to leaf in a dependency structure, revealing how deeply embedded linguistic elements

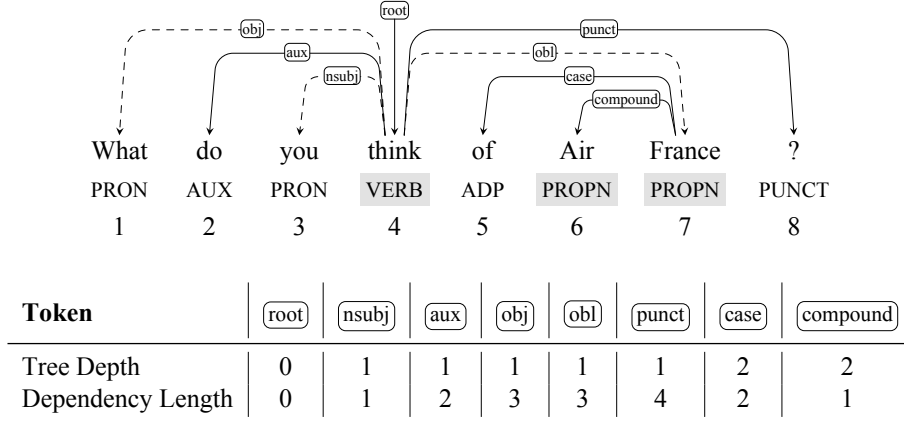


Figure 4: Dependency parse diagram showing grammatical relations, token indices (1-8) and POS tags, with dashed arcs highlighting verbal edges, function words in gray, and a table listing dependency distance and tree depth.

are within a sentence. For token index i in sentence S , Max Depth is defined as:

$$\text{MTD} = \max_{\text{token}(i) \in S} \text{Depth}(i) = 2 \quad (4)$$

Average Verbal Edges, sometimes called verbal arity, is a measure of direct dependents (arguments and modifiers) attached to each verb in a sentence. In a dependency structure, these correspond to edges from a verb to its governing words, such as objects, subjects, or adjuncts, but excluding punctuation and auxiliary verbs (Brunato et al., 2020).

$$\overline{\text{ve}} = \frac{1}{|\text{verbs}|} \sum_{v \in \text{verbs}} \text{dependent}(v) = 3 \quad (5)$$

Average Subordinate Chain Length is calculated as the ratio of the combined length of all subordinate clauses and the total number of clauses in a sentence. It reflects the level of propositional embedding and recursion. Although the dependency structure in Figure 4 contains no subordination, it remains crucial for capturing the clausal hierarchy of nested sentences.

$$\text{ASC} = \frac{\text{sum of sub. chain lengths}}{\text{number of sub. chains}} = 0 \quad (6)$$

B Experimental Details

All experiments were conducted using NVIDIA A100 80GB GPUs. Each probing experiment took approximately 5-10 minutes of training time, while fine-tuning experiments took one hour per language-task combination. The complete experimental suite (including baselines) involved over 3300 individual runs across 7 languages, 12 transformer layers, and multiple tasks with control conditions. This includes experiments with linear algorithms, ensembles, and the fine-tuned model.

Training was carried out with batch sizes of 16, gradient accumulation steps of 2-4, and automatic mixed precision. All experiments used fixed random seeds to ensure reproducibility. The total computational cost was approximately 80 GPU hours on A100 hardware.

For fine-tuning experiments, learning rates were set to 1e-5 for the encoder and 1e-3 for the task head, with early stopping based on validation performance monitored over a patience window of 5 epochs. Probe training used Adam optimizer with learning rate 1e-3 with early stopping when validation loss plateaued.

C Additional Results

This appendix provides additional per-language and per-metric performance data to supplement the main analysis. Table 4, Table 5, and Table 6 present detailed results for all seven languages across both classification and regression tasks, including selectivity scores for baseline methods and layer-specific performance indicators for optimal and weakest probe configurations. Figure 5 shows layer-wise error curves for all complexity metrics across languages.

		Question Type Classification				Combined Complexity Regression			
		$Acc.$	$\overline{control}$	$\Delta Acc.$	\hat{S}	MSE	$\overline{control}$	ΔMSE	\hat{S}
Dummy baseline	ar	71.4	71.4	0	0	0.059	0.059	0	0
	en	50.0	50.0	0	0	0.038	0.039	0	0
	fi	50.0	50.0	0	0	0.040	0.040	0	0
	id	50.0	50.0	0	0	0.040	0.040	0	0
	ja	50.0	50.0	0	0	0.063	0.063	0	0
	ko	50.0	50.0	0	0	0.036	0.036	0	0
	ru	50.0	50.0	0	0	0.059	0.059	0	0
Linear predictors	ar	90.9	47.2	43.7	0.92	0.045	0.064	0.019	0.29
	en	83.6	53.9	29.7	0.55	0.023	0.043	0.020	0.46
	fi	84.5	46.1	0.83	0.85	0.037	0.043	0.006	0.14
	id	67.3	47.5	19.8	0.41	0.028	0.046	0.018	0.39
	ja	64.1	51.1	13.0	0.25	0.039	0.064	0.015	0.23
	ko	66.4	46.3	20.1	0.43	0.023	0.039	0.016	0.41
	ru	86.4	46.7	0.85	0.85	0.032	0.069	0.037	0.53
Gradient boosting	ar	97.4	53.2	44.4	0.83	0.034	0.063	0.029	0.46
	en	80.9	51.8	29.1	0.56	0.018	0.043	0.025	0.58
	fi	87.2	45.7	41.5	0.91	0.032	0.042	0.01	0.24
	id	65.5	53.3	12.2	0.23	0.026	0.043	0.017	0.39
	ja	64.1	50.0	14.1	0.28	0.037	0.061	0.024	0.39
	ko	73.6	49.7	23.9	0.48	0.031	0.038	0.007	0.18
	ru	77.2	48.8	28.4	0.51	0.039	0.061	0.022	0.36
Optimal Probe	ar	85.7 (2)	71.4	14.3	0.20	0.030 (4)	0.067	0.037	0.55
	en	97.3 (5)	50.0	47.3	0.95	0.017 (1)	0.048	0.031	0.64
	fi	94.5 (5)	50.0	44.5	0.89	0.025 (1)	0.050	0.025	0.50
	id	80.9 (6)	50.0	30.9	0.62	0.024 (4)	0.047	0.023	0.49
	ja	82.6 (10)	39.8	42.8	1.07	0.016 (4)	0.073	0.057	0.78
	ko	76.4 (9)	50.0	26.4	0.53	0.043 (3)	0.093	0.050	0.53
	ru	97.3 (11)	50.0	47.3	0.95	0.039 (6)	0.069	0.030	0.43
Weakest Probe	ar	62.5 (12)	71.4	8.9	0.12	0.057 (12)	0.061	0.004	0.07
	en	89.4 (2)	50.0	39.4	0.79	0.043 (12)	0.045	0.002	0.04
	fi	83.6 (3)	50.0	33.6	0.67	0.042 (12)	0.043	0.001	0.03
	id	62.7 (12)	50.0	12.7	0.25	0.042 (12)	0.046	0.004	0.09
	ja	63.0 (5)	40.2	22.8	0.57	0.058 (12)	0.061	0.003	0.05
	ko	63.6 (1)	50.0	13.6	0.27	0.041 (2)	0.053	0.012	0.22
	ru	90.0 (2)	50.0	40.0	0.80	0.067 (10)	0.075	0.008	0.11
Fine-tuned Glot500	ar	74.1	-	-	-	0.042	-	-	-
	en	91.8	-	-	-	0.020	-	-	-
	fi	92.3	-	-	-	0.030	-	-	-
	id	73.6	-	-	-	0.030	-	-	-
	ja	88.0	-	-	-	0.029	-	-	-
	ko	91.1	-	-	-	0.031	-	-	-
	ru	96.4	-	-	-	0.045	-	-	-

Table 4: Performance metrics for question type classification (accuracy) and combined complexity regression (MSE) tasks across seven languages.

		Dependency Length		Max. Tree Depth		Sub. Chain Length	
		MSE	\hat{S}	MSE	\hat{S}	MSE	\hat{S}
Dummy baseline	ar	0.065	0	0.052	0	0.077	0
	en	0.009	0	0.029	0	0.027	0
	fi	0.026	0	0.031	0	0.054	0
	id	0.036	0	0.033	0	0.069	0
	ja	0.108	0	0.083	0	0.092	0
	ko	0.027	0	0.037	0	0.054	0
	ru	0.017	0	0.025	0	0.054	0
Linear predictors	ar	0.045	0.29	0.028	0.48	0.054	0.34
	en	0.007	0.3	0.013	0.60	0.015	0.51
	fi	0.024	0.17	0.036	0	0.041	0.27
	id	0.037	0.01	0.024	0.33	0.053	0.30
	ja	0.09	0.18	0.065	0.22	0.076	0.25
	ko	0.022	0.23	0.025	0.36	0.044	0.31
	ru	0.022	0	0.019	0.29	0.035	0.42
Gradient boosting	ar	0.057	0.15	0.028	0.44	0.059	0.24
	en	0.007	0.3	0.014	0.55	0.025	0.10
	fi	0.027	0.03	0.022	0.29	0.051	0.11
	id	0.04	0	0.026	0.21	0.055	0.29
	ja	0.105	0.04	0.063	0.24	0.081	0.14
	ko	0.029	0.05	0.032	0.18	0.063	0.01
	ru	0.019	0	0.017	0.35	0.044	0.22
Optimal Probe	ar	0.045 (6)	0.42	0.028 (6)	0.48	0.069 (6)	0.12
	en	0.090 (6)	0.23	0.016 (8)	0.46	0.022 (6)	0.25
	fi	0.025 (8)	0.18	0.016 (7)	0.52	0.047 (12)	-0.01
	id	0.030 (12)	0	0.024 (1)	0.34	0.049 (1)	0.46
	ja	0.087 (1)	0.10	0.072 (9)	0.10	0.053 (6)	0.47
	ko	0.023 (8)	0.18	0.020 (2)	0.57	0.047 (5)	0.26
	ru	0.013 (4)	0.29	0.016 (6)	0.41	0.049 (5)	0.14
Weakest Probe	ar	0.073 (12)	-0.13	0.053 (12)	0.05	0.080 (12)	-0.04
	en	0.015 (10)	-0.29	0.029 (12)	0.06	0.031 (3)	0.06
	fi	0.030 (2)	0.07	0.037 (12)	-0.05	0.073 (10)	0.08
	id	0.049 (11)	0.16	0.033 (12)	0.05	0.081 (11)	0.06
	ja	0.122 (3)	0.06	0.103 (10)	-0.10	0.094 (12)	-0.03
	ko	0.042 (3)	0.18	0.037 (12)	0.02	0.070 (7)	-0.05
	ru	0.020 (11)	0.07	0.028 (12)	0	0.058 (6)	0.03
Fine-tuned Glot500	ar	0.056	-	0.038	-	0.069	-
	en	0.008	-	0.022	-	0.019	-
	fi	0.002	-	0.023	-	0.045	-
	id	0.031	-	0.028	-	0.043	-
	ja	0.105	-	0.068	-	0.061	-
	ko	0.025	-	0.029	-	0.046	-
	ru	0.015	-	0.017	-	0.046	-

Table 5: Performance metrics for linguistic complexity sub-metric regression tasks across seven languages (Part 1: Dependency Length, Tree Depth, Subordinate Chain Length).

		Verbal Edges		Lexical Density		N Tokens	
		MSE	\hat{S}	MSE	\hat{S}	MSE	\hat{S}
Dummy baseline	ar	0.060	0	0.067	0	0.078	0
	en	0.060	0	0.028	0	0.029	0
	fi	0.060	0	0.055	0	0.014	0
	id	0.065	0	0.053	0	0.039	0
	ja	0.107	0	0.063	0	0.061	0
	ko	0.041	0	0.107	0	0.078	0
	ru	0.044	0	0.071	0	0.012	0
Linear predictors	ar	0.09	0.32	0.057	0.15	0.042	0.46
	en	0.041	0.36	0.027	0.17	0.034	0.59
	fi	0.068	0.34	0.070	-0.12	0.015	0.05
	id	0.070	0.06	0.033	0.47	0.037	0.11
	ja	0.108	0.10	0.09	-0.36	0.045	0.26
	ko	0.045	0.02	0.070	0.37	0.056	0.30
	ru	0.047	0.10	0.049	0.33	0.013	0.08
Gradient boosting	ar	0.107	0.13	0.067	0.02	0.032	0.59
	en	0.104	0.23	0.028	0.10	0.013	0.56
	fi	0.070	0.32	0.069	-0.11	0.009	0.33
	id	0.090	-0.25	0.046	0.26	0.022	0.47
	ja	0.104	0.08	0.080	-0.33	0.040	0.33
	ko	0.046	-0.04	0.082	0.26	0.077	0.06
	ru	0.044	0.08	0.061	0.14	0.007	0.47
Optimal Probe	ar	0.103 (1)	0.23	0.054 (3)	0.10	0.037 (4)	0.59
	en	0.043 (1)	0.35	0.025 (6)	0.11	0.010 (3)	0.63
	fi	0.080 (12)	-0.01	0.039 (2)	0.14	0.006 (1)	0.59
	id	0.046 (9)	0.35	0.036 (3)	0.21	0.025 (3)	0.32
	ja	0.007 (6)	0.40	0.071 (7)	0	0.023 (5)	0.66
	ko	0.034 (12)	0	0.062 (8)	0.13	0.073 (9)	0.18
	ru	0.041 (9)	0.18	0.037 (7)	0.14	0.004 (5)	0.68
Weakest Probe	ar	0.140 (7)	0	0.065 (5)	-0.02	0.079 (12)	0
	en	0.076 (8)	0.04	0.030 (12)	0.02	0.023 (12)	0.17
	fi	0.112 (5)	-0.13	0.051 (12)	-0.03	0.016 (12)	-0.03
	id	0.062 (12)	0.04	0.046 (12)	0.04	0.034 (7)	0.08
	ja	0.094 (12)	0.06	0.093 (10)	-0.14	0.063 (12)	0.03
	ko	0.036 (11)	-0.04	0.074 (6)	-0.07	0.104 (3)	0.12
	ru	0.057 (8)	-0.08	0.051 (12)	-0.07	0.016 (12)	-0.09
Fine-tuned Glot500	ar	0.030	-	0.055	-	0.056	-
	en	0.039	-	0.023	-	0.020	-
	fi	0.079	-	0.044	-	0.011	-
	id	0.045	-	0.038	-	0.027	-
	ja	0.078	-	0.071	-	0.035	-
	ko	0.034	-	0.074	-	0.070	-
	ru	0.038	-	0.043	-	0.006	-

Table 6: Performance metrics for linguistic complexity sub-metric regression tasks across seven languages (Part 2: Verbal Edges, Lexical Density, N Tokens).

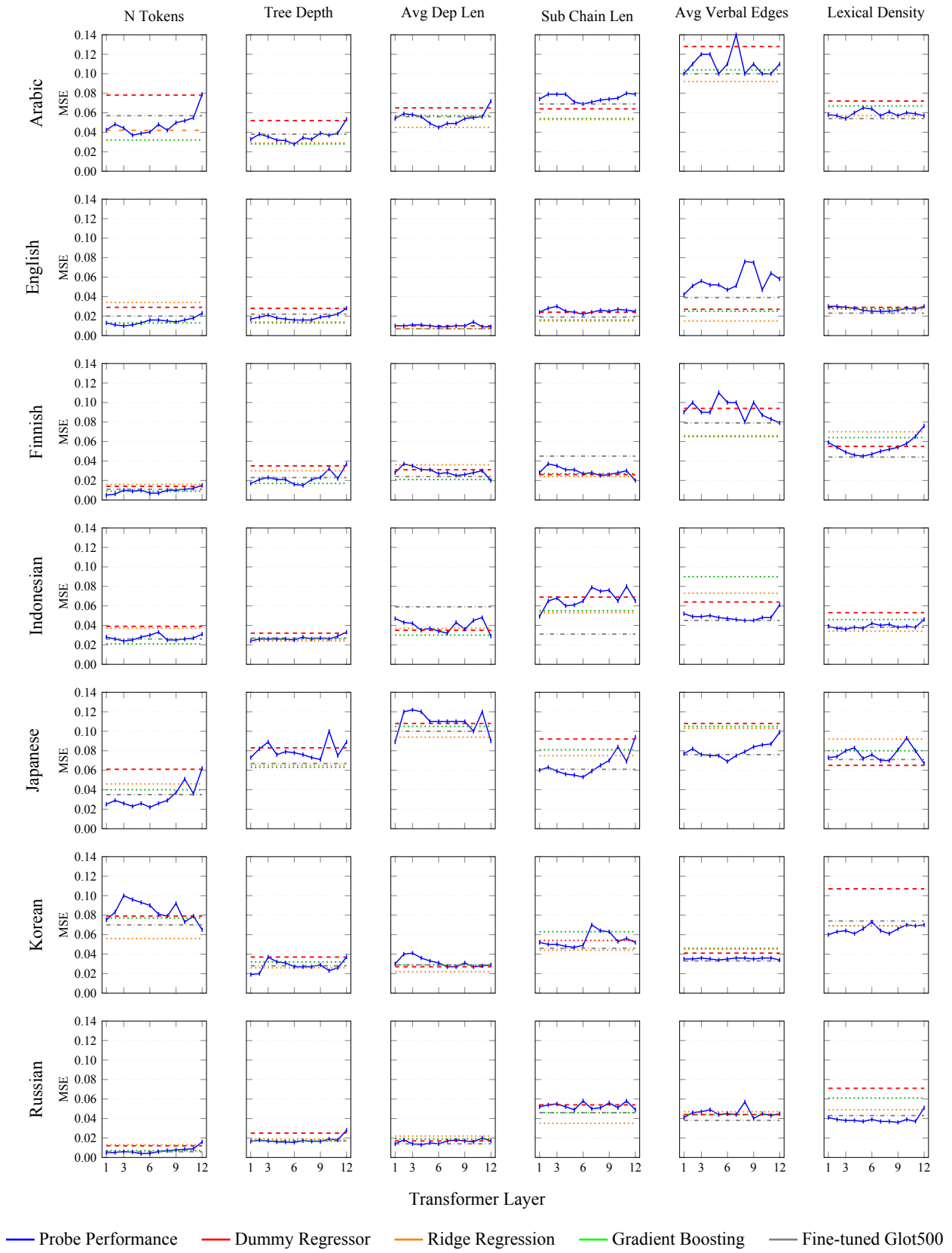


Figure 5: Performance metrics across languages and transformer layers

ENTROPY2VEC: Crosslingual Language Modeling Entropy as End-to-End Learnable Language Representations

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Abstract

We introduce ENTROPY2VEC, a novel framework for deriving cross-lingual language representations by leveraging the entropy of monolingual language models. Unlike traditional typological inventories that suffer from feature sparsity and static snapshots, ENTROPY2VEC uses the inherent uncertainty in language models to capture typological relationships between languages. By training a language model on a single language, we hypothesize that the entropy of its predictions reflects its structural similarity to other languages: Low entropy indicates high similarity, while high entropy suggests greater divergence. This approach yields dense, non-sparse language embeddings that are adaptable to different timeframes and free from missing values. Empirical evaluations demonstrate that ENTROPY2VEC embeddings align with established typological categories and achieved competitive performance in downstream multilingual NLP tasks, such as those addressed by the LinguAlchemy framework.

1 Introduction

Linguistic typology provides a framework for classifying languages based on shared structural features, offering insights into language universals and diversity. Databases like the World Atlas of Language Structures (WALS) (Haspelmath, 2005), AUTOTYP (Bickel and Nichols, 2002), URIEL (Littell et al., 2017), and URIEL⁺ (Khan et al., 2025) catalog these features, serving as valuable resources for researchers and practitioners in the field of computational linguistics and beyond. However, these inventories face significant limitations: they often cover only a subset of languages, leading to missing values, and they represent static snapshots of linguistic knowledge, neglecting the dynamic and evolutionary nature of languages.

Recent advancements in neural language modeling have enabled the extraction of continuous representations of languages through pre-trained models.

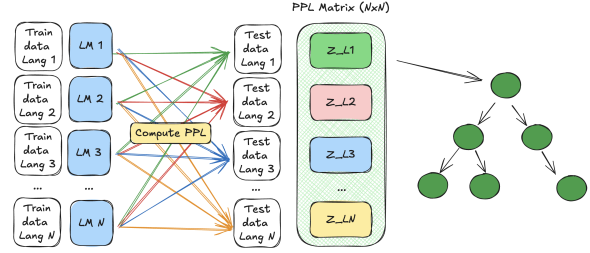


Figure 1: ENTROPY2VEC framework. Monolingual LMs are trained per language, and cross-lingual perplexity is used as an unsupervised signal to derive language vectors and induce typological trees, aligning well with expert-curated taxonomies.

These embeddings capture semantic and syntactic properties, facilitating cross-lingual transfer in various NLP tasks. Nonetheless, existing methods primarily focus on monolingual or bilingual settings and do not explicitly model the typological relationships between languages. Moreover, they often rely on manually curated features, which may not generalize well across languages or over time.

To address these challenges, we propose ENTROPY2VEC, a framework that derives language representations based on the entropy of monolingual language models (LMs). Entropy, a measure of uncertainty in information theory, reflects the predictability of a language’s structure. By training a language model on a single language and analyzing its entropy when applied to other languages, we can infer typological similarities and differences. This approach offers several advantages: it is data-driven, scalable, and inherently adaptable to new languages and evolving linguistic features.

In this paper, we demonstrate that ENTROPY2VEC embeddings align with established typological categories, such as phonological, morphological, and syntactic features. We also show that these embeddings outperform traditional typological inventories in downstream multilingual NLP tasks, including language identification, typol-

ogy prediction, and cross-lingual transfer. By integrating ENTROPY2VEC into the LinguAlchemy framework (Adilazuarda et al., 2024), we achieve competitive generalization across languages, especially those underrepresented in existing typological resources.

2 Related Works

Typological Language Inventories Traditional typological inventories, such as WALS (Haspelmath, 2005), AUTOTYP (Bickel and Nichols, 2002), URIEL (Littell et al., 2017), and URIEL⁺ (Khan et al., 2025), have been instrumental in documenting linguistic diversity and informing computational models. However, these resources are limited by their static nature and the incomplete coverage of the world’s languages. For instance, WALS provides typological data for only a fraction of the estimated 7,000 languages, leading to missing values that can hinder the performance of NLP models. ENTROPY2VEC addresses these limitations by deriving LMs from the entropy of monolingual LMs. This approach is inherently dynamic, as it can adapt to new languages and evolving linguistic features without the need for manual curation. Moreover, it provides dense, non-sparse embeddings that capture the probabilistic structure of languages, offering a more nuanced understanding of typological relationships.

Language Vector in NLP Language vectors, or embeddings, have become foundational in modern NLP, enabling models to represent words, sentences, and even entire languages as continuous vectors in a high-dimensional space. Techniques like Word2Vec, GloVe, and FastText have demonstrated that such embeddings capture semantic and syntactic properties, facilitating tasks like word similarity, analogy reasoning, and machine translation. These embeddings are typically learned from large corpora and reflect the statistical patterns in language use. However, they often treat languages as isolated entities, without explicitly modeling the relationships between them. Recent advancements, such as multilingual BERT and XLM-R, have sought to address this by training models on multiple languages simultaneously, capturing shared structures and enabling cross-lingual transfer. ENTROPY2VEC contributes to this landscape by offering a novel perspective on language representation. Instead of relying solely on large-scale pre-training on vast corpora, ENTROPY2VEC

leverages the entropy of monolingual LMs to infer typological relationships between languages. This approach not only aligns with existing language representation models but also extends their capabilities by incorporating typological insights, thereby enhancing multilingual understanding and transfer learning

3 ENTROPY2VEC

3.1 Unsupervised Language Modeling

Unsupervised language modeling uses an autoregressive approach, where the LM predicts the next token based on the previous ones. Mathematically, given a sequence of tokens $[x_1, x_2, \dots, x_t]$, the LM defines a probability distribution over the next token x_{t+1} conditioned on all previous tokens. This can be formally expressed as:

$$x_{t+1} = \arg \max_x P(x \mid x_1, x_2, \dots, x_t; \theta)$$

where θ represents the parameters of the model. The goal of training is to maximize the likelihood of the observed data, which is equivalent to minimizing the cross-entropy loss. Formally, given a dataset $\mathcal{D} = (x_1^{(1)}, \dots, x_{n_1}^{(1)}), \dots, (x_1^{(N)}, \dots, x_{n_N}^{(N)})$, the cross-entropy loss is defined as:

$$\mathcal{L}(\theta, \mathcal{D}) = -\frac{1}{N} \sum_{i=1}^N \sum_{t=1}^{n_i} \log P(x_t^{(i)} \mid x_1^{(i)}, \dots, x_{t-1}^{(i)}; \theta)$$

This encourages the model θ to assign high probability to the actual next tokens in the training data. The autoregressive nature of these models allows them to generate coherent and contextually relevant text by sequentially predicting tokens (Radford et al., 2019; Brown et al., 2020; Cahyawijaya et al., 2021), making them highly effective for building strong language representations (Workshop et al., 2023; Cohere et al., 2025).

3.2 LM Entropy as Language Vectors

Although having a strong language representation, LMs can only produce meaningful representation on languages that they have been pre-trained on (Winata et al., 2023; Cahyawijaya et al., 2023c) and closely similar languages (Cahyawijaya et al., 2023b, 2024). The cross-lingual generalization often diminish when the corresponding model is faced with languages that are low-resource (Bang et al., 2023; Cahyawijaya et al., 2023a) and distant from the languages it has been trained on (Lovenia et al., 2024; Cahyawijaya, 2024; Bean et al., 2024).

As the cross-lingual generalization of LMs depends on the closeness of the language, we argue that this limitation can actually be exploited to build a language vector which is a vector that provides a global representation of a certain language. More specifically, using a set of monolingual LMs $\{\theta_{L_1}, \theta_{L_2}, \dots, \theta_{L_n}\}$ each trained on a specific language L_i and a set of monolingual corpora $\{\mathcal{D}^{L_1}, \mathcal{D}^{L_2}, \dots, \mathcal{D}^{L_n}\}$, we build the vector representation of languages $\{Z^{L_1}, Z^{L_2}, \dots, Z^{L_n}\}, Z^{L_i} \in \mathbb{R}^n$ by computing the average cross-entropy of the corresponding language model θ_i on each corpus \mathcal{D}_j . Formally, we define the language vector Z^{L_i} as:

$$Z^{L_i} = [\mathcal{L}(\theta_i, \mathcal{D}_1), \mathcal{L}(\theta_i, \mathcal{D}_2), \dots, \mathcal{L}(\theta_i, \mathcal{D}_n)]$$

We call our method of deriving language vector from the entropy of LMs as ENTROPY2VEC. Unlike other existing language vectors like URIEL (Littell et al., 2017) and URIEL⁺ (Khan et al., 2025), which derive their language vectors from various linguistic inventories, e.g., WALS (Dryer and Haspelmath, 2013), AUTOTYP (Bickel et al., 2023), etc., our method provides a fully unsupervised, data-driven approach for building a language vector. Moreover, our vector can evolve following the actual evolution of languages by updating each of the monolingual LMs with more recent data on each of the corresponding languages. ENTROPY2VEC leverages the inherent patterns and structures within large-scale textual data, eliminating the need for manual feature engineering or reliance on predefined linguistic inventories. By continuously updating the models with new data, our approach ensures that the language vectors remain dynamic and reflective of the ever-changing nature of human language.

4 ENTROPY2VEC and Language Typology

To assess the validity of ENTROPY2VEC, we compare it against several established language vector and tree baselines: URIEL (Littell et al., 2017) and URIEL⁺ (Khan et al., 2025) vectors, as well as the Glottolog tree (Nordhoff and Hammarström, 2011). For the first two, we derive a hierarchical clustering tree representing inter-language distances based on geographical and syntactic features. We then evaluate how well the trees induced from ENTROPY2VEC vectors replicate these known typological groupings, and whether they reveal novel or diverging relationships.

4.1 Experiment Setting

Dataset Our data source is the Glot500c corpus (Imani et al., 2023), from which we gather textual data for 33 distinct languages which are also present in URIEL, URIEL⁺, and Glottolog. For each language, we cap the data at a maximum of 1M sentences and split this data into 7:2:1 (train, validation, test) split after collating the sentence to cap each instance to 1024 characters to support model’s max ingestion length. The details of the quantity and split per language can be observed in Appendix A.

Training Strategy We choose GPT-2 as our pre-trained language model for learning language representations, where the model is configured with an embedding dimension of 512, 4 transformer layers, and 8 attention heads. More details—including tokenizer configurations, optimization parameters, and the precise methodology for perplexity extraction—are elaborated further in Appendix B. Training is conducted by using the same settings for all 33 languages to extract their perplexity, a measure of how well the language model predicts the test data. This perplexity scores, reflecting the model’s "surprise" by a language’s characteristics, are used to derive language vectors denoted as $\{Z^{L_1}, Z^{L_2}, \dots, Z^{L_n}\}$, where each Z^{L_i} represents a specific language. From now on, the entirety of these vectors will be termed as ENTROPY2VEC.

Forming Typological Trees We generate hierarchical language clusters from the learned vector representations Z^L using the DBSCAN algorithm, selected for its ability to discover clusters of arbitrary shape without requiring a predefined number of clusters. This choice is motivated by the non-uniform density and structure of real-world language typologies, which traditional linkage-based methods fail to capture due to its complexity (Appendix C). The resulting clusters are then transformed into tree structures and post-processed to ensure compatibility with downstream evaluation. This includes standardizing hierarchical level labels (e.g., **family**, **subfamily**, and **language** in URIEL and URIEL⁺) to maintain parent-child relationships naming convention consistency. We set the same clustering hyperparameters for all experiments to **min_samples** = 0.3 and **epsilon** = 0.1. We apply these settings to all of our vector variations, including the pure ENTROPY2VEC and the its concatenated variants with URIEL or URIEL⁺.

Language Vector	Glottolog	
	MAE (\downarrow)	RF (\downarrow)
Language Features		
URIEL _{Geo}	11.11	13.0
URIEL _{Syntax}	9.35	18.0
URIEL ⁺ _{Geo}	11.15	13.0
URIEL ⁺ _{Syntax}	11.15	13.0
ENTROPY2VEC	8.60	17.0
Concatenated Features		
URIEL _{Geo} + Ours	9.64	13.0
URIEL _{Syntax} + Ours	8.58	16.0
URIEL ⁺ _{Geo} + Ours	7.88	19.0
URIEL ⁺ _{Syntax} + Ours	10.12	12.0

Table 1: Comparison of tree distance metrics between various language vector configurations and the Glottolog baseline tree. Lower MAE values and lower RF scores indicate better tree reconstruction quality. **Ours** refers to ENTROPY2VEC vectors, while “+ Ours” indicates feature concatenation with min-max normalization.

Glottog, most of the Phillipine languages (Reid and Liao, 2004) – i.e., Tagalog (tgl), Cebuano (ceb), Waray Waray (war), Pampanga (pam), and Pangasinan (pag) –, also clustered together with the Malayic due to the shared morphosyntactic features between the two groups.

We further quantify the similarity distance between these typological trees and the Glottolog ground truth typological tree as described in §4.1. The distance measures from the hierarchical clustering trees generated from different language vectors are shown in Table 1. These metrics indicate how well the generated typological trees align with the typological tree from Glottolog. Overall, the results demonstrate that tree from ENTROPY2VEC, URIEL, and URIEL⁺ have similar alignment to Glottolog, where ENTROPY2VEC yields best LCA MAE with slightly lower RF scores in comparison to URIEL and URIEL⁺ vectors, indicating that ENTROPY2VEC captures key linguistic relationships similar to these vectors without supervision.

Combination of Language Features We also compare the base representation (Z^L) with concatenated features ($\Phi(A, B)$). Across MAE and RF, we observe that concatenation does not consistently yield improvements. Although some com-

Language	ISO639-3	Family	Script	Resource
<i>Seen Languages</i>				
English*	eng	Indo-European	Latn	HRL
Vietnamese*	vie	Austroasiatic	Latn	HRL
Indonesian*	ind	Austronesian	Latn	HRL
Thai*	tha	Kra–Dai	Thai	HRL
Tamil*	tam	Dravidian	Taml	LRL
Burmese*	mya	Sino-Tibetan	Mymr	LRL
Ilocano	ilo	Austronesian	Latn	LRL
Javanese†	jav	Austronesian	Latn	LRL
Minangkabau	min	Austronesian	Latn	LRL
Sundanese	sun	Austronesian	Latn	LRL
Cebuano	ceb	Austronesian	Latn	LRL
Tagalog†	tgl	Austronesian	Latn	LRL
Standard Malay†	zsm	Austronesian	Latn	LRL
<i>Unseen Languages</i>				
German*	deu	Indo-European	Latn	HRL
French*	fra	Indo-European	Latn	HRL
Hindi*	hin	Indo-European	Deva	HRL
Italian*	ita	Indo-European	Latn	HRL
Spanish*	spa	Indo-European	Latn	HRL
Lao	lao	Kra–Dai	Laoo	LRL
Khmer*	khm	Austroasiatic	Khmr	LRL
Banjar	bjn	Austronesian	Latn	LRL
Balinese	ban	Austronesian	Latn	LRL
Mizo (Lushai)	lus	Sino-Tibetan	Latn	LRL
Waray	war	Austronesian	Latn	LRL
Buginese	bug	Austronesian	Latn	LRL
Pangasinan	pag	Austronesian	Latn	LRL
Acehnese	ace	Austronesian	Latn	LRL
Sanskrit	san	Indo-European	Deva	LRL
Fijian	fij	Austronesian	Latn	LRL
Telugu*	tel	Dravidian	Telu	LRL
Tok Pisin	tpi	Creole	Latn	LRL
Marathi	mar	Indo-European	Deva	LRL

Table 2: Detailed list of languages used in the seen and unseen evaluation in SIB-200. * the language is used in MASSIVE in the corresponding subset. † the languages is used as part of unseen language evaluation in MASSIVE.

binations show slight gains, others show worse performance. For example, the combined ENTROPY2VEC and URIEL⁺Geo variant achieves the lowest MAE (7.88), indicating a closer approximation to the reference tree in terms of distances between the edges. Conversely, the combined ENTROPY2VEC and URIEL⁺Syntax variant produces the best RF score (12.0), reflecting fewer topological errors. However, these improvements are not synergic across both metrics, suggesting that combining features may introduce redundancy or conflicting signals rather than complementarity.

Dissimilarity to Language Typology Despite the similarity, there are still some inconsistencies between trees and measurement of the distance between the expected ground truth typological tree from Glottolog and comparing the similarities and differences between different typological trees generated from different language features are not straightforward. While our ENTROPY2VEC tree broadly reflects syntactic and geographical relationships, several misalignments persist, as shown in

Language Vectors	OVR Avg.	SIB-200					MASSIVE				
		Seen		Unseen		Avg.	Seen		Unseen		Avg.
		HRL	LRL	HRL	LRL		HRL	LRL	HRL	LRL	
XLM-R											
URIEL _{Geo}	77.71	79.3	78.3	79.8	77.7	78.8	80.48	76.11	75.09	74.94	76.7
URIEL _{Syntax}	77.19	78.9	77.9	78.5	77.2	78.1	80.19	75.56	74.68	74.48	76.2
URIEL ⁺ _{Geo}	77.56	79.9	78.6	80.7	77.9	79.3	79.89	75.15	74.25	74.03	75.8
URIEL ⁺ _{Syntax}	79.07	82.4	81.3	82.8	80.7	81.8	80.16	75.71	74.85	74.70	76.4
ENTROPY2VEC (Ours)	<u>79.06</u>	82.3	81.0	82.6	80.4	<u>81.6</u>	80.31	76.16	75.00	74.73	<u>76.6</u>
URIEL _{Geo} + Ours	76.72	78.2	77.2	77.6	76.4	77.3	80.12	75.36	74.46	74.42	76.1
URIEL _{Syntax} + Ours	78.85	82.1	80.7	82.3	79.9	81.3	80.50	75.84	74.86	74.67	76.5
URIEL ⁺ _{Geo} + Ours	77.47	80.5	79.0	81.3	78.1	79.7	79.34	74.69	73.44	73.32	75.2
URIEL ⁺ _{Syntax} + Ours	78.78	81.7	80.7	82.1	80.2	81.2	80.30	75.84	74.80	74.57	76.4

Table 3: Accuracy comparison of different language vectors for LinguAlchemy regularization on the XLM-R backbone, using SIB and MASSIVE benchmark averages. **Bold** numbers indicate the best average performance, while underlined numbers indicate the second-best. We report overall performance across different settings, including seen and unseen languages during training, as well as **H**igh- vs. **L**ow-resource languages. For XLM-R, we observe that vector concatenation does not increase performance compared to their standalone counterparts, as discussed detail in subsection 5.2

Figure 2c. For example, in the predicted tree, **lao** is grouped with **tam** and **tha** under `Unsplit_L3_1` cluster node rather than with its expected Mainland Southeast Asian cluster (**vie**, **khm**) as appears in the gold-standard `Unsplit_L1_2`. Regarding the cluster sensitivity, **bpy** appears in a broad mixed group (`Cluster_L1_5`) with **jav**, **bsb**, and **war**, rather than with Tibeto-Burman-influenced languages like **lus** and **mya** as in the gold-standard `Unsplit_L1_3`. Similarly, the Malayic languages **min**, **zlm**, and **zsm** are dispersed across different branches instead of being tightly grouped under a single parent, as in `Unsplit_L1_1`. These suggest that there still lies a challenge in maintaining the persistence syntactical or geographical relationships between language groups at more granular level.

5 ENTROPY2VEC as Language Vectors

In the previous section, we demonstrate that ENTROPY2VEC is able to represent meaningful linguistic properties such as language family relation, syntax similarity, and geographical distance. In this section, we establish the applicability of ENTROPY2VEC and compare it to other existing language vectors such as URIEL (Littell et al., 2017) and URIEL⁺ (Khan et al., 2025). We compare the effectiveness of ENTROPY2VEC and other language vectors by measuring the LMs performance when applying the vectors on downstream tasks.

5.1 Experiment Setting

Training Strategy To evaluate the downstream effectiveness of ENTROPY2VEC, we utilize ENTROPY2VEC as a language vector to regularize the LMs during the fine-tuning process with LinguAlchemy (Adilazuarda et al., 2024). LinguAlchemy utilize language vectors to bring better cross-lingual generalization for low-resource and unseen languages. In this case, the downstream improvement on the low-resource and unseen languages with LinguAlchemy can be attributed to the quality of the language vector.

Dataset We incorporate SIB-200 (Adelani et al., 2024) and MASSIVE (FitzGerald et al., 2023) as our evaluation dataset. In our evaluation, we filter out the training and evaluation data to only cover the languages that are related to our 33 supported languages. This yields 13 languages for training and seen-language evaluation with additional of 19 languages for unseen evaluations for SIB-200; and 6 languages for training and seen-language evaluation with additional of 10 languages for unseen evaluations for MASSIVE. The list of languages covered for training and unseen evaluations are shown in Table 2.

5.2 Result and Analysis

Performance Across Different Settings This section discusses the impact of different language vectors to the quality of LMs across different language resource levels. The XLM-R results in Table

Language Vectors	OVR Avg.	SIB-200					MASSIVE				
		Seen		Unseen		Avg.	Seen		Unseen		Avg.
		HRL	LRL	HRL	LRL		HRL	LRL	HRL	LRL	
<i>mBERT</i>											
URIEL _{Geo}	67.61	69.4	70.9	72.7	70.2	70.8	72.40	65.24	60.25	59.77	64.9
URIEL _{Syntax}	67.49	68.8	70.2	72.5	69.6	70.3	72.63	65.53	60.56	60.14	64.7
URIEL ⁺ _{Geo}	66.67	68.3	69.6	72.2	68.7	69.7	71.76	64.32	59.36	59.06	63.6
URIEL ⁺ _{Syntax}	67.51	69.1	70.6	72.0	69.8	70.4	72.63	65.38	60.55	60.12	64.7
ENTROPY2VEC (Ours)	67.59	68.9	70.2	72.1	69.4	70.2	72.98	65.85	60.98	60.37	65.1
URIEL _{Geo} + Ours	68.16	70.2	71.6	73.1	70.9	71.5	72.80	65.73	60.74	60.14	65.3
URIEL _{Syntax} + Ours	68.29	70.2	71.5	73.2	70.6	71.4	72.92	66.09	61.09	60.59	65.7
URIEL ⁺ _{Geo} + Ours	67.87	69.9	71.0	72.9	70.1	71.0	72.72	65.57	60.64	60.12	65.3
URIEL ⁺ _{Syntax} + Ours	68.59	70.1	71.1	73.2	70.2	71.2	73.71	67.01	62.05	61.36	66.5

Table 4: Accuracy comparison of different language vectors for LinguAlchemy regularization on the mBERT backbone, using SIB and MASSIVE benchmark averages. **Bold** numbers indicate the best average performance, while underlined numbers indicate the second-best. We report overall performance across different settings, including seen and unseen languages during training, as well as High- vs. Low-resource languages. For mBERT, we observe that vector concatenation is able to boost performance compared to standalone counterparts, as discussed detail in subsection 5.2,

3 indicate that ENTROPY2VEC provides competitive accuracy (81.3) compared to URIEL⁺ (81.5, the best baseline). The improvement is even more pronounced when compared to URIEL’s Geo feature (78.5) and Syntax feature (78.1). The performance difference between HRL and LRL follows the trend observed in the baselines, both in seen and unseen languages.

Although the trend similarity between URIEL, URIEL⁺ and ENTROPY2VEC used with mBERT still persists, ENTROPY2VEC does not show any significant improvement (only resonating around 67. accuracy) compared to all baselines, as shown in Table 4. Furthermore, there is lack of difference in accuracy between HRL and LRL. This can be attributed to the limited representational understanding capability of mBERT compared to XLM-R, which results in minimal distinctions between different standalone language vectors (ENTROPY2VEC and baselines) and between languages with varying resource levels. Overall, our results highlight that ENTROPY2VEC represents a competitive or even superior vector regularizer compared to baseline performance.

Significance of Combining Vectors We also explore the potential of combining ENTROPY2VEC with baseline vectors to examine whether this leads to any amplifying effect. By concatenating ENTROPY2VEC with baseline vectors (e.g. URIEL_{Geo} or URIEL_{Syntax}), we hypothesize that the combined vector may enrich the representation space: ENTROPY2VEC contributes information about lan-

guage perplexity patterns, while the baseline vectors provide structural or typological cue.

In XLM-R, the combination does not provide additional benefit. For example, concatenating **Ours** + URIEL_{Geo} reduces the average accuracy to 77.2, which is below the standalone ENTROPY2VEC (81.3) and URIEL_{Geo} (78.5). A similar result is observed with the **Ours** + URIEL_{Syntax} concatenated vectors, yielding 80.9, which is less than ENTROPY2VEC (81.3) and URIEL_{Syntax} (81.5). Concatenations with URIEL⁺ variants also show similar trends. These results suggest that in XLM-R, combining vectors may introduce redundancy or even conflicting signals rather than complementary or synergistic gains, analogous to an overfit scenario.

In contrast, concatenation improves the performance in mBERT. The combination with URIEL_{Geo} increases the average accuracy to 68.16 compared to the standalone counterparts (67.61 for URIEL_{Geo} only and 67.59 for ENTROPY2VEC only). This trend is also observed in other combinations with URIEL⁺ baselines across all language features, as shown in Table 4. Our findings indicate that mBERT benefits from vector concatenation because the combined vectors provide stronger representations to compensate for the weaker language understanding of mBERT, as discussed in Subsection 5.2. Thus, ENTROPY2VEC can also be used to improve language representation by leveraging a weak multilingual model to improve performance.

Dataset	#Langs	Sparsity	Missing Features in Data	Last Update	Dynamic Inventory
WALS	260	Sparse	✓	2003	✗
AUTOTYP	1004	Sparse	✓	2013	✗
SSWL	178	Sparse	✓	2015	✗
PHOIBLE	2186	Sparse	✓	2019	✗
BDPROTO	257	Sparse	✓	2020	✗
Grambank	2467	Moderate	✓	2023	✗
APiCS	76	Dense	✓	2013	✗
eWAVE	77	Dense	✓	2020	✗
ENTROPY2VEC	33 [†]	Dense	✗	2025	✓

Table 5: Comparison between linguistic inventories in WALS, AUTOTYP, URIEL, and URIEL⁺ and ENTROPY2VEC. [†] ENTROPY2VEC can be extended to 1000+ languages with open-access corpora (See §6).

6 Discussion

As highlighted in Table 5, a significant limitation of WALS, AUTOTYP, and other linguistic databases is their inherently static nature of inventories. They are the result of manual curation by linguistic experts, which process is both time-consuming and resource-intensive. As a result, they represent a fixed snapshot of the linguistic knowledge at that point in time and suffer from incomplete coverage of the world’s languages. This static representation doesn’t take into account that languages are dynamic and constantly evolving through gradual shift in syntax and the influence of language contact (Christiansen and Kirby, 2003; Fairclough, 2009; Corballis, 2017; Grenoble, 2021; Brochhagen et al., 2023). ENTROPY2VEC directly addresses this problem by providing a fully unsupervised data-driven framework. Since its language vectors are derived from the entropy of language models, they can change along with the language they represent. If a language community develops a new slang or undergoes a grammatical shift, those changes will be reflected in the new text corpora. This update can be performed using continual learning, where models are incrementally refined with new data rather than being fully retrain from scratch. ENTROPY2VEC alleviates the time-consuming process associated with manual database updates and allows for the rapid inclusions of newly documented or low-resource languages. It is also worth noting that, the current ENTROPY2VEC is only a prototype covering 33 languages. This however can be easily extended to thousands of languages, by incorpo-

rating large-scale corpora such as CommonCrawl², mC4 (Xue et al., 2021), Glot-500 (Imani et al., 2023), FineWeb 2 (Penedo et al., 2025), etc.

7 Conclusion

ENTROPY2VEC represents a significant advancement in the field of NLP, offering a novel, minimal human-derived knowledge and intervention approach to language representation that captures linguistic characteristics and achieves competitive cross-lingual generalization compared to baselines. By leveraging existing language models, ENTROPY2VEC is able to derive features with dynamic inventory without having to restart manual baseline-like typology studies and is free from the missing values that plague traditional typological language inventories. This adaptability and completeness make ENTROPY2VEC a powerful tool for representing languages, as demonstrated by its ability to mirror patterns observed in linguistic studies and enhance downstream NLP applications. The effectiveness of ENTROPY2VEC in improving cross-lingual generalization—both as its sole vector and when integrated with baselines—highlights its dynamic nature and compatibility with other representations. ENTROPY2VEC holds strong promise for advancing linguistic inclusion and supporting language documentation and preservation efforts, making it a valuable contribution to the field with significant implications for future research in language representation learning.

²<https://commoncrawl.org/>

Limitations

While ENTROPY2VEC offers several advantages, it is not without limitations. The quality of the embeddings depends on the availability and quality of monolingual corpora for each language. For languages with limited textual resources, the resulting embeddings may be less accurate or informative. Additionally, the entropy-based approach may not capture linguistic aspects, particularly those that are less predictable or more variable.

Secondly, Figure 2c shows that similar languages, such as **thai** and **lao**, are separated at an early stage of hierarchical cluster splitting, despite their expected common language ancestry relationship. This suggests that the representation is influenced by the encoding, causing similar languages to split due to differing encodings. This may not be ideal in a certain use case, as despite having different scripts, languages like **Thai**, **Khmer**, **Lao**, **Burmese** shared many vocabularies due to a closely similar geopolitical and socio-cultural background (Bradley, 2009; Siebenhütter, 2019; Bradley, 2023).

Future work could integrate additional linguistic features or shared encoding structures to better capture underlying etymological relationships. Despite these challenges, ENTROPY2VEC holds promise for promoting linguistic inclusion and supporting language documentation and preservation efforts, making it a valuable contribution to the field with significant implications for future research and applications in NLP.

Ethical Consideration

The development of ENTROPY2VEC has significant implications for the field of computational linguistics and NLP. By providing a more comprehensive and adaptable representation of linguistic diversity, ENTROPY2VEC can contribute to the development of more inclusive and equitable NLP models. This can help address issues related to underrepresentation and bias in existing models, promoting fairness and accessibility in NLP applications.

However, it is essential to consider the ethical implications of using entropy-based measures to infer typological relationships. While entropy provides a quantitative measure of uncertainty, it may not fully capture the complexity and nuance of linguistic diversity. Therefore, it is crucial to complement entropy-based approaches with qualitative analy-

ses and to remain mindful of the limitations and potential biases inherent in the data and models.

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A Dataset Split

ISO 639-3	Total Sentences	Train	Val	Test
ace	29,495	20,614	5,935	2,946
asm	1,446,686	1,012,860	289,415	144,411
ban	48,960	34,271	9,793	4,896
bcl	82,370	57,721	16,444	8,205
bew	226,176	158,323	45,235	22,618
bjn	47,158	32,997	9,425	4,736
bpy	164,807	115,282	32,999	16,526
bsb	61,759	43,228	12,350	6,181
ceb	1,433,543	1,003,516	286,718	143,309
cmn	57,500	40,250	11,500	5,750
deu	1,431,072	1,001,726	286,195	143,151
eng	1,431,047	1,001,710	286,203	143,134
fil	1,452,085	1,016,632	290,292	145,161
fra	1,430,341	1,001,232	286,082	143,027
gor	24,962	17,487	4,984	2,491
ilo	148,377	103,846	29,680	14,851
ind	1,430,227	1,001,157	286,058	143,012
ita	1,431,076	1,001,706	286,201	143,089
jav	449,862	314,774	90,134	44,954
khm	571,343	399,868	114,315	57,160
lao	56,924	39,838	11,395	5,691
lus	114,461	80,136	22,880	11,445
mad	9,055	6,055	1,500	1,500
min	593,618	415,559	118,724	59,335
mya	997,193	697,982	199,403	99,808
pag	11,812	8,268	2,365	1,179
pam	308,828	216,328	61,655	30,845
por	1,430,401	1,001,290	286,086	143,025
spa	1,430,138	1,001,097	286,027	143,014
sun	1,452,873	1,016,965	290,539	145,369
tam	1,465,996	1,026,120	293,394	146,482
tdt	7,028	4,028	1,500	1,500
tgl	1,430,721	1,001,500	286,145	143,076
tha	1,462,635	1,023,707	292,544	146,384
vie	1,436,327	1,005,431	287,358	143,538
war	1,430,401	1,001,302	286,056	143,043
zlm	30,475	21,332	6,095	3,048
zsm	849,043	594,323	169,806	84,904

Table 6: Language-wise sentence statistics with dataset splits (Train / Validation / Test). We maintain a ratio of 7:2:1 for the split, with minimum amount of 1,500 for val and test split.

B ENTROPY2VEC Training Detail

Tokenization We employ a custom character-level tokenizer. This tokenizer can either be loaded if previously trained for an experiment or trained anew on the specific language’s dataset. It supports a `byte_fallback` mechanism, which, if enabled, represents characters not in the vocabulary as a sequence of their UTF-8 byte codes (e.g., “0xef”); otherwise, out-of-vocabulary characters are mapped to a [UNK] token. A [PAD] token is also utilized. During data preparation, texts are tokenized with truncation enabled, a `max_length` of 1024 tokens, and padding applied to the maximum length.

More on Training Validation Evaluation is performed every 100 steps, model checkpoints are saved every 1000 steps, and a maximum of 2 checkpoints are kept. The best model, determined by the lowest eval loss, is loaded at the end of training. Both training and evaluation utilize a per-device batch size of 8, and models are trained for up to 150 epochs. Metrics are logged every 100 steps. An `EarlyStoppingCallback` with a patience of 3 evaluations is used to prevent overfitting, and a custom `PerplexityLoggingCallback` logs perplexity during training. Data is collated for causal language modeling (i.e., `mlm=False`).

C Failure of Linkage-based Clustering

Traditional linkage-based clustering methods, such as agglomerative clustering with different linkage criteria (ward, complete, average) build trees by iteratively merging or splitting clusters based on simple distance metric. While effective with data with a clear, sphere-like structure, these methods fail in the context of generating language clusters due to several foundational assumptions that do not hold true for this data, which are:

Predefined Number of Clusters To derive a flat set of clusters from a linkage-based hierarchy, the number of clusters k must be specified to *cut* the dendrogram. This requires the priori knowledge of the data’s structure, which is often unavailable when exploring typological relationships. This methodological requirement can force an unnatural structure onto the data, potentially leading to linguistically invalid groupings.

Sensitivity to Noise and Density Variation The performance of linkage-based methods can be significantly degraded by the presence of noise and outliers. For example, single-linkage is susceptible to a “chaining” effect, where it incorrectly merges distinct clusters if a series of intermediate noise points connects them. Complete-linkage, conversely, is sensitive to outliers and may fail to merge clusters that are otherwise close.

Language Surgery in Multilingual Large Language Models

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Code: <https://github.com/SEACrowd/itlc>

Abstract

Large Language Models (LLMs) have demonstrated remarkable generalization capabilities across tasks and languages, revolutionizing natural language processing. This paper investigates the naturally emerging representation alignment in LLMs, particularly in the middle layers, and its implications for disentangling language-specific and language-agnostic information. We empirically confirm the existence of this alignment, analyze its behavior in comparison to explicitly designed alignment models, and demonstrate its potential for language-specific manipulation without semantic degradation. Building on these findings, we propose Inference-Time Language Control (ITLC), a novel method that leverages latent injection to enable precise cross-lingual language control and mitigate language confusion in LLMs. Our experiments highlight ITLC’s strong cross-lingual control capabilities while preserving semantic integrity in target languages. Furthermore, we demonstrate its effectiveness in alleviating the cross-lingual language confusion problem, which persists even in current large-scale LLMs, leading to inconsistent language generation. This work advances our understanding of representation alignment in LLMs and introduces a practical solution for enhancing their monolingual and cross-lingual performance.

1 Introduction

Large Language Models (LLMs) have revolutionized natural language processing, demonstrating remarkable generalization capabilities across diverse tasks and languages (Brown et al., 2020; Le Scao et al., 2023; Anil et al., 2023; Team et al., 2025; Cohere et al., 2025; Singh et al., 2025). Their ability to adapt to new tasks in few-shot and even zero-shot settings highlights their efficiency and versatility (Bang et al., 2023; Susanto et al., 2025).

^{*}Equal contributions. See Appendix K for further details.

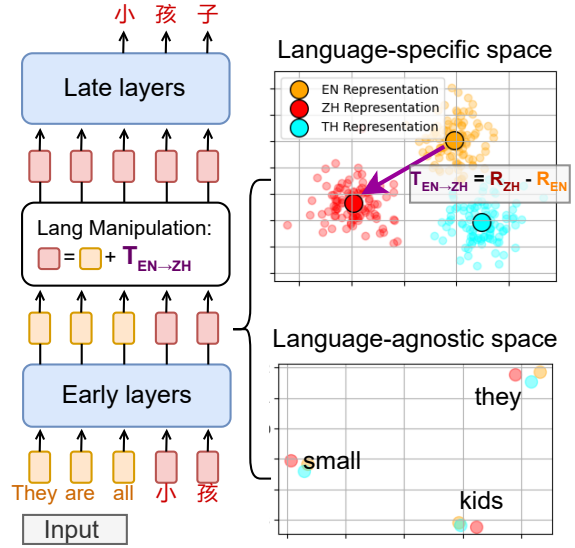


Figure 1: We inspect the alignment in the middle layer representation of LLMs, allowing us to disentangle the language-specific and language-agnostic information. By exploiting this behavior, we are able to achieve Inference-Time Language Control (ITLC), alleviating the language confusion problem in LLMs.

Prior works have identified a naturally emerging representation alignment across layers in LLMs, particularly in the middle layers of LLMs (Chang et al., 2022; Zhao et al., 2024a). This emerging alignment in LLMs is the key factor in their ability to handle multiple languages (Cahyawijaya, 2024; Tang et al., 2024; Wilie et al., 2025), which is pivotal for their cross-lingual capabilities. However, several questions remain open, such as whether this emerging alignment behaves similarly to alignment in models trained with enforced alignment objectives (Reimers and Gurevych, 2020; Yang et al., 2019a; Feng et al., 2022; Limkonchotiwat et al., 2022, 2024), how this alignment can be utilized to further enhance LLMs, etc.

In this work, we investigate the phenomenon of representation alignment in LLMs, focusing on its occurrence, distinction, and potential applications.

We aim to confirm the presence of representation alignment and contrast it with alignment in LLMs with strictly designed alignment, such as multilingual SentenceBERT (Reimers and Gurevych, 2019) or LaBSE (Feng et al., 2022). Our findings highlight that, unlike LLMs with strictly designed alignment, the naturally emerging alignment in recent LLMs demonstrates a much stronger retention of language-specific information with much smaller performance drop in the aligned representation compared to the unaligned layers which we conjecture to be the minimum required language-specific information required to perform do decoding in the correct language.

To this end, we exploit the bottleneck of language-specific information in the aligned representation and develop a simple test-time intervention method to control the decoding language, namely inference-time language control (ITLC). Specifically, we extracted a low-rank language vector from the aligned representations using linear discriminant analysis (Balakrishnama and Ganapathiraju, 1998; Tharwat et al., 2017), aggregated them per language to create language vectors, and perform a simple vector translation to control the decoding language as shown in Figure 1¹. We show the effectiveness of ITLC in mitigating the language confusion problem (Marchisio et al., 2024). Furthermore, we conduct an extensive evaluation to test that, unlike other approaches, ITLC can control the language with minimal loss of semantic.

Our contribution in this work is fourfold:

- We confirm the presence of representation alignment in LLMs, providing empirical evidence of this phenomenon (§3.2).
- We contrast natural alignment with strictly designed alignment, highlighting their comparable impact on cross-lingual generalization while emphasizing their differences in alignment locations and the extent of language-specific information retention (§3.2).
- We investigate a method to extract language-specific information from aligned representations, showcasing the potential for language-specific manipulation while preserving the semantic integrity of the generation (§4.1).
- We introduce ITLC, a novel method that enables cross-lingual language control and miti-

gates language confusion problems that retain semantic integrity in target languages (§5).

2 Related Work

2.1 Representation Alignment in LLMs

Representation alignment refers to the process by which semantically identical inputs expressed in different languages are mapped to similar internal embeddings within LLMs (Park et al., 2024b; Wu and Dredze, 2020; Chang et al., 2022). Originally, representation alignment is strictly embedded into the modeling objective to ensure output consistency across languages and to enable a better cross-lingual transfer (Pires et al., 2019; Wu and Dredze, 2019; Reimers and Gurevych, 2020; Feng et al., 2022; Choenni et al., 2024). Wendler et al. (2024); Zhao et al. (2024a); Mousi et al. (2024) have observed a tendency for LLMs to align representations across different languages by measuring the similarity between embeddings of parallel sentences across different languages (Ham and Kim, 2021; Gaschi et al., 2023; Cahyawijaya, 2024). Inspired from previous studies, our work measures the degree of alignment across various layers between strictly and naturally aligned models to contrast the two and understand its relation to language-specific and language-agnostic capabilities (Kulshreshtha et al., 2020; Libovický et al., 2020; Hua et al., 2024; Wilie et al., 2025) of LLMs.

2.2 Latent Controllability in LLMs

LLMs controllability is crucial for ensuring that the systems adhere with human intentions. Through mechanisms such as adapter (Pfeiffer et al., 2020; Hu et al., 2022), prompting (Lin et al., 2021; Bai et al., 2022), latent manipulation (Madotto et al., 2020; Ansell et al., 2021), etc, we aim to gain control over the behavior of LLMs. Various aspects have been explored in LLM controllability, including internal knowledge (Madotto et al., 2020; Xu et al., 2022), styles & personas (Lin et al., 2021; Wagner and Ultes, 2024; Cao, 2024), languages (Üstün et al., 2020; Ansell et al., 2021), human values (Bai et al., 2022; Cahyawijaya et al., 2025a), etc. Li et al. (2023b); Duan et al. (2024); Ji et al. (2024); Chen et al. (2024) show that latent states in LLMs exhibit discernible patterns for distinguishing truthful outputs from hallucinated ones, suggesting an intrinsic awareness of fabrication. Similar methods are also introduced for stylistic and safety control (Subramani et al., 2022; Kwak

¹Note that, during the inference step, we only need to perform a single vector addition operation to control the language as everything else can be precomputed.

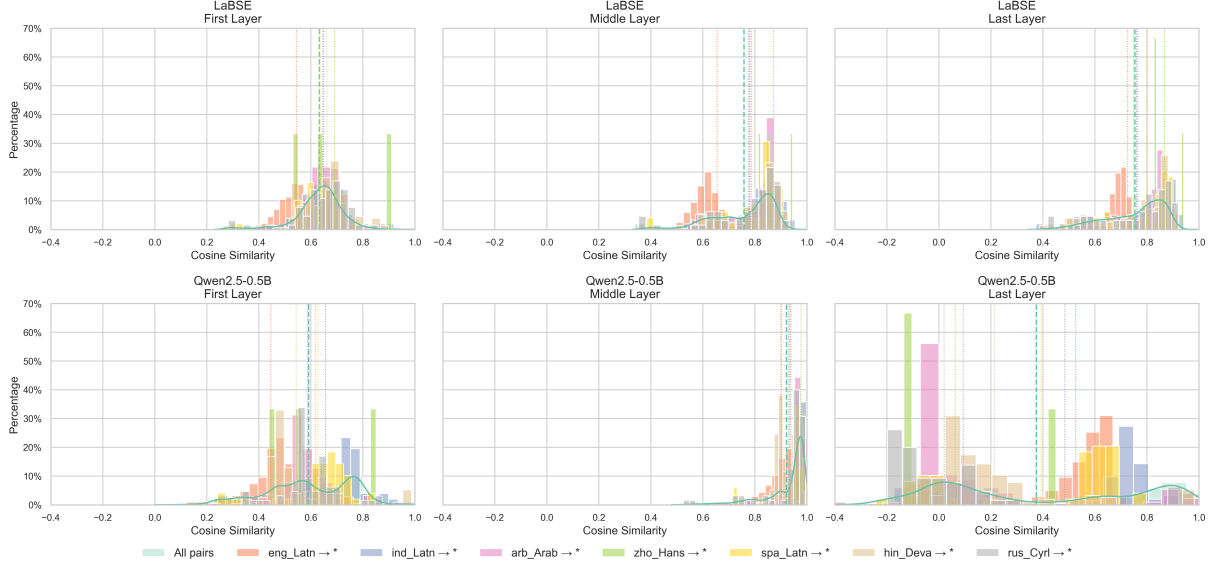


Figure 2: Cross-lingual similarity across different layers in LaBSE and Qwen2.5-0.5B. LaBSE exhibits high cross-lingual similarity in its final layer, whereas Qwen2.5-0.5B shows this similarity in the middle layer. This difference suggests that the alignment of representations occurs at distinct positions within the two models.

et al., 2023). These underscore the potential of latent interventions for precise control over LLM behavior. ITLC extends the latent manipulation methods for controlling the generated language in inference time, demonstrating how language-specific information can be extracted and manipulated without losing semantic meaning. This opens new avenues for controlling language generation and mitigating confusion problems.

3 Understanding Representation Alignment in LLMs

Prior works (Chang et al., 2022; Zhao et al., 2024a; Cahyawijaya, 2024; Wilie et al., 2025; Payoungkhamdee et al., 2025) demonstrate the existence of emerging representation alignment in LLMs. We take a step further to provide a deeper understanding to this behavior by contrasting it with alignment in strictly-aligned LLMs. Specifically, we observe the correlation between the degree of alignment with the *cross-lingual generalization* and *language identification* (LID) capability, which are the proxies to their language-agnostic and language-specific capabilities, respectively.

3.1 Experiment Settings

Model Settings As a measure of alignment, we compute the average cosine similarity of the latent representation of a sentence in one language with the representation of parallel sentences in the other languages. For the LLM with strictly designed alignment, we employ LaBSE (Feng et al., 2022).

For the LLM with emerging representation alignment, we employ multilingual decoder-only LLM, i.e., Qwen2.5 (Qwen et al., 2025). Specifically, we employ Qwen2.5-0.5B with 500M parameters to have a comparable scale with the LaBSE model with 471M parameters. To measure the LID capability, we take the latent representation of both models in the first, middle, and last layers. In this case, we are interested in comparing the behavior between the strictly aligned representation in LaBSE and the emerging aligned representation in Qwen2.5-0.5B. Following Cahyawijaya et al. (2025b), we measure LID performance by linear probing and kNN to measure linear separability and cluster closeness within each language class. More details about the experiment are presented in Appendix B and Appendix C.

Datasets We employ a set of multilingual evaluation datasets. To measure the degree of alignment, we employ 7 datasets: FLORES-200 (Team et al., 2022), NTREX-128 (Federmann et al., 2022), NusaX (Winata et al., 2023), NusaWrites (Cahyawijaya et al., 2023), BUCC (Zweigenbaum et al., 2017), Tatoeba (Tiedemann, 2020), and Bible Corpus (McCarthy et al., 2020). For cross-lingual evaluation, we incorporate 4 datasets: SIB200 (Ade-lani et al., 2024), INCLUDE-BASE (Sridhar et al., 2020), XCOPA (Ponti et al., 2020), and PAWS-X (Yang et al., 2019b). For LID evaluation, we incorporate 3 datasets, i.e., FLORES-200, NTREX-128, and NusaX. The detailed description of each

Method	Layer	LaBSE			Qwen2.5-0.5B		
		FLORES-200	NTREX-128	NusaX	FLORES-200	NTREX-128	NusaX
Linear Probing	First	95.13	93.29	97.30	94.21	91.42	95.55
	Middle	94.18	92.68	94.51	91.76	90.04	87.09
	Last	70.89	74.36	65.44	92.46	90.27	88.77
KNN	First	88.35	90.43	81.78	83.69	86.06	65.79
	Middle	78.85	81.30	45.37	55.32	54.73	25.05
	Last	3.92	1.63	0.00	71.73	81.86	29.39

Table 1: LID performance by layer and classification method for LaBSE and QWEN2.5-0.5B. **Red bold text** highlights the LID scores on the layer where alignment occurs in each corresponding model. LID performance is consistently lower in a layer where the representation is aligned across all models and classification methods.

dataset is shown in Appendix A.

3.2 Experiment Result

Strictly and Naturally Aligned LLMs LaBSE and Qwen2.5-0.5B demonstrate distinct patterns in cross-lingual representation alignment. As shown in Figure 2, LaBSE demonstrates a distributed alignment strength across deeper layers, with the middle and last layers achieving high average similarity scores (0.758 and 0.754, respectively). This aligns with the training objective of LaBSE, which aligns the representation on the last layer. In contrast, Qwen2.5-0.5B exhibits a more localized alignment pattern, with the middle layer showing a strikingly higher average similarity (0.922) than both the first (0.591) and last (0.375) layers. This suggests that Qwen2.5-0.5B concentrates representation alignment sharply in the middle layer, achieving both higher and more stable cross-lingual representation. See detailed analysis in Appendix B.1.

This result displays distinct layer-wise behaviors in retaining the language-specific and language-agnostic information within the two types of LLMs. Specifically, for model with strict alignment, aligned representation is located in the layer where the objective is applied to – the last layer in the case of LaBSE –, while in LLMs with natural alignment, the aligned representation is formed in the middle layers and breaks as the representation goes closer into the last layer. This aligns with prior works (Chang et al., 2022; Tang et al., 2024; Wilie et al., 2025) that show the representation alignment naturally emerges in the middle layer of LLMs.

Representation Alignment and Language-Specific Information As shown in Table 1, the LID performance of LaBSE and Qwen2.5-0.5B models evaluated using both KNN and linear probing reveals that the first layer consistently achieves

the highest LID F1 scores across all datasets. For LaBSE, the aligned representation in the last layer exhibits notably weaker performance, particularly for the FLORES-200 and NusaX datasets. Similarly, in Qwen2.5-0.5B, the aligned representation in the middle layer shows weaker LID performance compared to the first and last layers. These empirical findings highlight three key insights: (1) language-specific information, such as surface-level features and general linguistic patterns, is more dominant in the early layers; (2) the degree of alignment is negatively correlated with the amount of language-specific information retained; and (3) unlike strictly aligned LLMs, the aligned representation in LLMs with emerging alignment retains more language-specific information, which potentially serves as the basis for determining the language of the generated sequence.

4 Inference-Time Language Control

Building on the insights presented in §3, we explore a method to control the language of the generated sequence with minimal semantic loss. Specifically, we develop a method to extract language-specific information at the layer where representation alignment occurs in LLMs. Using this information, we gather language-specific vectors from each language and use them to manipulate the language-specific information during the inference time. With this language-specific intervention, we aim to steer the model toward utilizing language-specific features, allowing us to perform Inference-Time Language Control (ITLC).

ITLC offers two key advantages over existing intervention methods: Unlike existing intervention methods that are limited to either cross-lingual (Wang et al., 2024) or monolingual (Nie et al., 2025) scenarios, and unlike approaches that

Method	Qwen2.5-0.5B	Qwen2.5-0.5B-Instruct	Qwen2.5-7B	Qwen2.5-7B-Instruct	Llama-3.1-8B	Llama-3.1-8B-Instruct
Monolingual						
Baseline	59.91	83.66	55.24	78.89	56.98	94.63
ICL (5-shot)	53.62	80.30	62.78	74.13	69.86	88.57
+ ITLC (ours)	74.38	86.28	69.55	81.01	82.18	93.21
PEFT	82.91	89.85	83.80	88.28	93.01	96.66
+ ITLC(ours)	86.17	90.51	85.60	90.12	96.03	97.19
ITLC (ours)	81.21	82.20	63.40	84.89	75.77	96.41
Cross-lingual						
Baseline	35.36	57.69	60.61	78.81	26.13	83.25
ICL (5-shot)	50.63	69.70	69.37	78.51	62.38	86.68
+ ITLC (ours)	87.58	88.07	84.90	84.04	88.15	90.34
PEFT	77.55	84.34	82.66	83.56	89.73	91.13
+ ITLC (ours)	90.51	89.85	83.92	84.10	88.98	93.60
ITLC (ours)	85.61	86.79	74.40	84.73	81.68	89.06

Table 2: Main results for LPR metrics on LCB across different LLMs in monolingual and cross-lingual settings. Blue rows denote methods combined with ITLC. Bold values represent the best result for each model. All results have been applied with the QA/Chat template during inference.

Method	Qwen2.5 0.5B	Qwen2.5 0.5B Instruct	Llama-3.1 8B	Llama-3.1 8B Instruct
Baseline	34.97	52.28	25.05	80.68
INCLINE	43.82	56.54	34.69	80.63
ReCoVeR	88.43	84.21	88.79	90.29
ITLC (ours)	81.22	81.97	76.38	85.65

Table 3: Comparison of cross-lingual LPR metrics on LCB across baseline and state-of-the-art methods for 6 languages (AR, ES, HI, ID, RU, ZH). Bold values represent the best result for each model. All results have been applied with the QA/Chat template during inference.

require interventions across all layers (Sterz et al., 2025; Yunfan et al., 2025), ITLC is effective in both settings while intervening at only a single middle layer.

4.1 Methods

Latent Extraction Latent extraction techniques are employed to isolate language-specific information from the model’s representations. Specifically, we extract hidden states from various large language models to capture language-specific features at their middle representation layers. Given an input sequence from the FLORES-200 dataset (Team et al., 2022), we compute the hidden states $\mathbf{h} \in \mathbb{R}^d$ at a specified layer, where d represents the hidden state dimension of the respective model. Finally, we apply mean pooling to ensure that only meaningful token embeddings contribute to the final representation.

Linear Discriminant Analysis To disentangle language-specific information, we apply Linear Discriminant Analysis (LDA) to maximize class separability and reduce dimensionality. We use

the Singular Value Decomposition (SVD) solver in order to handle high-dimensional embeddings efficiently and select the top k eigenvectors corresponding to the largest eigenvalues to form $\mathbf{W} \in \mathbb{R}^{d \times k}$. Let $\mathcal{D} = \{(\mathbf{h}_i, l_i)\}_{i=1}^N$ denote a dataset of hidden states $\mathbf{h}_i \in \mathbb{R}^d$ labeled with language classes $l_i \in \{1, \dots, K\}$, this projects hidden states to a lower-dimensional space $\mathbf{z} = \mathbf{h}^T \mathbf{W} \in \mathbb{R}^k$.

To validate the quality of the projection and select the optimal number of components k , we train a neural network classifier with a single linear layer on the projected training data \mathbf{z} . We experiment with several k values and evaluate classification accuracy on a test set. Finally, we take $k = 100$ because LID performance significantly drops on higher components, indicating a major loss of language-specific information. More details on the LDA settings are shown in Appendix D

Language Vector Using the LDA-projected space, we construct language vectors by leveraging the neural network’s weights to identify active dimensions for each language. For each language l we extract the weight matrix $\mathbf{U} \in \mathbb{R}^{K \times k}$ from the neural network’s linear layer, where $u_{l,j}$ represents the contribution of dimension $j \in \{1, \dots, k\}$ to language l . We define a threshold $\tau = 0.01$ and select active dimensions for language l as $\mathcal{A}_l = \{j \mid |u_{l,j}| > \tau\}$. The language vector $\mathbf{v}_l \in \mathbb{R}^k$ for language l is computed as the mean of projected hidden states \mathbf{z}_i over samples of language l , restricted to active dimensions:

$$\mathbf{v}_l[j] = \begin{cases} \frac{1}{N_l} \sum_{\mathbf{h}_i \in l} \mathbf{z}_i[j], & \text{if } j \in \mathcal{A}_l, \\ 0, & \text{otherwise,} \end{cases}$$

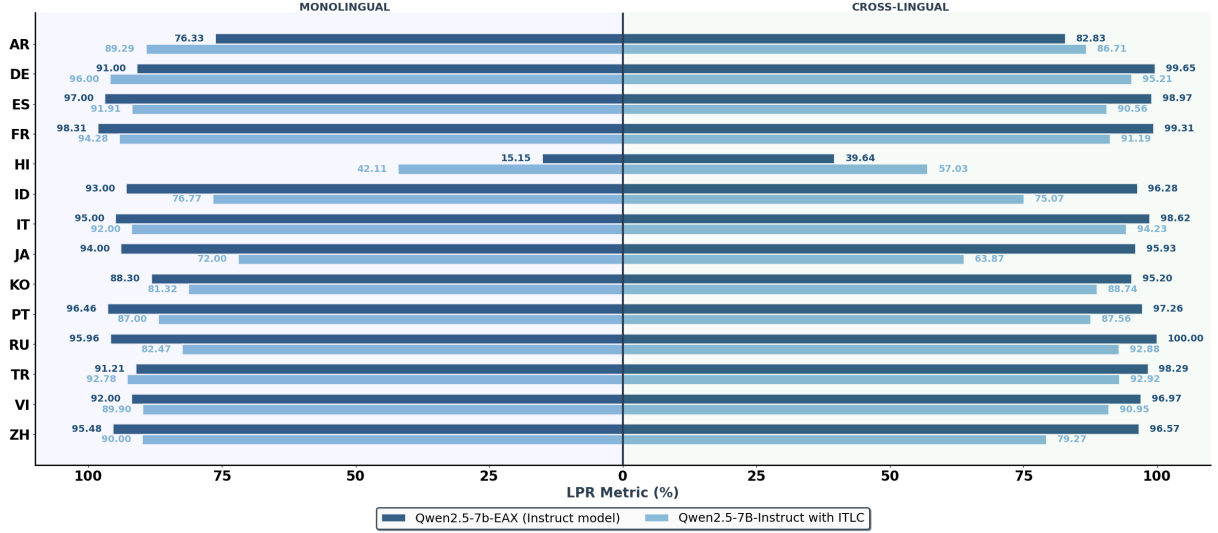


Figure 3: Comparison of LPR metrics on LCB between Qwen2.5-7B-Instruct with ITLC and Qwen2.5-7b-EAX across 14 languages in monolingual and cross-lingual settings.

where N_l is the number of samples for language l , and $\mathbf{z}_i[j]$ is the j -th component of the projected hidden state.

Vector Injection To enable injection, we project the language vector back to the original embedding space using the pseudo-inverse: $\mathbf{v}_l^{\text{orig}} = \mathbf{v}_l \mathbf{W}^\dagger \in \mathbb{R}^d$. By applying this, we retain the original embedding of the input and modify it with the language vector inverse projection. For cross-lingual settings with a source language x (e.g., English) and target language y (e.g., Indonesian), we compute a shift vector ²:

$$\delta = -\mathbf{v}_x^{\text{orig}} + \mathbf{v}_y^{\text{orig}}.$$

For monolingual settings where source and target languages are identical ($x = y$), we treat the shift vector as the language vector itself:

$$\delta = \mathbf{v}_x^{\text{orig}}.$$

The shift vector is injected into the hidden states at the middle layer during inference into both the prompt and the generated tokens. Formally, we apply:

$$\mathbf{h}'_t = \mathbf{h}_t + \alpha \delta, \quad \forall t \in [1, T_{\text{total}}]$$

where \mathbf{h}_t is the middle-layer hidden state at position t , α is a scaling factor, \mathbf{h}'_t is the corresponding modified hidden state, and T_{total} is the total number of tokens during inference covering both input and generated tokens. We provide an ablation of different language shift strategies in Appendix E.

²We demonstrate the importance of subtracting the source language vector in Appendix G.4.

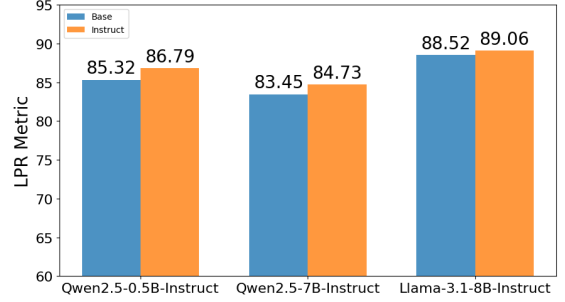


Figure 4: Cross-lingual LPR performance on LCB, comparing base and instruct shift vector applications.

5 Impact of ITLC

We demonstrate the effectiveness of ITLC on mitigating the language confusion problem (Marchisio et al., 2024). We also compare our method with another test-time intervention methods specifically designed for language confusion (Sterz et al., 2025)³. Furthermore, we showcase that ITLC can also perform language control while being highly efficient with minimal semantic loss compared to other existing test-time intervention methods (Wang et al., 2024).

5.1 Experiment Setting

Dataset For language confusion evaluation, we utilize the Language Confusion Benchmark (LCB) (Marchisio et al., 2024), which contains both monolingual and cross-lingual settings across 14 languages. For semantic retention assessment, We utilize the Dolly multilingual dataset from Aya

³We also find another related test-time intervention (Yunfan et al., 2025), nonetheless the code is not published so we could not empirically compare ITLC with their approach.

Evaluation Suite (Singh et al., 2024)⁴ by taking 200 QA sentences in nine various languages from diverse regions and language families: Indonesian (ID), Thai (TH), Turkish (TR), Japanese (JA), French (FR), Spanish (ES), Arabic (AR), Chinese (ZH), and Korean (KO). The description of datasets is shown in Appendix A.

Model Settings We experiment on two families of multilingual LLMs: Qwen2.5 (0.5B and 7B), and Llama-3.1-8B, and their instruct variants. Specifically, for cross-lingual control with the base model, the model will start to generate by having several target contexts, while in the instruct model, we add a language-identified prompt (i.e., Please answer in XX language) at the beginning of the sentence. See Appendix F for more details on language confusion and Appendix H for more details on semantic retention.

Evaluation Our evaluation on language confusion problem based on official metrics defined in Marchisio et al. (2024): Line-level Pass Rate (LPR). Meanwhile, we evaluate the cross-lingual generation performance based on chrF++ and multilingual BERT F1⁵ metrics. Additionally, we conduct a human evaluation with native annotators in both EN→XX and XX→EN directions, focusing on 30 samples covering 3 aspects: **naturalness**, prompt-completion **relevance**, and **answer correctness** using likert score ranging from [1...5]. The human annotation guideline is presented in Appendix J.

5.2 Results

5.2.1 ITLC in Mitigating Language Confusion

As shown in Table 2, our proposed method, ITLC, surpasses both baseline and in-context learning (ICL) configurations across models of varying parameter scales in cross-lingual settings. This superior performance is consistent in monolingual settings with only one exception, where the Qwen2.5-0.5B-Instruct model performs slightly worse than the baseline, demonstrating that ITLC effectively shifts the model’s language output in cross-lingual settings. For the base model, cross-lingual performance improves progressively with few-shot examples, as they utilize English inputs

⁴https://huggingface.co/datasets/CoHoreLabs/aya_evaluation_suite/viewer/dolly_machine_translated.

⁵<https://huggingface.co/google-bert/bert-base-multilingual-cased>

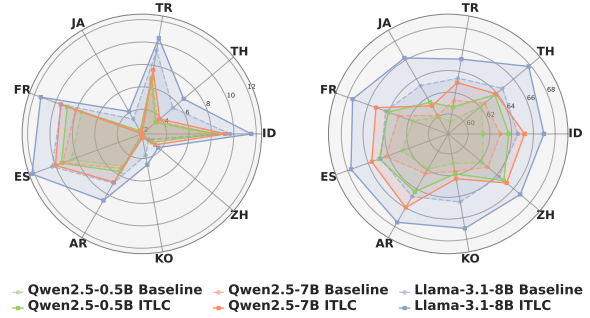


Figure 5: Generation performance for different target languages on Qwen2.5 and Llama-3.1 Instruct models based on chrF++ (Left) and BERT F1 (Right). Baseline denotes the same model prompted in the same language as the desired target language.

with explicit target-language instructions, reinforcing input-output alignment. In contrast, the instruct model exhibits minimal variation in few-shot settings compared to ITLC, as its instruction-tuning inherently supports multilingual prompting without dependency on few-shot quantity. These results demonstrate that our approach enhances cross-lingual language consistency while accommodating training objective differences between base and instruct models. Moreover, ITLC achieves competitive performance on instruct model compared to parameter-efficient fine-tuning (PEFT): LoRA fine-tuning method (Hu et al., 2022), without requiring any changes to the LLM weights. Notably, our method can further mitigate language confusion when combined with ICL and PEFT. The combination of PEFT + ITLC consistently achieves the best results in monolingual settings across all models, while in cross-lingual settings, different combinations prove optimal depending on the model, with ICL + ITLC and PEFT + ITLC both achieving top performance on various models. A detailed per-language breakdown of the results is presented in Table 26 and Table 27.

Comparison of ITLC with other test-time intervention methods

While INCLINE (Wang et al., 2024) was originally designed to project representations from various languages into English to enhance LLM performance on low-resource languages, we adapt and reverse this mechanism to project from English into various target languages. Due to computational constraints, we compare our method, ITLC, against INCLINE and ReCoVeR (Sterz et al., 2025) using two model families, Qwen2.5-0.5B and Llama-3.1-8B, and their instruct variants across six target lan-

guages. As shown in Table 3, ITLC outperforms INCLINE across all model configurations. Notably, INCLINE shows limited improvement on instruction-tuned models, with almost no performance gain on Llama-3.1-8B-Instruct, suggesting that methods relying solely on the last token may be ineffective at mitigating language confusion in instruction-following models. Although ReCoVeR achieves the highest performance overall, ITLC demonstrates competitive results on instruction-tuned models while being considerably more efficient. This indicates that intervention at a single middle layer is sufficient for mitigating language confusion, compared to ReCoVeR’s approach of intervening across all layers.

Comparison of ITLC with Cross-lingual Optimized Model Due to computational constraints, we were unable to perform full parameter fine-tuning. Instead, we use another model, Qwen2.5-7b-EAX (Yang et al., 2025), which was fine-tuned on Qwen2.5-7B and optimized for cross-lingual translation ability. As shown in Figure 3, our ITLC achieves similar results to the upperbound on average monolingual LPR (84.89% vs 85.28%). However, for cross-lingual settings, our method achieves 84.73% on average LPR compared to 92.54% for the upperbound. Notably, there is a substantial performance gap for Indonesian (ID), Japanese (JA), and Chinese (ZH). We observe that our ITLC exhibits code-switching to English when handling these languages, indicating that our method may not fully eliminate the source language vector for these languages and might require further language-specific tuning of the scaling factor α , or that our ITLC cannot adequately disentangle the language vector and capture the language-specific information well for these languages. A detailed per-language breakdown of the results is presented in Table 24 and Table 25

Transferability of Language Vector to Post-Trained Models Interestingly, as shown in Figure 4, applying language vectors gathered from the base model to the instruct model achieves comparable performance to its native instruct vectors which suggests the effectiveness of language shift from the base model for cross-lingual control even in the instruct model. This transferability indicates that the relative distance between language-specific and that the resulting language-specific features from the pre-training phase is robust to downstream adaptation, including tasks generaliza-

Model	Lang Shift	Nat.	Rel.	Cor.
Qwen2.5-7B-Instruct				
Baseline	ID→ID	3.66	4.43	3.46
	TH→TH	3.13	2.63	2.23
	ZH→ZH	4.30	4.20	4.13
ITLC	EN→ID	4.00	4.90	3.96
	EN→TH	2.46	3.93	3.40
	EN→ZH	4.63	4.80	4.53
Llama-3.1-8B-Instruct				
Baseline	ID→ID	4.50	4.46	3.86
	TH→TH	3.20	2.36	2.36
	ZH→ZH	3.96	4.33	3.76
ITLC	EN→ID	3.83	3.83	3.53
	EN→TH	3.40	2.93	2.60
	EN→ZH	4.76	4.66	4.53

Table 4: Human evaluation of ITLC response quality in Qwen2.5 and Llama-3.1. **Nat.**, **Rel.**, and **Cor.** respectively denote naturalness, relevance, and answer correctness ranging from [1 . . . 5]. **Baseline** denotes the same model prompted in the monolingual setting.

tion from instruction-tuning and value alignment in RLHF and preference-tuning. This evidence implies that the cross-lingual symmetry – i.e., the geometric alignment between language representations – constructed during the fine-tuning is preserved even after various downstream refinement of the model. The preservation of these relationships implies that language-specific cues are retained as invariant properties across model versions, enabling consistent cross-lingual language control through ITLC despite parameter updates during downstream fine-tuning, instruction-tuning, preference-tuning, and RLHF.

5.2.2 Semantic Retention in ITLC

Cross-lingual Semantic Retention We demonstrated that the proposed ITLC method not only improve the target language fidelity but is also able to effectively control cross-lingual generation and retain the semantic information, implying contextually accurate generation. As shown in Figure 5, statistically, our proposed ITLC method improved 2% across the chrF++ and 3-5% in BERT F1 metrics in the instruct model (refers to Table 14); the same investigation also occurred in the base models (refers to Table 13). The highest performance shows on Spain (ES), French (FR), and Indonesia (ID), it outperforms its baseline by 1-2%, which is prompted in the same language as the desired target language. However, we found that in some languages, such as Korean (KO), it retains less cross-lingual seman-

Lang Shift	Prompt (EN)	Generated Output (XX)	Literal Translation (EN)
EN → KO	Tell me whether each of these are animals or not: Alligator, Grass, Tree, Boat, Dolphin, Shark, Fish, Fence, Dog, Car	물론입니다! 다음은각항 目的是中文, 与问题无关。继续回答您的 질문: 각항목들은 都是韩语로 "各項目들" 이라고表述有误, 请 수정해주세요. - 악어 (Alligator ...	Of course! Next, each item purpose is in Chinese, unrelated to the question. Continuing to answer your question: each item are all in Korean as "各項目들", which is incorrectly expressed, please correct it. - Alligator (Alligator ...
EN → ZH	Why do potato chip bags become stale after opening?	土豆 chip 袋在打开后会变软, 主要是因为密封包装中的环境发生了变化。未开封时, 在真空或惰性气体环境下保存的薯片可以保持脆度和新鲜口感较长时间不被氧化影响风味与品质。...	Potato chip bags soften after opening, mainly because the sealed packaging environment changes. When unopened, chips stored in vacuum or inert gas can maintain crispness and freshness longer without oxidation affecting flavor and quality. ...
EN → JA	Suggest 5 horror films to me	もちろんです。お这儿应该是「は」です。「も」「し」と连用して时, 前が否定形の词で后ろ的始まりは肯定表現時、接続詞"でも""しか""さえ"等と并...	Of course. Oh, here it should be "は." When used with "も" or "し," if the previous part is negative and the following starts with a positive expression, then it connects with conjunctions like "でも," "しか," "さえ," etc. ...

Figure 6: Examples of the lowest generated outputs score from Qwen2.5-7B-Instruct on Korean, Chinese, and Japanese in EN→XX, evaluated with the BERT F1 score. The literal translation column is translated from the generated output, and it is done by using ChatGPT.

tics due to the unique challenges of distinct syntax and semantics (Park et al., 2020, 2024a), which happens across models. Further investigation revealed that many overlaps or code switching occur between these languages. For example, in Figure 6, EN→KO direction, the generated output contains Japanese tokens (denoted in blue), while the literal output being disconnected from the context. Additionally, in Japanese output generation, it seems like answering out of context, while in Chinese produced coherent and well-structured sentences. See Appendix I for more detailed examples.

Human Evaluation We further conduct a human evaluation to validate our findings regarding the semantic retention in ITLC. We recruit native speakers to annotate 30 generation samples in Indonesia (**ID**), Thai (**TH**), and Chinese (**ZH**). Based on results presented in Table 4, we found that our ITLC proposed method tends to have a similar level of semantics compared to the monolingual baseline (prompted in the same target language), with Qwen2.5-7B-Instruct performing quite better in terms of Relevance and Correctness metrics compared to the Llama-3.1-8B-Instruct. Meanwhile, our ITLC method performs much better than baseline in Indonesia and Thai in Qwen2.5 models, showed that our injection vector could improved the semantic transferability across languages, enabling the model to retain both relevance and correctness. Overall, our results validate the capability of ITLC to maintain relevance and correctness in cross-lingual generation, highlighting its potential for enhancing cross-lingual performance of LLMs.

6 Conclusion

Our work explores the phenomenon of representation alignment in LLMs, confirming its occurrence and elucidating its behavior compared to strictly designed alignment models. We have demonstrated the potential for disentangling language-specific and language-agnostic information, enabling effective language-specific manipulation without semantic loss. Furthermore, we have shown the practical applications of language control manipulation in enhancing language control and mitigating confusion problems. Our ITLC method demonstrates significant gains on the language confusion benchmark, achieving an average improvement of 9% in monolingual and 26.7% in cross-lingual settings. It also achieves comparable performance to existing test-time intervention approaches, while being much more efficient (requiring only a single middle layer intervention). Ultimately, our work not only advances the theoretical understanding of representation alignment in LLMs but also introduces a practical and effective solution for enhancing cross-lingual capabilities, paving the way for more robust and versatile LLLMs in multilingual contexts.

Limitations

The study has several limitations that should be considered when interpreting the results. First, the coverage of LLMs is limited to a specific set of models for representation alignment, particularly Qwen and LaBSE and only one model size (0.5B parameters), which may not be representative of all LLMs. The findings may not generalize to other models with different architectures or training data, as the behavior of representation alignment can vary significantly across different LLMs. Future

research should aim to include a more diverse range of models to validate the generalizability of the results.

Second, the evaluation is conducted on a limited number of languages, which may not capture the full spectrum of linguistic diversity. The study focuses on a subset of languages, and the results may not extend to languages with different typological features or those that are underrepresented in the training data. Expanding the evaluation to include a broader range of languages, especially low-resource languages, would provide a more comprehensive understanding of the model’s capabilities and limitations.

Moreover, The scaling factor α affects different models differently, requiring careful adjustment for optimal performance. Due to the nature of Linear Discriminant Analysis (LDA), the number of components (`n_components`) is constrained by the number of target language classes. This constraint introduces a trade-off, the number of target language hidden states that need to be extracted depends on the chosen `n_components`, potentially causing computational overhead, and vice versa.

Additionally, the human evaluation is based on only 30 samples per language, which may not provide a comprehensive assessment of the model’s performance. While the sample size is sufficient for preliminary analysis, a larger dataset would be necessary to draw more robust conclusions. Increasing the number of samples and involving a more diverse group of evaluators could enhance the reliability and validity of the findings.

Ethical Considerations

The research involves the use of LLMs, which might raise ethical considerations regarding bias, fairness, and transparency on the generated results. To ensure ethical conduct, the study adheres to the following principles: (1) Bias Mitigation: The models used are evaluated for potential biases, and efforts are made to mitigate any identified biases. (2) Fairness: The evaluation is conducted across multiple languages from diverse regions and language families to ensure fairness and inclusivity. (3) Transparency: The methodology and results are presented transparently to allow for replication and verification. (4) Privacy: No personal data is used in the evaluation, and all data is anonymized to protect privacy. (5) Accountability: The researchers take responsibility for the ethical implications of

the study and are committed to addressing any concerns that may arise.

We also acknowledge that our research utilized AI tools for writing, rewriting, and generating code. Although these tools offer significant advantages in terms of efficiency and productivity, their use raises important ethical considerations. We recognize the potential for bias and errors inherent in AI-generated content and have taken steps to mitigate these risks through rigorous human review and validation. Furthermore, we are mindful of the potential impact on the broader software development community, particularly regarding job displacement and the need for upskilling. We believe that responsible AI integration should prioritize transparency, accountability, and the empowerment of human developers, ensuring that these tools augment rather than replace human expertise. This research aims to contribute to the ongoing dialogue on ethical AI development and usage, advocating for a future where AI tools are harnessed responsibly to enhance human creativity and innovation in the field of software engineering.

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A Details of All Evaluation Datasets

The following tables present the full details of dataset sizes used in this study. Refer to Table 5, Table 6, Table 7, Table 8 and Table 9.

B Detail Experiment for Understanding Representation Alignment in LLMs

B.1 Cosine Similarity Distributions Across Datasets

To better understand the representational behavior of the models, we analyzed the distribution of cosine similarity scores across layers. For LaBSE, the average cosine similarity increases from the first layer (mean = 0.6335, std = 0.0920) to the middle layer (mean = 0.7580, std = 0.1182), and remains comparably high in the last layer (mean = 0.7544, std = 0.1150). This trend suggests that semantic alignment becomes stronger toward the middle and final layers, with relatively low variability, indicating consistent behavior across input samples. These observations align with prior findings that intermediate layers in multilingual encoders often capture the most transferable features.

In contrast, Qwen2.5-0.5B exhibits a markedly different pattern. While the middle layer achieves the highest average similarity (mean = 0.9218, std = 0.0871), the first layer has a lower mean and higher variance (mean = 0.5913, std = 0.1650), indicating less stable representations early in the network. Notably, the last layer shows a substantial drop in similarity (mean = 0.3745) and a sharp increase in variability (std = 0.3988), suggesting a divergence in representational behavior, potentially due to task-specific tuning or greater representational fragmentation. This may help explain the weaker correlations between cosine similarity and task performance observed in Qwen’s final layers.

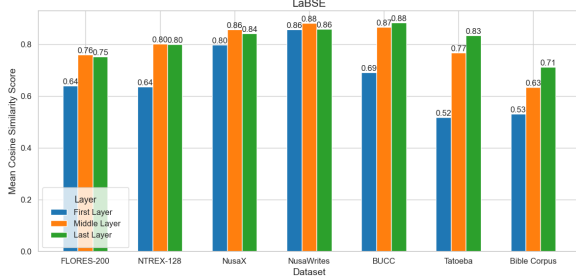
These findings reinforce the role of middle layers in capturing semantically meaningful and transferable representations, particularly in instruction-tuned or general-purpose multilingual models. See Figure 2 for the histogram plot and Figure 7 for the bar chart per alignment dataset.

B.2 Additional Analysis For Alignment and Downstream Correlation

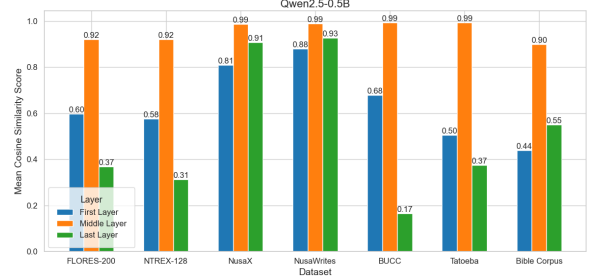
As shown in Table 10, the correlation between cosine similarity and downstream performance varies by dataset, layer, and model architecture. The following sections provide detailed interpretations.

Dataset	Train	Test	Total	# Languages
SIB200	143,705	41,820	185,525	205
INCLUDE-BASE	890	22,638	23,528	44
XCOPA	1,100	5,500	6,600	11
PAWS-X	345,807	14,000	359,807	7

Table 5: Dataset sizes and number of languages for downstream tasks.



(a) Mean Cosine Similarity Score on LaBSE Model



(b) Mean Cosine Similarity Score on Qwen2.5-0.5B Model

Figure 7: Layer-wise cosine similarity distributions of LaBSE and Qwen2.5-0.5B models across different datasets.

Dataset	Total	# Languages
FLORES-200	1,012	204
NTREX-128	1,997	128
NusaX	400	12
NusaWrites	14,800	9 (language pairs)
BUCC	35,000	4 (language pairs)
Tatoeba	88,877	112 (language pairs)
BibleCorpus	85,533	828 (language pairs)

Table 6: Total example counts and number of languages for alignment tasks. We only use test set for this alignment task.

Dataset	Train	Test	Total	# Languages
FLORES-200	997	1012	2,009	204
NTREX-128	-	1,997	1,997	128
NusaX	500	400	400	12

Table 7: Total example counts per language and number of languages for for LID tasks.

SIB200 For LaBSE, correlation values are consistently strong and statistically significant across all layers. The first (Pearson $r = 0.323$), middle (Pearson $r = 0.309$), and last (Pearson $r = 0.210$) layers all demonstrate meaningful positive correlations with performance ($p \approx 0$), indicating that

Dataset	Train	Test	Total	# Languages
FLORES-200	997	1012	2,009	204
Dolly	-	1,800	-	9

Table 8: Total example counts per language and number of languages for Language Control.

Dataset	Total	# Languages
<i>Monolingual</i>		
Aya	100	5
Dolly	100	5
Okapi	100	10
Native prompts	100	4
<i>Cross-lingual</i>		
Okapi	100	14
shareGPT	100	14
Complex prompts	99	14

Table 9: Total example counts per language and number of languages for Language Confusion tasks, taken from Language Confusion Benchmark. Only test set is available.

cosine similarity is well-aligned with task accuracy throughout the network. This suggests that SIB200 benefits from LaBSE’s cross-lingual representations, especially in the earlier and middle layers. In contrast, Qwen2.5-0.5B shows very weak but statistically significant correlations ($r \leq 0.12$ across all layers). While the trends are consistent, the effect sizes are negligible, suggesting that cosine similarity has limited practical influence on performance for Qwen2.5-0.5B on this dataset.

INCLUDE-BASE For LaBSE, correlations between cosine similarity and performance are negligible and statistically non-significant across all layers, with Pearson r values close to zero (-0.041 , 0.005 , -0.021). This suggests no meaningful alignment between representational similarity and task accuracy. In contrast, Qwen2.5-0.5B exhibits

Dataset	Model	Layer	Pearson r	R^2	p -value
SIB200	LaBSE	First	0.323	0.104	$<10^{-300}$
		Middle	0.309	0.096	$<10^{-300}$
		Last	0.210	0.044	$<10^{-205}$
	Qwen2.5-0.5B	First	0.060	0.004	$<10^{-17}$
		Middle	0.123	0.015	$<10^{-69}$
		Last	0.043	0.002	$<10^{-9}$
INCLUDE-BASE	LaBSE	First	-0.041	0.002	0.233
		Middle	0.005	0.000	0.884
		Last	-0.021	0.000	0.545
	Qwen2.5-0.5B	First	0.183	0.034	$<10^{-7}$
		Middle	0.142	0.020	$<10^{-4}$
		Last	0.168	0.028	$<10^{-6}$
XCOPA	LaBSE	First	-0.115	0.013	0.458
		Middle	-0.026	0.001	0.867
		Last	0.144	0.021	0.352
	Qwen2.5-0.5B	First	0.292	0.085	0.055
		Middle	-0.139	0.019	0.368
		Last	0.538	0.289	<0.001
PAWS-X	LaBSE	First	0.141	0.020	0.484
		Middle	0.270	0.073	0.173
		Last	0.146	0.021	0.467
	Qwen2.5-0.5B	First	0.228	0.052	0.252
		Middle	0.532	0.283	0.004
		Last	0.369	0.136	0.059

Table 10: Pearson correlation coefficients (r), R^2 , and p -values for the relationship between cosine similarity and task performance across different transformer layers on LaBSE and Qwen2.5-0.5B.

weak but statistically significant positive correlations (Pearson r range: 0.14–0.18), indicating that higher cosine similarity is marginally associated with improved performance. Despite the small effect sizes, these results highlight a slight but consistent behavioural alignment in Qwen2.5-0.5B on this dataset.

XCOPA For LaBSE, correlation values across layers are weak and statistically insignificant, suggesting minimal alignment between representational similarity and model performance. In contrast, Qwen2.5-0.5B exhibits a strong and statistically significant positive correlation in the last layer (Pearson $r = 0.538$, $p < 0.001$), implying that deeper representations may be more predictive for XCOPA.

PAWS-X LaBSE shows weak, non-significant positive correlations across layers. However, Qwen2.5-0.5B demonstrates a strong positive correlation in the middle layer (Pearson $r = 0.532$, $p \approx 0.004$), suggesting that intermediate representations capture more alignment-relevant features for paraphrase detection.

Downstream Performance Relative to Random Baselines To provide a clearer picture of cross-lingual generalization and behavior alignment, we present a set of bar charts

comparing the performance of LaBSE and Qwen2.5-0.5B across four downstream evaluation datasets—SIB200, INCLUDE-BASE, XCOPA, and PAWS-X—relative to their respective random baselines.

On XCOPA and PAWS-X, LaBSE yields near-random or below-random performance, indicating that its fixed representations struggle with cross-lingual commonsense reasoning and paraphrase detection. For SIB200, LaBSE performs slightly above the random baseline, suggesting limited task sensitivity in multilingual sentence similarity settings. However, its performance on INCLUDE-BASE remains weak, staying near or below the random baseline and highlighting deficiencies in broader multilingual alignment.

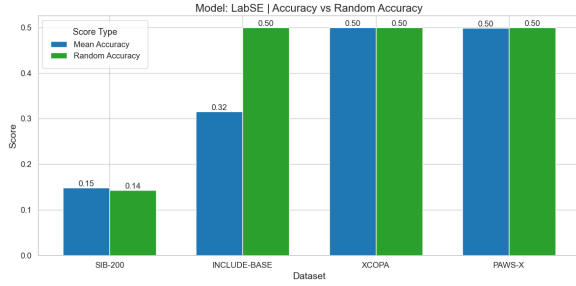
In contrast, Qwen2.5-0.5B demonstrates stronger generalization on both SIB200 and INCLUDE-BASE, significantly outperforming its baseline and showing evidence of better cross-lingual task adaptation. However, it faces challenges on XCOPA and PAWS-X, where its performance hovers around or falls below baseline, pointing to possible limitations in zero-shot commonsense reasoning and paraphrase understanding across languages.

These comparisons highlight the differing strengths and weaknesses of encoder-only and decoder-only multilingual models across select zero-shot evaluation tasks. See Figure 8.

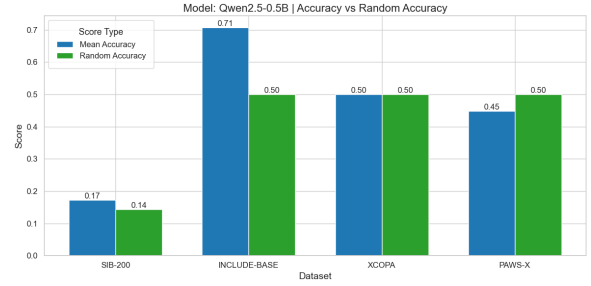
B.3 Additional Analysis For Alignment and LID Correlation

As shown in Table 11, the correlation between alignment (as measured by cosine similarity) and downstream LID performance varies notably across datasets, model architectures, and transformer layers. The following sections provide detailed interpretations for each dataset to contextualize these trends.

FLORES-200 On the FLORES-200 dataset, we observe a moderate negative correlation between cosine similarity and LID performance for both LaBSE and Qwen2.5-0.5B. The strength of the correlation increases in deeper layers, with the last layer showing the strongest correlation ($r = -0.707$, $p < 10^{-31}$) for LaBSE. Qwen2.5-0.5B, however, exhibits its strongest negative correlation in the middle layer ($r = -0.432$, $p < 10^{-9}$), indicating that as the embeddings become more aligned (i.e., higher cosine similarity), the language identity



(a) Performance of LaBSE across downstream tasks compared to random baselines.



(b) Performance of Qwen2.5-0.5B across downstream tasks compared to random baselines.

Figure 8: Comparison of LaBSE and Qwen2.5-0.5B performance across various downstream tasks and their corresponding random baselines.

Dataset	Model	Layer	Pearson r	R^2	p -value
FLORES-200	LaBSE	First	0.024	0.001	0.732
		Middle	-0.122	0.015	0.084
		Last	-0.707	0.500	$< 10^{-31}$
	Qwen2.5-0.5B	First	-0.142	0.020	0.043
		Middle	-0.432	0.186	$< 10^{-9}$
		Last	-0.278	0.077	$< 10^{-4}$
NTREX-128	LaBSE	First	0.254	0.065	0.012
		Middle	-0.173	0.030	0.089
		Last	-0.621	0.385	$< 10^{-11}$
	Qwen2.5-0.5B	First	-0.232	0.054	0.021
		Middle	-0.476	0.226	$< 10^{-6}$
		Last	-0.340	0.115	0.001
NusaX	LaBSE	First	-0.566	0.320	0.112
		Middle	-0.872	0.760	0.002
		Last	—	—	—
	Qwen2.5-0.5B	First	-0.455	0.207	0.218
		Middle	-0.873	0.763	0.002
		Last	-0.045	0.002	0.910

Table 11: Pearson correlation coefficients (r), R^2 , and p -values for the relationship between KNN LID F1 score using mean-pooled embedding and alignment cosine similarity across different transformer layers on LaBSE and Qwen2.5-0.5B.

signal tends to weaken, potentially due to semantic abstraction. The statistically significant p -values across all layers confirm the robustness of this relationship. These findings reinforce the idea that high alignment may come at the cost of LID separability, especially in final layers for LaBSE and middle layer for Qwen2.5-0.5B, where representations are more semantically homogenized.

NTREX-128 For NTREX-128, the correlation trends diverge between the two models. LaBSE exhibits its strongest negative correlation in the the last layer (Pearson $r = -0.621$, $p < 10^{-11}$), with a positive correlation in the first layer (Pearson $r = 0.254$, $p = 0.012$) and weak negative correlation in the middle (Pearson $r = -0.173$, $p = 0.089$). This suggests that early representations in LaBSE may still retain relatively distinct language features that diminish with depth. In con-

trast, Qwen2.5-0.5B shows more consistent negative correlations across all layers, particularly in the middle layer (Pearson $r = -0.476$, $p < 10^{-6}$). These results highlight a more uniform degradation of LID-relevant information in Qwen’s architecture compared to LaBSE.

NusaX For NusaX, alignment-LID correlations exhibit distinct patterns. LaBSE shows a weak correlation in the first layer (Pearson $r = -0.566$, $p = 0.112$), a highly negative correlation in the middle layer (Pearson $r = -0.872$, $p = 0.002$), and no measurable correlation in the last layer (—), which we assume reflects a perfect inverse relationship (Pearson $r \approx -1$) due to complete LID failure. Qwen2.5-0.5B follows a similar pattern, with its most negative correlation in the middle layer (Pearson $r = -0.873$, $p = 0.002$) and negligible correlations in the first (Pearson $r = -0.455$, $p = 0.218$) and last layers (Pearson $r = -0.045$, $p = 0.910$). The correlations for both models are the most negative observed across all datasets, suggesting alignment disproportionately degrades language signals in low-resource settings. This extreme inverse relationship likely stems from the models’ lack of prior exposure to NusaX languages during training, limiting their ability to retain language identity in aligned embeddings.

C LID Methods and Results

C.1 Methods

To investigate language-specific information in multilingual representations, we analyze two distinct paradigms: (1) frozen embeddings from pretrained decoder-only LLMs (Qwen-2.5) and (2) specialized multilingual sentence encoders (LaBSE). We evaluate whether linguistic identity is recoverable from their hidden states and how

Model	Method	Layer	FLORES-200		NTREX-128		NusaX	
			CLS	Mean	CLS	Mean	CLS	Mean
LaBSE	KNN	First	80.65	88.35	87.02	90.43	64.12	81.78
		Middle	65.11	78.85	71.37	81.30	33.89	45.37
		Last	7.65	3.92	3.45	1.63	0.54	0.00
	Linear Probing	First	93.47	95.13	92.21	93.29	89.16	97.30
		Middle	92.99	94.18	92.33	92.68	88.00	94.51
		Last	30.03	70.89	22.91	74.36	56.00	65.44
Qwen2.5-0.5B	KNN	First	–	83.69	–	86.06	–	65.79
		Middle	–	55.32	–	54.73	–	25.05
		Last	–	71.73	–	81.86	–	29.39
	Linear Probing	First	–	94.21	–	91.42	–	95.55
		Middle	–	91.76	–	90.04	–	87.09
		Last	–	92.46	–	90.27	–	88.77

Table 12: F1 score for KNN and linear classifiers by layer and pooling on FLORES-200, NTREX-128, and NusaX.

pooling strategies affect clusterability (via non-parametric KNN retrieval) and linear separability (via supervised classification heads).

KNN-based Language Identification We hypothesize that language identity manifests as separable clusters in the hidden space, which can be detected via non-parametric nearest-neighbor retrieval.

For both Qwen-2.5 and LaBSE, hidden states are extracted from the first ($\ell = 1$), middle ($\ell = m$), and final ($\ell = L$) layers. Let $\mathbf{H}^\ell \in \mathbb{R}^{T \times d}$ denote the hidden states at layer ℓ for a sequence of length T . Sentence-level embeddings are derived as follows:

- Qwen-2.5: Only mean pooling is applied:

$$\mathbf{e}_{\text{mean}}^\ell = \frac{1}{T} \sum_{t=1}^T \mathbf{H}_t^\ell \in \mathbb{R}^d.$$

- LaBSE: Both CLS and mean pooling are compared:

$$\mathbf{e}_{\text{CLS}}^\ell = \mathbf{H}_{[\text{CLS}]}^\ell, \quad \mathbf{e}_{\text{mean}}^\ell = \frac{1}{T} \sum_{t=1}^T \mathbf{H}_t^\ell \in \mathbb{R}^d.$$

For each layer $\ell \in \{1, m, L\}$ and pooling strategy $\text{pool} \in \{\text{mean}, \text{CLS}\}$, we construct reference sets:

$$\mathcal{R}_{\text{pool}}^\ell = \left\{ \left(\mathbf{e}_{\text{pool}}^{\ell, (i, j)}, y^{(j)} \right) \right\}_{i=1, j=1}^{200, 204},$$

where $y^{(j)}$ is the language label for the j -th language in FLORES-200, and i indexes the examples within each language. This results in a total of $200 \times 204 = 40,800$ reference embeddings. For Qwen-2.5, only $\mathcal{R}_{\text{mean}}^\ell$ is used, while LaBSE employs both $\mathcal{R}_{\text{CLS}}^\ell$ and $\mathcal{R}_{\text{mean}}^\ell$.

We evaluate on three test sets: Flores-200, NTREX-128, and NusaX. To ensure fair comparison, we retain only languages overlapping with the FLORES-200 train set:

$$\mathcal{L}_{\text{overlap}} = \mathcal{L}_{\text{test}} \cap \mathcal{L}_{\text{FLORES-train}},$$

where $\mathcal{L}_{\text{test}}$ is the language set of the test dataset, and $\mathcal{L}_{\text{FLORES-train}}$ contains the 204 languages in the FLORES-200 train set. For a test embedding $\mathbf{e}_{\text{test, pool}}^\ell$, we compute its L2 distance to all reference embeddings in $\mathcal{R}_{\text{pool}}^\ell$:

$$d\left(\mathbf{e}_{\text{test, pool}}^\ell, \mathbf{e}_{\text{ref, pool}}^{\ell, (i, j)}\right) = \left\| \mathbf{e}_{\text{test, pool}}^\ell - \mathbf{e}_{\text{ref, pool}}^{\ell, (i, j)} \right\|_2^2, \\ \forall i \in \{1, \dots, 200\}, \\ \forall j \in \{1, \dots, 204\}.$$

The predicted language \hat{y}_{test} is obtained via majority vote over the $k = 256$ nearest neighbors:

$$\hat{y}_{\text{test}} = \arg \max_{l \in \mathcal{L}_{\text{overlap}}} \sum_{(i, j) \in \mathcal{N}_k} \mathbf{1}(y^{(j)} = l),$$

where \mathcal{N}_k denotes the set of indices for the top- k neighbors, and $\mathbf{1}$ is the indicator function.

Linear Classification Head To complement our non-parametric analysis, we probe the linear separability of language identity in Qwen-2.5 and LaBSE embeddings. This evaluates whether linguistic boundaries are geometrically aligned with hyperplanes in the hidden space, which would suggest that language control can be achieved through simple affine transformations.

Similar to the KNN-based approach, embeddings are extracted identically. For each dataset $\mathcal{D} \in \{\text{FLORES-200}, \text{NTREX-128}, \text{NusaX}\}$ and

each layer $\ell \in \{1, m, L\}$ representing early, middle, and last layers respectively, we train a separate linear layer to map embeddings $\mathbf{e}^\ell \in \mathbb{R}^d$ to language logits $\mathbf{z}^\ell \in \mathbb{R}^C$, where C is the number of languages. The classifier for each layer is defined as:

$$\mathbf{z}^\ell = \mathbf{W}^\ell \mathbf{e}^\ell + \mathbf{b}^\ell, \quad \mathbf{W}^\ell \in \mathbb{R}^{C \times d}, \mathbf{b}^\ell \in \mathbb{R}^C,$$

with cross-entropy loss minimized during training.

C.2 Results

Our analysis reveals distinct layer-wise behaviors in language identification (LID) performance across LaBSE and Qwen2.5-0.5B models, focus on mean-pooled embedding.

KNN-based Language Identification The KNN method highlights significant performance variations across layers. As shown in Table 1, for LaBSE, the first layer achieves robust results, with mean F1 scores of 88.35% on FLORES-200, 90.43% on NTREX-128, and 81.78% on NusaX. Performance declines moderately in the middle layer, yielding 78.85% for FLORES-200, 81.30% for NTREX-128, and 45.37% for NusaX. The last layer exhibits catastrophic degradation, collapsing to 3.92%, 1.63%, and 0.00% on the respective datasets. This suggests that deeper LaBSE layers lose language-discriminative features critical for KNN classification.

For Qwen2.5-0.5B, the first layer similarly outperforms middle layers, with mean F1 scores of 83.69% on FLORES-200, 86.06% on NTREX-128, and 65.79% on NusaX. The middle layer shows the weakest results across all datasets: 55.32%, 54.73%, and 25.05%, respectively, while the last layer partially recovers to 71.73%, 81.86%, and 29.39%. This non-monotonic trend suggests limited retention of language-specific signals in the middle layer of Qwen2.5-0.5B.

LaBSE, trained for semantic alignment, shows severe degradation in its final layer, with near-zero F1 scores across datasets, as deeper layers erase language-specific signals required for KNN classification. In contrast, Qwen2.5-0.5B, a standard pre-trained LLM, experiences a performance dip in its middle layer but recovers partially in the final layer, retaining sufficient linguistic discriminability. This divergence underscores a key architectural trade-off: contrastive models like LaBSE discard lexical or syntactic patterns in deeper layers to prioritize semantic invariance, while standard LLMs preserve

partial language-identifying features across layers despite progressive abstraction.

Linear-probing-based Language Identification

For LaBSE, the First Layer consistently achieves the highest LID F1 scores across all datasets, with a significant drop in performance observed in the Last Layer. The NusaX dataset delivers the best overall results, particularly in the First Layer, where it reaches 97.30% F1 score. However, the Last Layer shows notably weaker performance, especially for the FLORES-200 and NusaX datasets. These findings suggest that earlier layers of LaBSE retain more language-identification-relevant features, such as surface-level linguistic cues, compared to deeper layers (see Table 1).

Similarly, in the Qwen2.5-0.5B model, the First Layer consistently outperforms the Middle Layer in LID F1 scores across all datasets. The NusaX dataset again produces the best results, with 95.55% F1 score, while NTREX-128 exhibits the lowest performance across all layers. These results indicate that the shallow First Layer of Qwen2.5-0.5B is more effective for language identification tasks than deeper layers, such as the Middle Layer, which shows weaker performance (refer to Table 1).

Overall, both models show that their highest LID performance occurs in the First Layer, with F1 scores declining as the layers get deeper. The NusaX dataset consistently yields the best performance, while the Last Layer in LaBSE and the Middle Layer in Qwen2.5-0.5B exhibit the weakest results. These trends suggest that shallow layers retain more language-specific information, which is crucial for language identification, likely due to their greater focus on surface-level features and general linguistic patterns. Table 12 further illustrate the comparative performance across layers and pooling techniques for both LaBSE and Qwen2.5-0.5B models.

Classifier Comparison: KNN vs. Linear Head

As shown in Table 12, linear classifiers achieve superior F1 scores compared to KNN across layers, suggesting their ability to identify language-discriminative features within linearly separable subspaces. However, linear methods exhibit attenuated performance gaps between layers, for instance, the difference between first and middle layers in Qwen2.5-0.5B is less than 5% with linear classifiers, while KNN reveals differences exceeding 30%. Similarly, LaBSE’s linear classifier reduces the last-layer performance gap to under 25%,

whereas KNN shows near-complete degradation. This contrast implies that parametric linear methods, while more accurate overall, may obscure layer-specific language information degradation due to their reliance on learned projections. In contrast, KNN’s non-parametric nature might more directly reflect the geometric structure of embeddings, amplifying sensitivity to layer-wise shifts in language information quality.

Pooling Method Comparison: CLS Token vs. Mean As shown in Table 12, the effectiveness of pooling strategies varies across layers. In first and middle layers, mean pooling achieves superior performance, with F1 margins exceeding 10% over CLS token pooling under KNN. However, in last layers, CLS token pooling shows limited resilience under KNN, marginally outperforming mean pooling in isolated cases despite near-random overall performance. Linear classifiers amplify mean pooling’s advantage across all layers, suggesting its robustness to layer-specific degradation.

This suggests that mean pooling better preserves language-discriminative signals across layers, likely due to its aggregation of token-level features. In contrast, the CLS token, optimized for semantic tasks, exhibits sharper performance declines in deeper layers, particularly under non-parametric methods like KNN. These observations highlight the interplay between pooling strategy, layer depth, and classification method in language identification tasks.

D Language Vector Setting

Linear Discriminant Analysis (LDA) (Balakrishnama and Ganapathiraju, 1998; Tharwat et al., 2017) is utilized to construct language vectors by extracting language-specific features from the Qwen2.5-0.5B model’s scaled hidden states, optimizing cross-lingual control through class separability. We evaluate various component sizes (20, 40, 50, 100, 150, 203) to balance LID accuracy and unused variance, fitting an LDA model and training a linear neural network (with 10 epochs, Adam optimizer, and CrossEntropyLoss) to achieve a peak accuracy of approximately 90.63% at 100 components. The unused variance is minimized, ensuring retained discriminative information for injection (δ) with pruning, which enhances language targeting while the Figure 10 visually confirms this optimal trade-off.

E Ablation on Language Shift Strategy

Language Shift Strategy We assess various strategies for injecting the language vector in ITLC. Specifically, we explore three strategies based on the temporal scope of the latent intervention: (1) prompt only, (2) generated tokens only, and (3) both phases. Let $\mathbf{h}_t^{(m)} \in \mathbb{R}^d$ denote the hidden state at position t in the middle layer m , and $\mathbf{h}_t^{(m)'} denotes its language-shifted counterpart:$

- **Prompt-Only** (prompt-only): Applies injection exclusively to input prompt processing:

$$\mathbf{h}_t^{(m)'} = \begin{cases} \mathbf{h}_t^{(m)} + \alpha\delta, & \forall t \in [1, T_{\text{input}}] \\ \mathbf{h}_t^{(m)}, & \forall t > T_{\text{input}} \end{cases}$$

- **Generated-Only** (gen-only): Restricts injection to autoregressive generation:

$$\mathbf{h}_t^{(m)'} = \begin{cases} \mathbf{h}_t^{(m)}, & \forall t \in [1, T_{\text{input}}] \\ \mathbf{h}_t^{(m)} + \alpha\delta, & \forall t \in [T_{\text{input}} + 1, T_{\text{total}}] \end{cases}$$

- **Prompt and Generated** (prompt-and-gen): Applies injection throughout both phases:

$$\mathbf{h}_t^{(m)'} = \mathbf{h}_t^{(m)} + \alpha\delta, \quad \forall t \in [1, T_{\text{total}}]$$

where T_{input} is the input prompt length and $T_{\text{total}} = T_{\text{input}} + N$ the total sequence length after generating N tokens.

Ablation Result All three language shift strategies are compared in cross-lingual setting using the Qwen2.5-0.5B and Qwen2.5-0.5B-Instruct, as shown in Figure 9. The **prompt-and-gen** strategy consistently achieves the strongest performance, followed by **gen-only** and then **prompt-only**. This indicates that while the **prompt-only** approach may aid the model in understanding the input context in the target language, and the **gen-only** strategy directly shifts the generation process into target language, while the **prompt-and-gen** method effectively combines both advantages via injecting the shift language vector into all timesteps.

F Experiment Settings for Language Confusion

F.1 Baseline

The results discussed is focus on Line-level Pass Rate (LPR). Word-level Pass Rate (WPR) is mostly excluded in discussion because WPR for Latin-script languages is compromised by its fundamental reliance on Unicode character ranges, a

Lang	Qwen2.5-0.5B				Qwen2.5-7B				Llama-3.1-8B			
	Baseline		ITLC		Baseline		ITLC		Baseline		ITLC	
	chrF++	BERT F1	chrF++	BERT F1	chrF++	BERT F1	chrF++	BERT F1	chrF++	BERT F1	chrF++	BERT F1
ID	7.71	61.38	8.46	63.74	8.21	62.98	9.26	65.19	8.63	60.58	8.91	64.94
TH	3.39	62.12	3.42	63.78	3.62	62.55	3.88	63.90	2.96	59.02	4.28	64.37
TR	6.42	59.36	6.78	60.67	6.94	61.31	7.59	62.96	8.37	58.20	8.62	63.76
JA	1.90	59.98	2.11	61.53	2.08	60.14	1.84	61.15	1.52	53.26	2.60	62.94
FR	7.53	61.63	8.89	64.03	8.11	63.03	9.51	65.24	7.97	59.86	8.90	64.51
ES	8.51	62.66	9.43	64.90	9.30	64.24	10.01	65.65	8.69	61.14	9.84	65.65
AR	5.11	61.89	5.68	64.31	5.35	62.39	6.78	65.98	4.28	59.70	6.45	65.59
KO	1.86	60.93	2.08	61.90	2.09	61.67	2.14	62.35	2.14	54.61	3.31	65.19
ZH	2.61	62.26	2.97	64.85	2.73	62.93	3.33	65.18	2.00	55.14	2.67	63.98
AVG	5.01	61.36	5.53	63.30	5.38	62.36	6.04	64.18	5.39	58.39	6.76	64.29

Table 13: Generation performance for different target languages on Qwen2.5 and Llama-3.1 base version. **Baseline** denotes the same model prompted in the same language as the desired target language. Bold values indicate the best score for each metric across all models and settings.

Lang	Qwen2.5-0.5B-Instruct				Qwen2.5-7B-Instruct				Llama-3.1-8B-Instruct			
	Baseline		ITLC		Baseline		ITLC		Baseline		ITLC	
	chrF++	BERT F1	chrF++	BERT F1	chrF++	BERT F1	chrF++	BERT F1	chrF++	BERT F1	chrF++	BERT F1
ID	7.71	61.38	8.46	63.74	8.21	62.98	9.26	65.19	9.67	64.58	11.55	66.97
TH	3.39	62.12	3.42	63.78	3.62	62.55	3.88	63.90	5.42	64.68	6.67	67.82
TR	6.42	59.36	6.78	60.67	6.94	61.31	7.59	62.96	9.37	63.37	10.49	65.15
JA	1.90	59.98	2.11	61.53	2.08	60.14	1.84	61.15	3.33	63.29	4.11	66.23
FR	7.53	61.63	8.89	64.03	8.11	63.03	9.51	65.24	9.44	64.28	11.40	67.52
ES	8.51	62.66	9.43	64.90	9.30	64.24	10.01	65.65	10.32	64.78	12.24	67.68
AR	5.11	61.89	5.68	64.31	5.35	62.39	6.78	65.98	6.88	64.82	8.66	67.55
KO	1.86	60.93	2.08	61.90	2.09	61.67	2.14	62.35	3.74	64.52	4.59	66.99
ZH	2.61	62.26	2.97	64.85	2.73	62.93	3.33	65.18	2.58	64.26	3.70	66.82
AVG	5.41	61.79	6.11	63.74	5.82	63.24	6.48	64.96	6.97	64.80	8.49	67.19

Table 14: Generation performance for different target languages on Qwen2.5 and Llama-3.1 Instruction version. **Baseline** denotes the same model prompted in the same language as the desired target language. Bold values indicate the best score within each model, and the overall best across models.

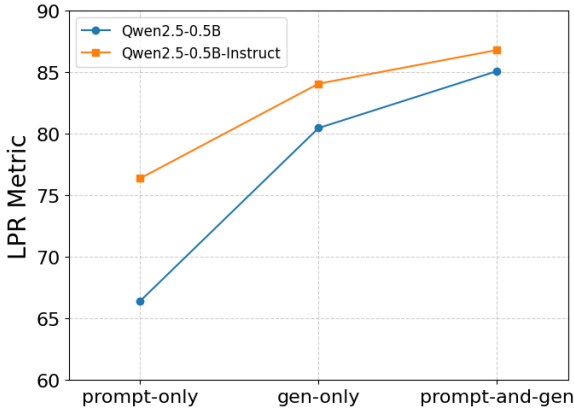


Figure 9: Cross-lingual LPR performance across different vector injection strategies.

limitation highlighted in (Marchisio et al., 2024). For Latin-script WPR evaluation, we use the following Unicode ranges: Basic Latin, Latin-1 Supplement, Latin Extended-A through Latin

Extended-G, and Latin Extended Additional ⁶. We use the following generation hyperparameters: max_new_tokens=256 and top_k=50. We apply nucleus sampling with top_p=0.9 and use a moderate temperature of 0.7.

F.2 In-context learning (ICL)

We follow all the original settings for ICL in the LCB benchmark. For the Q/A template, we use the Q: A: format, while the chat template adopts the model-specific instruction-tuning structure. Cross-lingual few-shot prompts follow the benchmark’s original setup, where English inputs include instructions such as Respond in <TARGET_LANG>. For monolingual few-shot prompts, both inputs and outputs are in the same language. It is important to note that the few-shot demonstrations are provided in languages distinct from the target language of the current task. This design aims to guide the

⁶Taken from Wikipedia: https://en.m.wikipedia.org/wiki/Unicode_block.

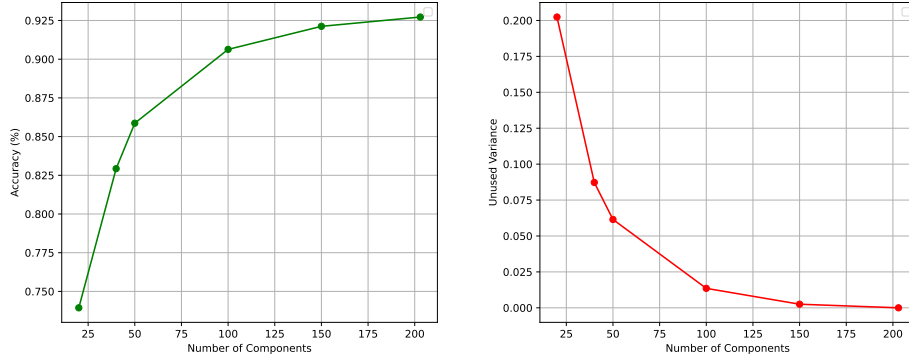


Figure 10: Controlling the number of language feature representations by using LDA performance accuracy (**Left**) and unused variance (**Right**) across number of components.

Lang Shift	Prompt (XX)	Generated Output (EN)	Translation (XX)
KO → EN	사과먹는 5가지방법은무엇일까요?	Here are five common ways to enjoy apples: 1. Raw and fresh : Eating an apple straight from the fruit bowl is a simple yet delicious way of enjoying it. 2. Juiced or blended into smoothies: Apples can be ju ...	What are 5 ways to eat apples?
ES → EN	¿ Cómo escapar de un helicóptero atrapado en el agua?	Si usted encuentra sí mismos stuck inside a helicopter that has crashed into the water: 1. Remain calm: Panic can cloud your judgment and increase risk of injury or drowning. 2. Verify everyone's safety first before attempting to escape from any...	How to escape from a helicopter trapped in water?
JA → EN	音楽家が音楽から収入を得る方法のリストを用意してください。	Here are some ways that a musician can earn income from their music: 1 "0307Live Performances: Playing concerts, gigs and shows at various venues such as clubs, festivals or events. 2Recording Music Sales : Selling albums through digital platforms like ...	Provide a list of ways musicians can earn income from their music craft. ...

Figure 11: Examples of generated outputs from Llama-3.1-8B-Instruct with injection in XX→EN.

model in understanding the task semantics rather than identifying the appropriate output language.

F.3 Inference-Time Language Control (ITLC)

We use the following scaling factor α values: for Qwen2.5-0.5B and Qwen2.5-0.5B-Instruct, $\alpha = 0.5$; for Qwen2.5-7B and Qwen2.5-7B-Instruct, $\alpha = 1.3$. For Llama-3.1-8B, $\alpha = 0.15$; and for Llama-3.1-8B-Instruct, $\alpha = 0.10$. See Appendix G.1 for details on the selection of scaling factor.

F.4 Parameter-Efficient Fine-Tuning (PEFT)

For training data preparation, we use the Alpaca subset from the Bactrian-X dataset (Li et al., 2023a). Specifically, we extract the first 1,000 rows per language across the 14 languages included in the LCB benchmark (500 for monolingual and 500 for cross-lingual), resulting in a total of 14,000 samples. For monolingual data, we directly use the same samples as in Bactrian-X. For cross-lingual data, we replace the inputs with their corresponding

English variants in Bactrian-X and append the instruction "Please respond in <TARGET_LANG>" to the prompt. For training data of the base model, we concatenate the inputs and outputs and treat the result as the output sequence without applying the Q/A template.

The model is trained for one epoch using the LoRA fine-tuning technique (Hu et al., 2022) with the following settings: warmup_ratio = 0.05, batch_size = 1, gradient_accumulation_steps = 16, learning_rate = 1e-4, lora_rank = 8, and lora_alpha = 32. We employ the MS-SWIFT framework (Zhao et al., 2024b) for model training, with all other hyperparameters kept at their default values.

F.5 Combination of ICL and ITLC

We apply ITLC only to the current input prompt using the scaling factor specified in Appendix F.3, but not to the few-shot examples, since the languages used in the few-shot examples differ from that of

Lang Shift	Prompt (EN)	Generated Output (XX)	Literal Translation (EN)
EN → TR	How can you open a can without using your hands?	Bir kâğıt parçasını, delikten geçir ve tutacak şekilde yerleştir. Kapağın üzerine basınçlı bir cisimle vurun (örneğin bıçak). Bu sayede metalin çarka girmesiyle ...	Pass a piece of paper through the hole and place it so that it holds. Strike the cover with a pressurized object (for example, a knife). In this way, with the metal entering the wheel... ..
EN → ES	Can you help me avoid credit card debt?	¡Claro que sí, puedo ayudarte a evitar deudas con tarjetas crédito. Aquí te presento algunas consejos: 1) Crea un presupuesto y controla tus gastos para saber cuántos ingresos tienes. ...	Of course! I can help you avoid credit card debt. Here are some tips: 1) Create a budget and track your expenses. This will help you understand how much income you have and where your money is going.
EN → TR	What shapes are made up of straight lines?	Evinizin değerini artırmak için bazı yollar şunlardır: 1. Dekorasyon: Evi modern ve şık bir şekilde dekore etmek, evin görünümünü iyileştirir. 2. Renk ...	Here are some ways to increase the value of your home: 1. Decoration: Decorating the house in a modern and stylish way improves its appearance. 2. Paint ...

Figure 12: Examples of generated outputs from Llama-3.1-8B-Instruct with injection in EN→XX.

the current task (see Appendix F.2).

F.6 Combination of PEFT and ITLC

The LDA is trained based on hidden states extracted from the pre-trained model. We do not retrain the LDA using new hidden states after PEFT. For other details, please refer to Appendix F.4 and Appendix F.3

F.7 INCLINE

We extract sentence representations from the FLORES-200 dataset (Team et al., 2022) and use the same scaling factor α as defined in Appendix F.3 during inference.

F.8 ReCoVeR

We extract sentence representations from the FLORES-200 dataset (Team et al., 2022) and apply a scaling factor of $\alpha = 0.2$ for Llama-3.1-8B and its instruct variant, and $\alpha = 0.3$ for Qwen2.5-0.5B and its instruct variant.

G Language Confusion Result

G.1 Ablation Study of Scaling for Different Language Vector Injection Strategies

As shown in Table 15, Table 16 and Table 17 Our analysis reveals distinct optimal scaling factors for cross-lingual LCPR across injection strategies: prompt-only achieves peak performance at scaling 0.8 (65.71), gen-only at 0.6 (71.35), and prompt-and-gen at 0.5 (78.93). Notably, prompt-and-gen outperforms other strategies, suggesting combined injection better preserves cross-lingual alignment. The scaling factor for the Qwen2.5-0.5B model family is adopted from our ablation study. However, due to computational constraints, a similar study was not feasible for the Qwen2.5-7B and

Scaling	Monolingual			Cross-lingual		
	LCPR	LPR	WPR	LCPR	LPR	WPR
prompt-0.1	64.86	81.01	65.67	33.97	23.75	74.74
prompt-0.2	66.39	82.14	66.75	38.88	28.91	75.37
prompt-0.3	65.59	82.86	65.78	46.03	37.86	72.56
prompt-0.4	65.45	82.79	65.53	57.20	51.97	72.27
prompt-0.5	65.87	82.73	62.50	62.93	61.63	73.43
prompt-0.6	64.92	82.64	65.24	63.91	63.83	73.20
prompt-0.7	64.78	81.03	65.52	64.63	66.09	71.74
prompt-0.8	63.69	80.40	65.28	65.71	66.41	74.24
prompt-0.9	61.25	75.81	64.15	64.59	64.79	73.30
prompt-1.0	60.39	74.98	63.87	62.97	63.35	72.79

Table 15: Performance (LCPR / LPR / WPR) of Qwen2.5-0.5B on LCB under the prompt-only setting with base shift vector, evaluated across different language vector scaling factors, α .

Scaling	Monolingual			Cross-lingual		
	LCPR	LPR	WPR	LCPR	LPR	WPR
gen-0.1	64.75	83.99	63.85	35.07	24.79	74.92
gen-0.2	65.35	85.09	65.01	39.93	28.96	75.92
gen-0.3	62.61	86.55	59.29	48.08	38.97	71.16
gen-0.4	59.61	86.23	54.95	57.49	57.82	64.37
gen-0.5	59.61	86.85	54.76	67.00	74.04	66.07
gen-0.6	60.05	87.49	58.14	71.35	80.46	67.67
gen-0.7	58.01	87.41	55.72	69.39	80.73	66.57
gen-0.8	52.45	82.78	52.35	65.84	75.74	65.93
gen-0.9	47.07	75.83	50.58	58.61	68.51	63.73
gen-1.0	40.44	71.15	54.91	51.25	61.85	61.83

Table 16: Performance (LCPR / LPR / WPR) of Qwen2.5-0.5B on LCB under the generated-only setting with base shift vector, evaluated across different language vector scaling factors, α .

Llama3.1-8B families. For these models, we instead conducted a limited manual evaluation, we randomly generated outputs for a range of scaling factors across different target languages and selected the best-performing value based on human assessment.

Scaling	Monolingual			Cross-lingual		
	LCPR	LPR	WPR	LCPR	LPR	WPR
prompt-and-gen-0.1	64.21	84.27	63.77	39.48	28.69	75.74
prompt-and-gen-0.2	63.25	86.34	61.76	50.04	41.18	75.07
prompt-and-gen-0.3	62.94	88.24	60.85	64.22	64.18	72.53
prompt-and-gen-0.4	60.79	88.06	59.09	75.88	80.58	75.78
prompt-and-gen-0.5	59.98	87.11	59.41	78.93	85.08	77.15
prompt-and-gen-0.6	57.01	86.37	55.90	77.21	84.13	74.90
prompt-and-gen-0.7	53.56	82.91	53.63	72.57	81.98	71.51
prompt-and-gen-0.8	49.00	77.27	51.33	68.22	76.80	70.08
prompt-and-gen-0.9	40.41	70.51	48.16	60.97	69.07	66.44
prompt-and-gen-1.0	36.60	70.01	51.30	52.51	61.07	63.82

Table 17: Performance (LCPR / LPR / WPR) of Qwen2.5-0.5B on LCB under the prompt-and-generated setting with base shift vector, evaluated across different language vector scaling factors, α .

G.2 Impact of In-context learning (ICL) on Monolingual and Cross-lingual Performance

As shown in Table 18, Table 19, Table 20, Table 21, Table 22 and Table 23, in the monolingual setting, the impact of few-shot prompting varies inconsistently across models. Qwen2.5-0.5B and Qwen2.5-0.5B-Instruct exhibit decreased LPR, while Qwen2.5-7B and Llama-3.1-8B show increased LPR. For instruction-tuned models, both Qwen2.5-7B-Instruct and Llama-3.1-8B-Instruct demonstrate reduced LPR. This unstable and unpredictable behavior may stem from the design of monolingual few-shot prompts, which introduce conflicting linguistic signals that models with limited capacity struggle to resolve effectively ⁷.

In the cross-lingual setting, few-shot prompting consistently improves performance across all base models (Qwen2.5-0.5B, Qwen2.5-7B, and Llama-3.1-8B). This improvement can be attributed to the few-shot examples, which utilize English inputs paired with explicit target-language directives, thereby reinforcing the desired input-output alignment. These results indicate that English-centric prompting effectively stimulates cross-lingual adaptation in base models. However, the effect differs for instruction-tuned models: while smaller models like Qwen2.5-0.5B-Instruct benefit from few-shot examples, larger models (Qwen2.5-7B-Instruct and Llama-3.1-8B-Instruct) show minimal gains. This stability suggests that instruction-tuning pre-aligns their multilingual capabilities, rendering additional in-context examples largely redundant.

The divergent impact of ICL across models in-

⁷Please refer to Appendix F.2.

Method	Monolingual			Cross-lingual		
	LCPR	LPR	WPR	LCPR	LPR	WPR
Qwen2.5-0.5B	65.27	81.58	65.15	29.41	19.75	73.45
+ Q/A template (0-shot)	59.26	59.91	73.35	44.68	35.36	75.94
+ PEFT	75.96	82.91	78.30	76.15	77.55	80.56
+ 1-shot	56.12	55.38	73.70	47.42	37.95	75.42
+ 2-shot	51.59	49.70	70.98	49.36	41.64	75.03
+ 3-shot	52.52	51.51	72.07	53.16	46.65	77.07
+ 4-shot	54.16	52.95	74.15	55.03	48.23	77.60
+ 5-shot	54.47	53.62	70.40	56.78	50.63	76.16
+ ITLC (apply base shift vector)						
+ prompt-only ($\alpha = 0.8$)	63.69	80.40	65.28	65.71	66.41	74.24
+ gen-only ($\alpha = 0.6$)	60.05	87.49	58.14	71.35	80.46	67.67
+ prompt-and-gen ($\alpha = 0.5$)	59.98	87.11	59.41	78.93	85.08	77.15
+ Q/A template	62.50	81.21	64.60	81.30	85.61	80.84
+ PEFT	73.68	86.17	73.26	87.66	90.51	86.15
+ 5-shot	57.65	74.38	61.13	81.51	87.58	79.01
+ ITLC (apply instruct shift vector)						
+ prompt-only ($\alpha = 0.8$)	63.11	79.95	64.18	63.08	63.77	73.04
+ gen-only ($\alpha = 0.6$)	55.89	86.38	55.32	68.70	78.99	65.36
+ prompt-and-gen ($\alpha = 0.5$)	58.48	87.24	57.21	76.06	82.31	75.74

Table 18: Performance (LCPR / LPR / WPR) of Qwen2.5-0.5B on LCB under monolingual and cross-lingual settings.

icates that the effectiveness of few-shot prompting might contingent upon the model’s instruction-following aptitude, contextual understanding, pre-existing upper-bound capability, and the depth of alignment achieved during its instruction-tuning process ⁸.

G.3 Chat/QA Template Efficacy Across Settings

The findings are consistent with those observed in the in-context learning (ICL) setting for LPR performance, with one key exception: applying the chat template to instruction-tuned models consistently yields better performance, as shown in Table 19.

G.4 Effect of Source Language Shift Vector

As shown in Figure 13, subtracting the source language shift vector reduces the model’s bias toward the source language (English) and guides the model to generate content in the target language more effectively, compared to directly adding the target language shift vector.

H Experiment setting for semantic retention and human evaluation

H.1 Generation Hyperparameter

The generation process for the language control and language confusion results uses specific hyperparameter to balance creativity and control. We set max_new_tokens=50, and set top_k to 50. We

⁸All discussed results are based on experiments that apply the official chat/QA templates during inference.

Method	Monolingual			Cross-lingual		
	LCPR	LPR	WPR	LCPR	LPR	WPR
Qwen2.5-0.5B-Instruct	74.79	82.61	77.94	38.75	27.22	78.40
+ Chat template (0-shot)	74.52	83.66	77.12	63.00	57.69	79.50
+ PEFT	80.13	89.85	77.77	79.46	84.34	80.01
+ 1-shot	72.94	78.83	77.79	66.82	61.42	82.12
+ 2-shot	73.95	78.41	79.43	68.19	64.21	80.99
+ 3-shot	74.61	78.88	76.99	69.43	65.94	81.42
+ 4-shot	75.82	80.89	80.07	69.56	67.28	79.62
+ 5-shot	75.44	80.30	79.36	71.43	69.70	79.74
+ ITLC (apply base shift vector)						
+ prompt-only ($\alpha = 0.8$)	67.33	74.82	76.35	76.05	77.68	81.11
+ gen-only ($\alpha = 0.6$)	67.00	84.07	65.83	75.56	82.42	74.51
+ prompt-and-gen ($\alpha = 0.5$)	67.73	81.70	68.96	81.51	85.32	80.55
+ ITLC (apply instruct shift vector)						
+ prompt-only ($\alpha = 0.8$)	66.78	74.96	73.08	73.26	76.37	79.20
+ gen-only ($\alpha = 0.6$)	67.42	83.64	65.46	73.95	84.06	71.40
+ prompt-and-gen ($\alpha = 0.5$)	68.20	82.20	68.05	80.96	86.79	78.84
+ 5-shot	68.93	86.28	66.47	83.98	88.07	82.00
+ PEFT	68.16	90.51	62.58	85.38	89.85	82.83

Table 19: Performance (LCPR / LPR / WPR) of Qwen2.5-0.5B-Instruct on LCB under monolingual and cross-lingual settings.

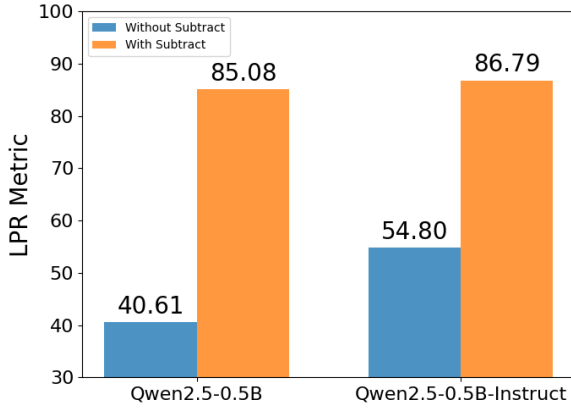


Figure 13: Cross-lingual LPR performance on LCB with and without subtracting the source language shift vector across Qwen2.5-0.5B and Qwen2.5-0.5B-Instruct, using prompt-and-gen injection strategy with $\alpha = 0.5$.

Method	Monolingual			Cross-lingual		
	LCPR	LPR	WPR	LCPR	LPR	WPR
Qwen2.5-7B	68.15	77.71	71.40	41.03	29.72	75.33
+ Q/A template (0-shot)	53.97	55.24	73.84	65.68	60.61	76.88
+ PEFT	73.46	83.80	72.80	78.93	82.66	79.51
+ 5-shot	63.23	62.78	75.77	72.15	69.37	79.45
+ ITLC (apply base shift vector)						
+ prompt-and-gen ($\alpha = 1.3$)	67.05	80.07	67.33	61.70	59.84	70.84
+ Q/A template	58.10	63.40	72.36	70.71	74.40	72.72
+ PEFT	73.12	85.60	72.40	78.25	83.92	78.39
+ 5-shot	65.24	69.55	73.42	79.60	84.90	77.13

Table 20: Performance (LCPR / LPR / WPR) of Qwen2.5-7B on LCB under monolingual and cross-lingual settings.

apply nucleus sampling with $\text{top}_p=0.9$, and use a moderate temperature of 0.7 to encourage focused yet varied outputs. To reduce repetitive phrases, we apply a repetition_penalty of 1.5. We keep all other hyperparameters at their model-specific default values and use each instruct model’s native

Method	Monolingual			Cross-lingual		
	LCPR	LPR	WPR	LCPR	LPR	WPR
Qwen2.5-7B-Instruct (with chat template)	60.83	78.89	58.78	66.16	78.81	62.37
+ 5-shot	54.46	74.13	53.93	65.79	78.51	61.44
+ PEFT	75.03	88.28	73.19	78.32	83.56	77.93
+ ITLC (apply base shift vector)						
+ prompt-and-gen ($\alpha = 1.3$)	62.44	85.89	56.76	66.91	83.45	60.34
+ ITLC (apply instruct shift vector)						
+ prompt-and-gen ($\alpha = 1.3$)	61.35	84.89	56.97	66.89	84.73	60.02
+ 5-shot	57.75	81.01	53.73	66.26	84.04	58.97
+ PEFT	75.62	90.12	72.33	77.50	84.10	76.70

Table 21: Performance (LCPR / LPR / WPR) of Qwen2.5-7B-Instruct on LCB under monolingual and cross-lingual settings.

Method	Monolingual			Cross-lingual		
	LCPR	LPR	WPR	LCPR	LPR	WPR
Llama-3.1-8B	43.52	44.07	59.66	1.46	0.74	88.10
+ Q/A template (0-shot)	63.68	56.98	82.26	39.01	26.13	87.27
+ PEFT	79.16	93.01	72.80	82.04	89.73	77.83
+ 5-shot	72.24	69.86	79.13	70.67	62.38	83.91
+ ITLC (apply base shift vector)						
+ prompt-and-gen ($\alpha = 0.15$)	50.97	60.77	57.07	60.69	69.69	57.74
+ Q/A template	73.13	75.77	77.28	81.29	81.68	82.78
+ PEFT	78.50	96.03	72.08	83.74	88.98	81.21
+ 5-shot	76.43	82.18	76.47	83.14	88.15	80.47

Table 22: Performance (LCPR / LPR / WPR) of Llama-3.1-8B on LCB under monolingual and cross-lingual settings.

Method	Monolingual			Cross-lingual		
	LCPR	LPR	WPR	LCPR	LPR	WPR
Llama-3.1-8B-Instruct (with chat template)	83.05	94.63	76.11	79.34	83.25	77.01
+ 5-shot	82.27	88.57	79.88	84.32	86.68	82.77
+ PEFT	79.00	96.66	71.00	81.26	91.13	75.29
+ ITLC (apply base shift vector)						
+ prompt-and-gen ($\alpha = 0.10$)	82.50	95.68	75.68	83.48	88.52	80.37
+ ITLC (apply instruct shift vector)						
+ prompt-and-gen ($\alpha = 0.10$)	81.76	96.41	74.51	82.91	89.06	78.99
+ 5-shot	85.25	93.21	79.82	86.60	90.34	83.95
+ PEFT	79.04	97.19	71.36	83.44	93.60	77.05

Table 23: Performance (LCPR / LPR / WPR) of Llama-3.1-8B-Instruct on LCB under monolingual and cross-lingual settings.

chat template.

H.2 Monolingual & Crosslingual Prompting

Our experiments on the baseline (monolingual) and ITLC (cross-lingual) settings use slightly different prompt strategies. Specifically, for the baseline, we aim to measure the upper bound of performance within a particular language, whereas ITLC involves different input and target languages.

To ensure fairness and consistency in model output generation, we designed distinct input prompts for the base model, Qwen2.5, and Llama-3.1. In the base version, to control the contextual generation in cross-lingual settings, we prepend an early portion of the target language output—approximately 30% of the sentence length—as a guidance signal for the model to continue generating coherent text. This approach helps ensure that the language vector

receives sufficient signal to produce linguistically and semantically coherent outputs.

Additionally, for non-Latin scripts such as Japanese and Chinese, we adopt a different segmentation strategy. Instead of splitting based on newlines, as in Latin-script languages, we apply language-specific tokenizers such as PyThaiNLP (Phatthiyaphaibun et al., 2023), Nagisa⁹, and Jieba¹⁰. The proportional segment length is then determined based on the number of tokens or phrases produced by these tokenizers.

I Additional Examples of Cross-lingual Generation

Figure 11 and Figure 12 present several examples of generated outputs across multiple source languages targeting English. Overall, our ITLC method successfully shifts to the desired target language and demonstrates effective cross-lingual generation.

J Annotation Guidelines

J.1 Context of the Annotation Task

The annotation task involves evaluating the quality of cross-lingual language generation, where a model generates responses in a target language based on input prompts in a source language. The goal is to assess how well the model performs in terms of naturalness, relevance, and answer correctness. This evaluation is crucial for understanding the model’s capabilities and identifying areas for improvement.

J.2 Detailed Scoring Guidelines

J.2.1 Naturalness (1-5):

- **1:** The response sounds very unnatural, robotic, or translated. It lacks fluency and typical language patterns of the target language, making it sound artificial and unnatural.
- **2:** The response is somewhat unnatural, with noticeable awkwardness or unnatural word choices. It may sound stilted or forced.
- **3:** The response is moderately natural, with some minor awkwardness but generally understandable. It flows reasonably well but has room for improvement.
- **4:** The response is mostly natural, with only slight deviations from typical language use. It

sounds almost native-like but may have minor imperfections.

- **5:** The response is completely natural, indistinguishable from text written by a native speaker. It flows smoothly and uses language patterns typical of the target language.

J.2.2 Relevance (1-5):

- **1:** The response is completely irrelevant to the input prompt. It fails to address the topic or question posed.
- **2:** The response is somewhat relevant but misses key points or goes off-topic. It may touch on related ideas but does not fully address the prompt.
- **3:** The response is moderately relevant, addressing some aspects of the prompt but lacking completeness. It covers some key points but omits important details.
- **4:** The response is highly relevant, addressing most key points of the prompt. It provides a comprehensive answer but may miss minor details.
- **5:** The response is completely relevant, fully addressing all aspects of the prompt. It covers all key points and provides a thorough answer.

J.2.3 Correctness (1-5):

- **1:** The response contains major factual errors or inaccuracies. It provides incorrect information or contradicts known facts.
- **2:** The response contains some factual errors or inaccuracies. It may be partially correct but includes misleading or incorrect details.
- **3:** The response is mostly correct but may have minor inaccuracies or omissions. It is generally accurate but requires minor corrections.
- **4:** The response is highly accurate, with only minor details potentially incorrect. It is reliable and trustworthy but may have small errors.
- **5:** The response is completely accurate and factually correct. It provides precise and reliable information without any errors.

J.3 Additional Notes

- **Contextual Understanding:** Annotators should consider the context of the input prompt and the intended audience when evaluating naturalness and relevance. A response

⁹<https://github.com/taishi-i/nagisa>

¹⁰<https://github.com/fxsjy/jieba>

that is natural and relevant in one context may not be in another.

- **Consistency:** Annotators should strive for consistency in their annotations across different examples. This helps ensure that the evaluation is fair and reliable.
- **Examples:** Providing clear examples of each rating level for each category can help annotators understand the expected standards and make consistent judgments.
- **Feedback:** Encourage annotators to provide feedback on ambiguous cases or areas where the guidelines could be improved. This can help refine the annotation process and improve the quality of the evaluations.

K Authors' Contributions

Joanito Agili Lopo is primarily responsible for developing the methodology as well as conducting experiments related to semantic retention and human evaluation. Muhammad Ravi Shulthan Habibi is responsible for the representation alignment and language identification (LID) experiments using linear probing. Tack Hwa Wong co-developed the methodology with Joanito Agili Lopo and is responsible for the LID experiments using k-nearest neighbours (KNN), as well as all experiments related to language confusion and language confusion benchmark (LCB). Samuel Cahyawijaya provided the research topic, overall direction, ideas, and guidance throughout the entire work. All co-first authors contributed to the writing of the first draft, and all authors participated in the review and editing process.

Model	Cross-lingual						
	AVG	AR	ES	HI	ID	RU	ZH
Qwen2.5-0.5B	34.97	31.72	48.12	3.03	42.44	48.77	35.74
+ INCLINE	43.82	34.94	74.17	6.58	56.38	59.22	31.63
+ ReCoVeR	88.43	99.66	97.02	64.67	84.88	98.99	85.38
+ ITLC (ours)	81.22	98.32	94.61	32.32	83.17	97.65	81.25
Llama-3.1-8B	25.05	10.60	37.63	25.71	38.13	17.61	20.59
+ INCLINE	34.69	19.61	39.25	38.92	40.46	32.36	37.56
+ ReCoVeR	88.79	100.00	84.30	93.44	70.97	98.69	85.37
+ ITLC (ours)	76.38	90.41	83.57	76.43	62.37	97.29	48.24

Table 24: LPR metrics for the base model on LCB across baseline and state-of-the-art methods, with a detailed language-wise breakdown for cross-lingual settings. All results have been applied with the QA/Chat template during inference.

Model	Cross-lingual						
	AVG	AR	ES	HI	ID	RU	ZH
Qwen2.5-0.5B-Instruct	52.28	65.41	72.65	3.02	54.35	77.12	41.14
+ INCLINE	56.54	68.35	80.35	1.13	52.19	68.08	69.16
+ ReCoVeR	84.21	100.00	97.66	60.36	58.86	99.31	89.04
+ ITLC (ours)	81.97	98.97	95.31	49.03	64.39	98.98	85.13
Llama-3.1-8B-Instruct	80.68	87.12	89.27	82.76	73.89	87.93	63.14
+ INCLINE	80.63	86.80	89.60	81.10	70.21	86.58	69.51
+ ReCoVeR	90.29	100.00	93.30	95.24	67.96	99.32	85.92
+ ITLC (ours)	85.65	95.60	92.96	93.97	72.55	95.98	62.84

Table 25: LPR metrics for the instruct model on LCB across baseline and state-of-the-art methods, with a detailed language-wise breakdown for cross-lingual settings. All results have been applied with the QA/Chat template during inference.

Monolingual																
Model	AVG	AR	DE	EN	ES	FR	HI	ID	IT	JA	KO	PT	RU	TR	VI	ZH
Qwen2.5-0.5B	59.91	45.84	78.79	97.00	75.20	64.67	0.00	57.00	76.00	32.00	54.55	64.00	64.29	30.00	81.82	77.50
+ ICL (5-shot)	53.62	56.12	84.00	96.44	64.86	54.53	4.17	64.00	65.66	19.19	40.40	45.00	73.74	25.00	68.37	42.81
+ ITLC (ours)	74.38	77.94	94.00	99.49	94.33	89.67	0.00	78.00	77.00	55.56	74.75	79.50	87.00	55.00	74.00	79.50
+ PEFT	82.91	94.00	99.00	70.50	93.00	94.67	0.00	90.00	98.00	64.00	86.00	91.00	95.00	92.00	94.00	82.50
+ ITLC (ours)	86.17	99.33	100.00	77.00	99.33	99.33	8.25	94.00	100.00	57.00	81.82	98.00	98.00	99.00	90.00	91.50
+ ITLC (ours)	81.21	91.00	96.00	97.98	98.67	98.00	0.00	84.00	100.00	58.00	81.00	95.00	81.00	75.00	70.00	92.50
Qwen2.5-7B	55.24	29.43	73.00	98.48	70.04	66.17	1.01	63.00	78.00	39.00	22.68	65.00	36.08	26.80	83.00	76.85
+ ICL (5-shot)	62.78	43.26	79.00	96.39	71.84	74.02	15.96	73.74	82.00	59.00	44.79	50.36	65.66	56.25	82.00	47.50
+ ITLC (ours)	69.55	51.22	86.87	97.94	77.44	82.25	8.70	86.00	91.00	64.00	53.54	64.50	77.55	56.25	89.00	57.00
+ PEFT	83.80	95.00	99.00	49.58	94.00	94.00	6.06	91.00	97.98	75.00	85.00	91.94	96.00	94.00	100.00	88.50
+ ITLC (ours)	85.60	98.67	99.00	52.97	97.67	95.67	8.00	95.00	94.00	76.00	89.00	95.00	97.00	97.00	100.00	89.00
+ ITLC (ours)	63.40	52.79	76.00	98.99	84.71	77.53	0.00	75.00	78.00	45.92	31.00	77.44	60.61	21.65	85.86	85.50
Llama-3.1-8B	56.98	39.57	55.00	95.38	69.56	59.43	30.21	57.58	55.56	25.51	43.30	71.29	67.37	81.82	61.00	42.19
+ ICL (5-shot)	69.86	67.53	75.00	95.47	69.33	63.67	63.64	73.00	73.00	67.00	49.00	67.82	70.00	70.00	76.00	67.50
+ ITLC (ours)	82.18	79.26	90.00	99.50	92.67	84.00	65.00	66.00	90.00	87.00	68.37	86.92	89.00	70.00	87.00	78.00
+ PEFT	93.01	98.00	98.00	69.50	94.67	92.00	92.00	84.00	99.00	94.00	93.00	93.50	97.00	95.00	98.00	97.50
+ ITLC (ours)	96.03	100.00	97.00	91.50	97.67	97.33	96.00	91.00	99.00	95.00	97.00	92.50	99.00	99.00	98.00	90.50
+ ITLC (ours)	75.77	62.08	78.00	99.00	89.29	84.02	50.00	66.67	81.00	58.76	76.84	85.78	93.81	86.73	75.51	49.00
Cross-lingual																
Model	AVG	AR	DE	EN	ES	FR	HI	ID	IT	JA	KO	PT	RU	TR	VI	ZH
Qwen2.5-0.5B	35.36	31.72	43.27	–	48.12	46.45	3.03	42.44	40.33	14.40	10.12	45.11	48.77	34.23	51.28	35.74
+ ICL (5-shot)	50.63	54.79	63.97	–	54.62	63.02	12.07	61.97	63.05	24.74	29.57	55.90	67.84	61.61	69.21	26.38
+ ITLC (ours)	87.58	99.66	97.99	–	96.62	97.33	39.07	85.52	95.26	72.91	88.95	90.95	98.99	91.96	92.63	78.24
+ PEFT	77.55	89.25	90.26	–	90.94	90.94	11.04	75.41	88.25	68.52	65.32	82.23	90.94	83.53	90.26	68.84
+ ITLC (ours)	90.51	100.00	99.67	–	96.65	97.32	63.78	85.61	98.99	69.22	88.97	90.97	99.67	96.99	96.99	82.26
+ ITLC (ours)	85.61	98.32	96.97	–	94.61	95.63	32.32	83.17	99.00	61.20	82.55	88.28	97.65	92.96	94.60	81.25
Qwen2.5-7B	60.61	62.24	67.82	–	71.07	68.68	24.87	60.80	67.31	51.90	50.29	68.40	69.21	59.40	72.07	54.42
+ ICL (5-shot)	69.37	70.22	77.42	–	75.04	75.20	36.45	70.53	81.43	59.16	59.26	70.02	84.24	77.05	79.20	55.94
+ ITLC (ours)	84.90	88.57	95.50	–	90.40	92.14	65.67	84.03	90.37	57.86	85.17	88.74	94.48	91.58	90.92	73.18
+ PEFT	82.66	93.62	93.23	–	89.27	89.93	24.20	83.16	86.25	76.87	80.56	86.84	95.29	91.57	90.93	75.53
+ ITLC (ours)	83.92	97.65	97.95	–	96.99	95.31	30.78	87.60	93.97	35.09	74.47	92.59	97.65	96.99	96.98	80.89
+ ITLC (ours)	74.40	83.00	89.49	–	89.51	87.43	27.12	76.65	87.42	32.80	58.81	87.35	91.49	82.97	85.93	61.61
Llama-3.1-8B	26.13	10.60	28.03	–	37.63	36.09	25.71	38.13	37.14	18.88	16.49	31.77	17.61	20.14	27.05	20.59
+ ICL (5-shot)	62.38	65.02	60.66	–	66.88	56.64	65.72	71.81	65.46	46.49	68.77	56.07	69.50	73.40	63.12	43.83
+ ITLC (ours)	88.15	85.24	96.97	–	87.62	84.40	76.23	76.51	87.56	93.79	96.94	89.34	99.66	92.87	92.58	74.44
+ PEFT	89.73	93.61	92.27	–	91.28	93.64	93.62	76.16	89.60	85.57	85.50	89.22	94.24	92.28	94.30	84.90
+ ITLC (ours)	88.98	98.99	96.96	–	86.21	75.21	98.65	67.22	89.96	88.95	95.61	84.58	99.33	95.31	92.96	75.86
+ ITLC (ours)	81.68	90.41	96.13	–	83.57	71.68	76.43	62.37	89.12	75.72	89.11	82.56	97.29	87.75	93.09	48.24

Table 26: LPR metrics for the base model on LCB, with a detailed language-wise breakdown for both monolingual and cross-lingual settings. All results have been applied with the QA/Chat template during inference.

Monolingual																
Model	AVG	AR	DE	EN	ES	FR	HI	ID	IT	JA	KO	PT	RU	TR	VI	ZH
Qwen2.5-0.5B-Instruct	83.66	96.33	94.00	99.50	89.67	95.33	0.00	70.00	94.00	82.00	83.51	87.00	95.00	89.00	87.63	92.00
+ ICL (5-shot)	80.30	93.56	95.00	97.50	87.67	89.67	2.04	69.00	94.00	67.00	78.72	83.50	89.90	86.00	87.88	83.00
+ ITLC (ours)	86.28	98.33	98.00	98.50	97.67	96.67	13.00	82.00	98.00	80.00	77.00	94.00	89.00	96.00	95.00	81.00
+ PEFT	89.85	99.00	99.00	96.50	95.67	97.67	14.43	87.00	100.00	83.00	93.94	95.50	100.00	95.00	99.00	92.00
+ ITLC (ours)	90.51	100.00	98.00	100.00	98.67	100.00	29.00	94.00	100.00	80.00	81.00	98.00	88.00	99.00	99.00	93.00
+ ITLC (ours)	82.20	100.00	99.00	100.00	98.67	98.33	7.00	74.00	100.00	80.00	72.00	95.50	39.00	95.00	82.00	92.50
Qwen2.5-7B-Instruct	78.89	81.03	96.00	95.49	87.17	87.97	31.58	72.00	91.00	55.00	61.54	84.50	81.32	88.89	87.88	82.00
+ ICL (5-shot)	74.13	70.08	91.92	90.91	77.12	83.72	38.46	64.65	84.85	50.00	68.66	79.72	71.28	77.66	86.87	76.00
+ ITLC (ours)	81.01	80.85	92.00	92.88	86.68	86.45	51.61	68.00	87.88	75.00	81.32	83.27	71.58	90.43	84.21	83.00
+ PEFT	88.28	97.66	92.00	99.00	93.30	94.56	13.40	88.00	97.00	84.00	84.38	95.00	94.95	99.00	99.00	93.00
+ ITLC (ours)	90.12	99.33	98.00	98.49	96.99	96.00	20.20	89.00	96.00	80.00	91.75	96.50	97.00	97.00	99.00	96.50
+ ITLC (ours)	84.89	89.29	96.00	95.50	91.91	94.28	42.11	76.77	92.00	72.00	81.32	87.00	82.47	92.78	89.90	90.00
Llama-3.1-8B-Instruct	94.63	97.00	99.00	98.00	95.67	95.33	90.00	82.00	97.00	95.00	89.00	91.00	98.00	100.00	100.00	92.50
+ ICL (5-shot)	88.57	93.33	99.00	16.50	95.67	96.33	92.00	89.00	97.00	86.00	96.00	89.50	94.00	94.79	100.00	89.50
+ ITLC (ours)	93.21	97.00	98.00	46.74	96.00	98.00	99.00	90.00	99.00	95.00	98.00	95.00	99.00	92.86	100.00	94.50
+ PEFT	96.66	98.67	97.00	97.50	95.33	98.00	96.00	95.00	99.00	91.00	91.00	97.00	95.96	100.00	100.00	98.50
+ ITLC (ours)	97.19	100.00	100.00	98.99	97.67	97.67	95.00	89.00	100.00	93.00	94.00	96.50	98.00	100.00	100.00	98.00
+ ITLC (ours)	96.41	99.33	99.00	99.00	96.33	98.00	94.00	88.00	99.00	92.00	97.00	94.50	100.00	98.00	100.00	92.00
Cross-lingual																
Model	AVG	AR	DE	EN	ES	FR	HI	ID	IT	JA	KO	PT	RU	TR	VI	ZH
Qwen2.5-0.5B-Instruct	57.69	65.41	72.12	–	72.65	71.82	3.02	54.35	63.95	45.09	39.18	68.47	77.12	62.79	70.60	41.14
+ ICL (5-shot)	69.70	81.82	83.57	–	79.01	80.73	8.38	67.25	80.70	61.51	63.66	73.39	83.97	79.14	75.93	56.71
+ ITLC (ours)	88.07	100.00	97.98	–	95.93	93.27	64.93	65.85	95.29	79.26	87.21	87.81	99.00	96.63	97.99	71.78
+ PEFT	84.34	91.72	92.75	–	93.50	93.16	14.45	85.75	94.12	85.07	77.16	90.56	95.55	90.59	96.50	79.85
+ ITLC (ours)	89.85	100.00	98.65	–	95.95	93.95	61.88	76.10	96.94	77.24	86.95	92.65	98.98	96.29	98.30	84.00
+ ITLC (ours)	86.79	98.97	97.64	–	95.31	92.27	49.03	64.39	97.31	73.24	79.27	91.98	98.98	93.25	98.32	85.13
Qwen2.5-7B-Instruct	78.81	81.96	88.38	–	83.92	84.49	52.64	73.14	82.92	71.04	79.19	85.16	80.32	88.54	77.73	73.85
+ ICL (5-shot)	78.51	79.33	92.24	–	84.59	86.68	58.27	66.12	87.17	67.86	78.04	80.94	85.12	84.47	73.78	74.52
+ ITLC (ours)	84.04	86.46	96.95	–	87.60	91.83	62.21	70.94	91.90	69.84	87.71	87.16	90.19	92.39	85.86	75.53
+ PEFT	83.56	94.54	91.04	–	91.73	91.22	27.18	82.67	87.85	79.03	82.33	87.08	95.29	88.69	91.48	79.72
+ ITLC (ours)	84.10	98.65	98.26	–	94.55	96.23	26.55	84.20	96.29	37.19	80.42	92.61	96.64	95.22	96.31	84.23
+ ITLC (ours)	84.73	86.71	95.21	–	90.56	91.19	57.03	75.07	94.23	63.87	88.74	87.56	92.88	92.92	90.95	79.27
Llama-3.1-8B-Instruct	83.25	87.12	89.92	–	89.27	85.58	82.76	73.89	89.25	71.51	80.10	82.57	87.93	90.52	91.94	63.14
+ ICL (5-shot)	86.68	86.24	91.60	–	89.60	91.94	86.17	74.53	90.26	81.89	90.80	80.90	92.18	90.26	94.29	72.83
+ ITLC (ours)	90.34	92.62	97.32	–	93.63	90.88	95.30	71.87	94.27	89.95	95.96	85.53	96.31	94.63	93.63	72.86
+ PEFT	91.13	95.22	94.18	–	95.30	94.96	92.22	79.09	94.20	87.18	89.06	86.86	93.82	91.28	93.57	88.84
+ ITLC (ours)	93.60	97.54	96.96	–	94.64	94.59	96.93	80.14	93.91	93.96	94.54	91.29	96.94	96.26	96.27	86.46
+ ITLC (ours)	89.06	95.60	97.99	–	92.96	93.64	93.97	72.55	92.62	83.60	91.98	83.94	95.98	93.95	95.30	62.84

Table 27: LPR metrics for the instruct model on LCB, with a detailed language-wise breakdown for both monolingual and cross-lingual settings. All results have been applied with the QA/Chat template during inference.

Relevant for the Right Reasons? Investigating Lexical Biases in Zero-Shot and Instruction-Tuned Rerankers

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Abstract

Large Language Models (LLMs) show strong potential for reranking documents in information retrieval (IR), but training with monolingual data often leads to monolingual overfitting and lexical bias, limiting generalization in cross-lingual IR (CLIR). To overcome these issues, we investigate instruction-tuning LLaMA-3.1-8B-Instruct on English and multilingual code-switched data, and evaluate on mMARCO and XQuAD-R. Results show that instruction-tuning on code-switched data substantially improves CLIR performance, while monolingual tuning remains more effective for monolingual reranking. We introduce a novel measure to analyze the relationship between lexical overlap and reranking performance, showing that the two factors are correlated. We finally conduct a causal analysis using counterfactual examples, where we evaluate whether rewriting passages that share overlapping keywords with the query causes models to change their relevance predictions. Overall, we find that code-switching serves as an effective and lightweight strategy to improve cross-lingual generalization in LLM-based re-ranking, while our analyses show that lexical overlap remains a major factor that can mislead reranking models.

1 Introduction

Large Language Models (LLMs) such as LLaMA-3 (Dubey et al., 2024), GPT-4 (OpenAI et al., 2024), Gemini (Team et al., 2025), and Mistral (Jiang et al., 2023) have shown strong performance across a wide range of NLP tasks. In information retrieval (IR), which aims to return relevant documents from large text collections given a user query, recent advances have led to growing interest in leveraging LLMs as rerankers. In particular, LLMs have been explored as pointwise (Zhuang et al., 2023; Sun et al., 2023), pairwise (Qin et al., 2024), or list-wise rerankers (Tang et al.,

Query

What is the population of Paris? (EN)

Relevant Passage

En 2023, environ 2,1 millions de personnes vivent dans la capitale française. [...] (FR)

(In 2023, about 2.1 million people live in the French capital. [...])

Non-Relevant Passage

La population de Paris a fortement augmenté ces derinères années. [...] (FR)

(The readership of Paris has increased significantly in recent years. [...])

Figure 1: The first passage is semantically relevant to the query but shares no lexical overlap. In contrast, the second passage contains lexical overlap with the query terms “population” and “Paris” but is topically unrelated. Lexically biased LLM rerankers may incorrectly favor the non-relevant passage.

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wise and pairwise strategies as well as the interaction between first-stage retrievers and second-stage rerankers. However, they do not investigate *how* LLMs make relevance judgments.

Understanding whether LLMs determine relevance for the right reasons (i.e., semantic relevance), or whether they are biased towards lexical matches (i.e., shortcuts) is crucial for *equitable information access* and ensuring the trustworthiness of LLM-based retrieval systems (Litschko et al., 2023b). Biases in cross-lingual retrieval settings have been well-studied in the context of multilingual pre-trained language models (mPLMs). Prior work includes studies on, e.g., language biases in mPLM-based bi-encoders (Laosaengpha et al., 2025; Huang et al., 2024; Yang et al., 2024; Roy et al., 2020). Our work is closest to (Litschko et al., 2023a), who study zero-shot cross-lingual transfer of mPLM-based cross-encoders, where models trained on English data have been found to exhibit poor transfer performance to cross-lingual reranking tasks. The authors show that this monolingual overfitting can be mitigated by training on code-switched data instead, which naturally reduces the lexical overlap between queries and documents. However, it remains unclear whether LLMs exhibit similar lexical biases when used as rerankers, and whether instruction-tuning those models on code-switched training data also leads to similar improvements. Figure 1 illustrates this issue for a single pairwise cross-lingual reranking step: the model incorrectly prefers a lexically overlapping but semantically irrelevant passage, suggesting that relevance judgments may not always reflect genuine semantic understanding. This motivates our central question: Are LLM-based reranker outputs relevant for the right reasons?

To address this, we investigate whether LLM-based rerankers are affected by monolingual overfitting and lexical bias, and how instruction tuning strategies change this behavior. Specifically, we compare direct zero-shot reranking (without further training) against instruction-tuning on monolingual English data, multilingual code-switched data and target language-pair data on both MoIR and CLIR. In addition to our reranking experiments, we also characterize the lexical bias through a correlation and causal analysis. Our main contributions are:

- We show that instruction-tuning pair-wise rerankers on code-switched data improves their cross-lingual reranking performance.

However, unlike mPLM-based cross-encoders, these gains come at the cost of a worse monolingual reranking performance.

- We introduce two overlap-sensitive metrics, ALOD and AP-LOD correlation, to quantify the link between lexical overlap and reranking quality. Our results show that the two are **positively correlated**. However, this correlation is weak, underpinning that lexical overlap are only one of multiple factors (and biases) influencing what rerankers deem relevant.
- We evaluate the **causal relationship** between lexical overlaps and reranking performance. Specifically, we construct counterfactual examples from previously incorrectly classified instances (see Figure 1) and investigate whether removing lexical overlap by rewriting the passage causes rerankers to recover from incorrect predictions.

2 Related Work

Shortcut Learning in Language Models. Several recent studies have investigated shortcut learning behavior in LLMs, where models rely on superficial features in the input, such as lexical overlap or specific keywords, instead of performing genuine semantic reasoning. Du et al. (2021) focus on BERT-based models and show that these models tend to favor shortcut tokens early in training. Tang et al. (2023) found that LLMs often rely on shallow cues from prompts during in-context learning, rather than understanding the task itself. Sun et al. (2024) showed that instruction tuning and reinforcement learning with human feedback can increase shortcut learning in LLMs across tasks such as reasoning. Yuan et al. (2024) provided a systematic evaluation of shortcut biases, including lexical overlap, in prompt-based inference. Hagstrom et al. (2025) found that LM-based rerankers can be misled by lexical similarities, often favoring candidates with high surface overlap over semantically more relevant passages on English-only retrieval tasks. The study shows that these biases can lead to significant drops in model accuracy. Taken together, these studies suggest that shortcut learning remains a major challenge for LLMs.

However, these works do not explore how shortcut bias behavior changes when LLMs are fine-tuned for monolingual and cross-lingual pairwise reranking. We fill this gap and study shortcut learning behavior in prompt-based reranking tasks, and

especially regarding the model’s sensitivity to lexical overlap.

Bias in Multilingual and Cross-lingual Contexts.

Gao et al. (2025) analyzed LLMs’ cross-lingual context retrieval ability on cross-lingual machine reading comprehension (xMRC). They observed a significant performance gap between monolingual and cross-lingual settings, and propose a two-phase explanation: the model first encodes the question and then retrieves the answer. This highlighted that performance degradation in xMRC is not solely due to output generation but is rooted in earlier stages of processing. While their work identifies where in the model such limitations arise, it does not fully clarify whether relevance decisions are based on semantic features or surface-level lexical shortcuts, which is the focus of our work.

Beyond retrieval tasks, cross-lingual inconsistencies have also been observed across a range of tasks involving semantic understanding, reasoning, and prompt sensitivity. Wang et al. (2024) found that multilingual models fail to achieve balanced performance across languages, with significant disparities depending on the language used. Lai et al. (2023) showed that ChatGPT performs better in English than in other languages, particularly on tasks requiring complex reasoning, with performance gaps especially notable in lower-resource languages. Furthermore, Etxaniz et al. (2024) showed that LLMs often fail to realize their full multilingual potential when prompted in non-English languages, highlighting an implicit preference for English in reasoning processes.

However, these studies do not examine how different instruction tuning strategies affect LLM performance in monolingual versus cross-lingual information retrieval tasks, nor do they address whether such biases differ under different training conditions. Our work aims to fill this gap by systematically comparing reranking behavior under monolingual and code-switched instruction tuning setups.

3 Methodology

We conduct three different types of analyses: First we investigate how well LLM rerankers instruction-tuned on English data generalize to other monolingual reranking (MoIR) and cross-lingual reranking (CLIR) tasks, or whether they suffer from monolingual overfitting (Section 3.1). We then propose a measure that captures the correlation between lexical overlap and reranking performance (Sec-

tion 3.2). Finally, we introduce an evaluation protocol that facilitates a causal analysis of the impact of lexical overlap on reranking performance at the instance-level (Section 3.3).

3.1 Pair-wise Reranking

This pipeline consists of three steps. (1) We convert monolingual and code-switched training sets into a unified instruction–output format. (2) We fine-tune the base LLM under different language settings. (3) We evaluate the tuned models using pairwise prompting with a sliding window, following (Qin et al., 2024). Each prompting unit is defined as $u(q, d_1, d_2)$, where q is a query and d_1, d_2 are two candidate documents. To obtain the full ranking, we apply a sliding window approach: starting from a randomly shuffled ranking, we iteratively traverse the list in reverse order, comparing and potentially swapping adjacent document pairs (stride = 1) based on model judgments. For each query, we repeat this process ten times to obtain the final top-10 reranked results. The prompting template we use is provided in Appendix A.

For reranking evaluation, we report the results using the metric MRR@10 implemented in the `ir_measures` package (MacAvaney et al., 2022). To further understand the impact of superficial token overlap, we introduce two complementary metrics to analyze the model’s reliance on lexical overlap, as discussed next.

3.2 Correlation Analysis

The first metric captures the average lexical overlap difference (**ALOD**) in lexical overlap between relevant and irrelevant documents (lexical overlap difference, **LOD**) for a given query. For a query q , we compute:

$$\text{LOD}_q = \frac{1}{|D_q^+|} \sum_{d \in D_q^+} \text{Overlap}(q, d) - \frac{1}{|D_q^-|} \sum_{d \in D_q^-} \text{Overlap}(q, d)$$

where D_q^+ and D_q^- denote the sets of relevant and irrelevant documents for query q , respectively, and $\text{Overlap}(q, d)$ denotes the lexical overlap score between q and d , computed as the number of shared tokens (after normalization and stopword removal). We opted for LOD_q instead of simple lexical overlap to ignore shared non-keyword tokens that can be found in both relevant and non-relevant documents. On the dataset-level, **ALOD** is the average

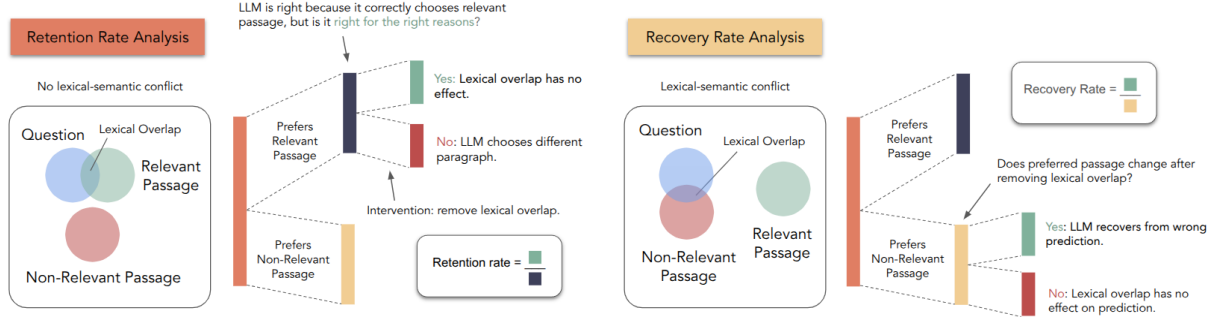


Figure 2: We conduct two types of causal analyses to understand how models determine relevance. **Left:** We use retention rate to measure the extent to which LLMs still correctly prefer the relevant passages (true positives) after removing lexical overlapping keywords. A high retention rate indicates a low lexical bias. **Right:** We use the recovery rate to measure the extent to which errors made by LLMs are due to being misguided by lexical biases. A high recovery rates indicate high lexical bias.

of LOD_q over all queries:

$$\text{ALOD} = \frac{1}{|Q|} \sum_{q \in Q} \text{LOD}(q)$$

ALOD quantifies the degree to which lexical bias can be present in monolingual and cross-lingual ranking datasets. This baseline version of ALOD provides a simple and transparent measure of lexical bias. In our reranking setup, we compute LOD based on the negative documents found in the top- k input ranking. To assess its robustness, we additionally experimented with alternative pre-processing settings, including stopword removal, lemmatization, and subword tokenization, as well as varying the number of negative documents per query. We find that while these variations changed the absolute ALOD values, the relative trends remained consistent with the comparisons above. This confirms that the ALOD metric is robust to preprocessing choices and evaluation settings. Detailed results are provided in Appendix F, Table 11.

The second is **AP-LOD Correlation**, which measures the Spearman correlation (Zar, 2005) between the average precision (AP) (Harman, 1992) of each query and its LOD. This correlation captures the alignment between lexical bias and actual ranking performance.

These metrics are applied to both MoIR and CLIR outputs to compare lexical reliance across language settings. Higher ALOD scores indicate a larger potential for models falling back to a lexically bias, while a high AP-LOD correlation shows that this is strongly related to the reranking performance of different models.

3.3 Causal Analysis

Inspired by counterfactual explanations (Verma et al., 2024) and adversarial robustness studies on multilingual embedding models (Michail et al., 2025), we design two types of counterfactual experiments to test to what extent lexical overlap impacts a model’s notion of relevance. Here, we conduct our analysis at the instance level, where each sample consists of a query, a relevant passage, and a non-relevant passage. We initially evaluate LLMs on queries that share tokens with the relevant and non-relevant passages, respectively. We then repeat our experiments with perturbed passages, where we remove the lexical overlap (intervention) and measure how it affects the model performance. The original dataset and perturbations are automatically generated with GPT-5 (OpenAI, 2025) (see prompt templates in Appendix D). Using synthetic examples allows us to disentangle the effects of semantic relevance and lexical bias in a controlled way. As shown in Figure 2, we investigate model predictions from two complementary perspectives:

Right for the right reasons? Here, we construct instances where the relevant passage shares keyword tokens with the question, while the non-relevant passage is lexically distinct from the query (Figure 6). We focus on instances where LLMs correctly prefer the relevant passage (henceforth, True Positives – TP), and test if removing lexical overlap (intervention; Figure 8) causes LLMs to change their preferred passages. We compute the **retention rate** as the fraction of TP instances where the intervention has no impact. High retention rates indicate a low lexical bias, where models prefer the relevant passage for the right (semantic) reasons.

Wrong because of lexical overlaps? In this experiment, we generate samples where only the non-relevant passages share keyword tokens with the query, while the relevant ones do not (Figure 7). Here we ask the question whether errors made by LLMs are due to an over-reliance on lexical cues. We focus on errors where models incorrectly prefer the non-relevant passage (henceforth, False Positives – FP), and compute the **recovery rate**, defined as the proportion of FP errors that are corrected after keyword overlap cues are removed (intervention; Figure 9). A high recovery rate indicates a high lexical bias and captures the extent to which models judge documents as relevant for the wrong reasons, specifically caused by lexical overlap.

To ensure the correctness of lexical-semantic conditions (see Figure 2), we prompted GPT-5 multiple times, each time generating 20 candidate examples for a given condition, and accumulated 240 candidates per condition before applying filtering criteria. In the lexical-semantic conflict dataset, the irrelevant passages share lexical tokens with the query while relevant passage do not, and vice versa for the other dataset. After filtering, we obtained 204 conflict and 200 non-conflict instances for the retention and recovery rate analyses.

4 Experimental Setup

4.1 Model and Baselines

We use Llama-3.1-8B-Instruct (Dubey et al., 2024) as the base model for zero-shot reranking (**Zero-shot** model) and instruction tuning. During both training and inference, we adopt the official LLaMA-3.1 chat template as the prompting format.¹ We compare this model against different models instruction-tuned on code-switched queries (**EN-XX-tuned**) or code-switched queries and documents (**XX-XX-tuned**). Hyperparameters are provided in Appendix B. An example prompt using the chat format is shown in Appendix C.

To assess the impact of instruction-tuning on lexical overlap behavior, we construct several variants of Llama-3.1-8B-Instruct.

The **EN-EN-tuned** model is instruction-tuned on English monolingual data and serves as our primary baseline. This setup corresponds to the standard zero-shot cross-lingual transfer setting (Lauscher et al., 2020).

¹https://www.llama.com/docs/model-cards-and-prompt-formats/llama3_1/

The **EN-XX-tuned** and **XX-XX-tuned** models are tuned on code-switched queries, and on both code-switched queries and documents, respectively, to evaluate the effect of multilingual and mixed-language supervision.

As an upper bound, we include the **Fine-tuned** model, which is directly instruction-tuned on the target language pairs and evaluated on corresponding reranking tasks. While this provides a performance reference, it is important to note that this baseline often cannot be reached in practice due to limited language coverage of existing machine translation systems and lack of available instruction-tuning training data.

4.2 Datasets

Following Litschko et al. (2023a), we use the multilingual MS MARCO dataset (mMARCO) dataset (Bonifacio et al., 2022) for model training and evaluation.² For instruction tuning, we reuse the public training data provided by Litschko et al. (2023a) in the HuggingFace repository,³ which was originally derived from the Train Triple Small set in the multilingual mMARCO dataset.⁴ For the code-switched training data. Specifically, we use the multilingual code-switched data (EN-XX and XX-XX code-switched data) with a translation probability $p = 0.5$. From this pool, for each language pair, we use a sample of 1 million instances for training.

For evaluation, we construct a reduced version of the dataset, denoted as top100.dev from the original top1000.dev set provided by mMARCO by keeping all qrels-marked relevant documents from top1000.dev, discarding queries without them, and randomly sampling non-relevant ones to obtain 100 documents per query. For each query, the order of its 100 documents is randomly shuffled.

To validate whether other findings generalize to other datasets, we also include the XQuAD-R (Roy et al., 2020) dataset. Here, too, we construct for each query input rankings consisting of top-100 documents. Following the original setup in Roy et al. (2020), we train the model using

²The mMARCO dataset includes 14 languages with varying levels of resource availability and writing systems: Arabic (AR), Chinese (ZH), Dutch (NL), English (EN), French (FR), German (DE), Hindi (HI), Indonesian (ID), Italian (IT), Japanese (JA), Portuguese (PT), Russian (RU), Spanish (ES), and Vietnamese (VI).

³<https://huggingface.co/datasets/r1itschk/cslir/tree/main>

⁴<https://github.com/spacemanidol/MSMARCO/blob/master/Ranking/README.md>

	EN	DE	AR	IT	RU	AVG	AVG _{X-X}	Δ^{ZS}	Δ^{ZS}_{X-X}
Zero-shot	51.14	38.73	29.57	38.58	36.42	38.89	35.83	-	-
EN-EN-tuned	72.41	62.08	55.34	62.30	61.57	62.74	60.32	+23.85	+24.50
EN-XX-tuned	70.72	60.27	45.45	59.31	57.93	58.74	55.74	+19.85	+19.92
XX-XX-tuned	70.50	60.86	45.64	61.46	57.79	59.25	56.44	+20.36	+20.62
Fine-tuned	-	64.79	57.91	65.28	62.35	64.55	62.58	+25.66	+26.76

Table 1: MoIR: Monolingual re-ranking results on mMARCO language pairs in terms of MRR@10. Results are reported per language and averaged in two ways: (1) **AVG** includes all monolingual pairs, and (2) **AVG_{X-X}** excludes EN-EN. Δ^{ZS} : Improvement over the zero-shot baseline, computed based on AVG. Δ^{ZS}_{X-X} : Improvement over the zero-shot baseline, computed based on AVG_{X-X}. **Bold**: The best performance for each language (excluding the fine-tuned baseline model).

	EN-DE	EN-IT	EN-AR	DE-IT	DE-RU	AR-IT	AR-RU	AVG	AVG _{X-X}	Δ^{ZS}	Δ^{ZS}_{X-X}
Zero-shot	46.14	46.22	40.64	35.72	34.19	25.52	25.78	36.31	30.30	-	-
EN-EN-tuned	62.87	62.90	52.61	54.00	53.43	40.96	42.42	52.74	47.71	+16.43	+17.40
EN-XX-tuned	64.21	63.55	51.17	53.31	52.09	33.31	34.31	50.28	43.25	+13.96	+12.95
XX-XX-tuned	64.63	64.51	51.70	56.32	54.39	41.34	41.01	53.42	48.26	+17.10	+17.96
Fine-tuned	66.21	66.54	59.38	61.09	60.01	53.53	52.53	59.90	56.79	+23.58	+26.49

Table 2: CLIR: Cross-lingual re-ranking results on mMARCO in terms of MRR@10.

the English-only SQuAD dataset and its machine-translated versions generated via Google Translate (Wu et al., 2016). For the code-switched version of the SQuAD-based training data, we implement the same code-switching method with a translation probability $p = 0.5$ following the approach in (Litschko et al., 2023a).

We evaluate our pairwise rerankers on a mix of high- and low-resource languages, covering diverse scripts and language families. Specifically, for mMARCO, we include monolingual re-ranking in English (EN), German (DE), Arabic (AR), Italian (IT), and cross-lingual re-ranking in EN-{DE, AR, IT}, DE-{IT, RU} and AR-IT. For XQuAD-R, we select three languages for MoIR (EN, DE, AR) and evaluate CLIR on the following language pairs: EN-{DE, AR}, DE-RU.

We conduct the lexical overlap perturbation experiment on the mMARCO dataset, focusing on four language pairs that include English: one monolingual pair (EN-EN) and three cross-lingual pairs (EN-DE, EN-IT, and EN-AR).

5 Results and Discussion

In the following, we first measure the performance gap of LLMs in monolingual reranking (MoIR) and cross-lingual reranking (CLIR). We specifically investigate how well different instruction-tuning strategies impact the generalization performance. We then validate our findings on XQuAD-R.

5.1 Overall Reranking Results

Cross-task Generalization Performance. Tables 1 and 2 report the MRR@10 scores on five MoIR and seven CLIR language pairs on mMARCO under different training conditions. We also report the average across all language-pairs and language-pairs that do not involve English. Across all settings, models perform better on MoIR than CLIR. For example, the Zero-shot model achieves an average MRR@10 of 0.389 for MoIR versus 0.363 for CLIR. When language-pairs involving are excluded, the gap widens (MoIR: 0.358, CLIR: 0.303). After EN-EN tuning, MoIR reaches 0.627, while CLIR falls behind with a MRR@10 of 0.527. This gap widens to 0.12 if language-pairs involving English are excluded. Similar patterns hold for EN-XX-tuned (0.587 vs. 0.503, gap: 0.084) and XX-XX-tuned (0.593 vs. 0.534, gap: 0.059).

These results show that monolingual reranking is generally easier for LLMs than cross-lingual reranking. This is expected since rerankers do not have to rely on interlingual semantics. Even under instruction-tuning on code-switched data, which improves overall CLIR performance, the gap between MoIR and CLIR remains substantial. This could be due to mismatching vocabularies, where models can rely less on lexical shortcuts in CLIR compared to MoIR. We will explore their correlation and causal relationships further in Section 6.

Instruction-Tuning on English versus Code-Switched Data. Across all MoIR and CLIR lan-

	MoIR					CLIR				
	EN	DE	AR	RU	AVG	EN-DE	EN-AR	DE-RU	AR-RU	AVG
Zero-shot	96.87	94.93	90.50	94.08	94.09	96.15	92.99	87.06	84.44	90.16
EN-EN-tuned	97.81	96.27	93.89	96.37	96.08	96.83	92.12	94.35	88.21	92.88
EN-XX-tuned	97.73	96.56	93.67	96.85	96.20	97.34	95.01	95.57	87.23	93.79
XX-XX-tuned	98.47	96.44	92.74	96.75	96.10	97.24	93.19	95.39	87.17	93.25
Fine-tuned	97.82	96.49	94.05	96.15	96.12	96.77	94.92	95.45	92.61	94.94

Table 3: MoIR and CLIR re-ranking results on XQuAD-R in terms of MRR@10.

guage pairs, models fine-tuned on the target language pair (Fine-tuned) consistently achieves the best performance, while the Zero-shot model performs the worst. This is expected because fine-tuning on cross-lingual data allows the model to jointly align interlingual semantics and learn ranking-specific features.

For all MoIR language pairs, the EN-EN-tuned model consistently outperform models trained on code-switched data, even on non-English monolingual pairs. For example, it achieves a MRR@10 score of 0.724 on English, outperforming both the EN-XX-tuned model (0.707) and XX-XX-tuned model (0.705). Similarly on Russian, where it yields a performance 0.616 MRR@10, also outperforming the EN-XX-tuned (0.579) and XX-XX-tuned (0.578) variants. We find a consistent trend of LLM rerankers performing worst on monolingual reranking in Arabic and Russian reranking tasks.

In contrast, CLIR performance generally benefits more from instruction-tuning on code-switched data. For example, on EN-DE, the XX-XX-tuned model attains 0.646, outperforming EN-EN-tuned (0.629). On AR-IT, it scores 0.413, slightly above EN-EN tuning (0.410). The only exceptions are EN-AR and AR-RU, where EN-EN-tuned reranker remains superior (0.526 vs. 0.512/0.517, and 0.424 vs. 0.343/0.410). The cross-lingual reranking performance tends to improve when the question and answer passage languages are typologically more similar. While the XX-XX-tuned model performs well on EN-DE (0.646) and EN-IT (0.645), it yields worse results on AR-IT (0.413) and AR-RU (0.410).

Overall, our results indicate that instruction-tuning on code-switched data improves cross-lingual reranking performance. However, contrary to findings reported on mBERT-based cross-encoders (Litschko et al., 2023a), we find a performance trade-off, where code-switching training data improves CLIR at the expense of perfor-

mance drops in MoIR. We hypothesize that this is related to the syntactic coherence, or the lack thereof in code-switched data,⁵ of passages provided in context. The results also reveal a clear English-centric bias: in MoIR, all rerankers achieve the strongest performance on reranking English passages; in CLIR, rerankers perform better on language-pairs involving English queries. Excluding CLIR language-pairs involving English leads to a sharp drops in CLIR performance, ranging from -0.031 (Fine-tuned reranker) to -0.070 MRR@10 (EN-XX-tuned reranker). The consistently weaker results on Arabic and Russian, and cross-lingual language-pairs involving those languages, suggests that LLM rerankers struggle to bridge the script gap (Chari et al., 2025).

5.2 Evaluation on XQuAD-R

Table 3 presents the reranking performance of models evaluated on XQuAD-R after instruction tuning on the (code-switched) English SQuAD dataset. The results generally follow similar trends to those observed on mMARCO, especially regarding the benefits of code-switching CLIR data. Consistent with our results on mMARCO, we find on CLIR that instruction-tuning variants improve upon the Zero-shot model (0.902), EN-XX-tuned (0.938) and XX-XX-tuned models (0.933) outperform the EN-EN-tuned model (0.930), and the model Fine-tuned on target the language-pairs performs best (0.949). While the results are overall much higher than those reported on mMARCO, we find that the improvements on CLIR from code switching are much smaller. Taken together, this suggests that the benefits of reducing the lexical overlap in instruction-tuning diminish as the reranking task become easier. In the rest of this paper we focus our analysis on the mMARCO dataset.

⁵The dictionaries used for code switching were induced from nearest cross-lingual neighbors in a multilingual word embedding space. Because of this, there is no guarantee that substituted words belong to the same word class.

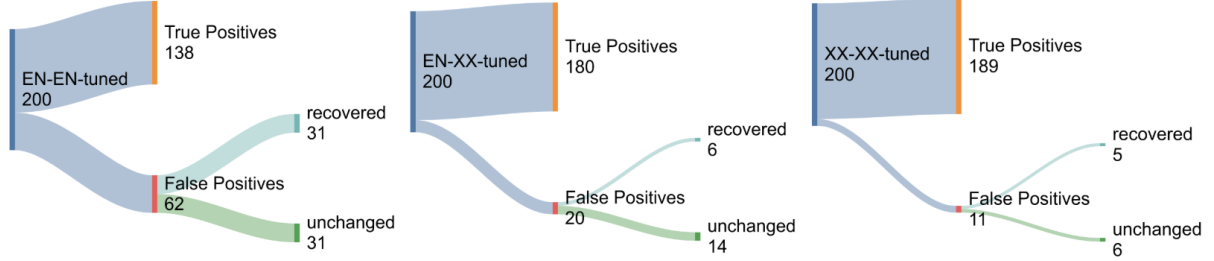


Figure 3: Results of the recovery rate analysis: Sankey diagrams illustrating model decisions on synthetic pairwise reranking experiments before and after perturbation. Non-relevant passages share overlapping keyword tokens with queries, while relevant passages have no overlap. Results are shown for the EN-EN-tuned, EN-XX-tuned, and XX-XX-tuned models. The Zero-shot model (not shown) obtained perfect results without any false positives.

	MoIR		CLIR	
	ALOD	$\rho^{\text{AP-LOD}}$	ALOD	$\rho^{\text{AP-LOD}}$
Zero-shot	0.90	22.10	0.20	10.49
EN-EN-tuned	0.90	28.16	0.20	18.19
EN-XX-tuned	0.90	25.61	0.20	14.46
XX-XX-tuned	0.90	21.85	0.20	14.81

Table 4: ALOD: Average lexical overlap difference computed separately for MoIR and CLIR on mMARCO. $\rho^{\text{AP-LOD}}$: Spearman correlation (in %) between the average precision of each query and its LOD across MoIR and CLIR on mMARCO.

6 Further Analysis

In Section 6.1, we first establish to what degree the reranking performance is correlated to the lexical overlap between queries and documents. We then investigate the reranking results at the instance level by inspecting individual pair-wise classification results (Section 6.2). Here, we evaluate whether removing lexical overlap causes models to recover from incorrect predictions.

6.1 Correlation Between Lexical Overlaps and Reranking Performance

Table 4 summarizes the ALOD and AP-LOD correlation across MoIR and CLIR on mMARCO. As expected, relevant documents exhibit higher lexical overlap with the query, and this signal is stronger in MoIR (0.90) than CLIR (0.20). Across all models, the AP-LOD correlation is consistently higher in MoIR than CLIR, confirming that MoIR reranking relies more heavily on surface-level overlap. In CLIR, due to vocabulary mismatch between query and document languages, lexical overlap is weak and often limited to named entities, forcing models to rely more on semantic relatedness features.

Among all models, EN-EN tuning shows the

strongest correlation between AP and lexical overlap, which means it relies heavily on surface word matching. Instruction-tuning on code-switched data also increases this reliance, though to a lesser extent, suggesting more semantic-driven decisions.

6.2 Causal Effect of Removing Lexical Overlap

Figure 3 and Table 5 summarize the results of models that have been instruction-tuned on the mMARCO dataset. For examples with lexical-semantic conflicts, the EN-EN-tuned model shows a recovery rate of 0.500, i.e., half of its false-positive predictions were corrected once lexical overlap cues were removed. This suggests a causal dependence on surface-level keyword overlap. By contrast, the two Code-switched-tuned models (EN-XX-tuned and XX-XX-tuned) show smaller recovery rates (0.300 and 0.455), suggesting that training rerankers on code-switched data indeed mitigates their lexical bias. However, it is important to interpret the results with caution, as the total number of false positives is relatively small.

For the examples without lexical-semantic conflicts, the Zero-shot achieves perfect retention (1.00), whereas the EN-EN-tuned and Code-switched-tuned models show slightly lower scores (0.975–0.995). This indicates that instruction-tuned models still exhibit a slight tendency to rely on lexical overlaps when correctly identifying the relevant passage. This observation aligns with our AP-LOD correlation analysis, where instruction-tuned models show stronger positive correlations between lexical overlap and relevance scores. Different from our reranking results (Section 5), we find that the Zero-shot model outperforms instruction-tuned models. This may be explained by domain differences: Both the

Model	Retention Rate Analysis			Recovery Rate Analysis		
	Accuracy	True Positives	Retention Rate	Accuracy	False Positives	Recovery Rate
Zero-shot	1.000	204 / 204	1.000	1.000	0 / 200	–
EN-EN-tuned	1.000	204 / 204	0.976	0.690	62 / 200	0.500
EN-XX-tuned	1.000	204 / 204	0.995	0.900	20 / 200	0.300
XX-XX-tuned	0.995	203 / 204	0.995	0.945	11 / 200	0.455

Table 5: Summary of causal analysis. **Left:** Results in terms of classification accuracy, number of instances where models correctly prefer relevant document (true positives; TP), and the fraction of TP instances where models still identify relevant passage after removing lexical overlap (retention rate). **Right:** Results in terms of classification accuracy, number of instances where models incorrectly prefer non-relevant document with lexical overlap (False Positives; FP), and the fraction of FP instances where the preferred passage changes after removing lexical overlap.

EN-EN-tuned and Code-switched-tuned models were fine-tuned on the mMARCO and XQuAD-R datasets, which improved their in-domain performance but reduced robustness when evaluated on our synthetic data.

Overall, our findings provide causal evidence that lexical overlap directly influences relevance judgments. Compared to the EN-EN-tuned model, instruction-tuning on code-switched data reduces but does not fully removes lexical bias.

7 Conclusion

In this study, we investigate to what extent LLM-based rerankers suffer from lexical biases as opposed to semantic relevance. Our results on MoIR and CLIR show that instruction-tuning on English data is most effective for monolingual retrieval, whereas code switching provides the largest benefits in CLIR. We also show that the correlation between reranking performance and lexical overlap is stronger for models trained on monolingual data compared to those trained on code-switched data. Our causal analysis reveals that spurious lexical cues can mislead the model, but their removal often restores correct semantic judgments. These findings highlight both the promise of code-switched data for improving cross-lingual generalization and the need to address lexical bias to ensure that LLMs are “relevant for the right reasons.”

8 Limitation and Future Work

Due to the high computational costs of instruction-tuning LLMs, we limit our study to the widely-used Llama-3.1-8B-Instruct model. In addition, the multilingual code-switched data was generated with a fixed translation probability of 0.5, leaving open how different translation probability might affect cross-lingual generalization and lexical bias. In future work, we plan to (1) detect lexical biases

at the model-internal level, in order to better understand how lexical overlap reliance and cross-lingual alignment are shaped by different training data, and (2) investigate methods for steering models away from undesired shortcut behavior. Finally, our causal analysis is limited to monolingual examples. We plan to extend this framework to cross-lingual settings in future work.

Acknowledgments

We acknowledge the support for BP through the ERC Consolidator Grant DIALECT 101043235.

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A Pairwise Re-ranking Prompt Template

System Prompt	
You are an expert in multilingual information retrieval. Your task is to determine which of the two passages is more relevant to the given query. Strict instructions:	
- Do NOT provide any explanation.	
- Do NOT include any additional words, punctuation, or formatting.	
- Answer with only Passage A or Passage B (without quotes).	
User Prompt	
Query: {query}	
Passage A: {doc1}	
Passage B: {doc2}	
Which passage is more relevant to the query?	
Respond with exactly one of the following options:	
Passage A	
Passage B	
Your answer:	

Figure 4: Prompt for pairwise re-ranking.

B Hyperparameters and Infrastructure

Hyperparameter	Value
Maximum sequence length	1024
Learning rate	2e-5
Batch size	32
Warm-up ratio	0.03
Optimizer	AdamW (Loshchilov and Hutter, 2017)
Re-ranking Model	Llama-3.1-8B-Instruct
LLM Parameters	8 Billion

Table 6: Hyperparameter values for re-ranking models used in our experiments.

Setup	Value
GPU	NVIDIA H100 SXM5-GPUs (94 GB)
Avg. Training Duration (per model)	45 h
Avg. Test Duration (per language pair)	87 h

Table 7: Computational environment. We use the Huggingface framework to train our models (von Werra et al., 2020), ir-measures for computing MRR@10 (MacAvaney et al., 2022), and Spearman correlation coefficients for correlation analysis.

C Prompting Format

```
<|begin_of_text|><|start_header_id|>system<|end_header_id|>
You are an expert in multilingual
information retrieval. Your task is to
determine which of the two passages is more
relevant to the given query.
<|eot_id|><|start_header_id|>user<|end_header_id|>
Query: ....
Passage A: ....
Passage B: ....
Which passage is more relevant to the query?
Your answer:<|eot_id|><|start_header_id|>
assistant<|end_header_id|>
```

Figure 5: A simplified example of a chat-formatted prompt using the official LLaMA-3.1 chat template. This example is only for illustration and does not reflect the full prompt used in our experiments. For the complete prompt we use, see Appendix A.

D GPT-5 Synthetic Data Generation Prompts

This appendix provides the exact GPT-5 prompt templates used for generating and perturbing the synthetic data described in Section 3.3. All prompts are shown in their natural-language form for reproducibility.

Prompt 1: Lexical-Semantic Non-Conflict Candidate Generation

Please generate 20 samples in jsonl format for pairwise semantic relevance reranking task. Each sample must follow the content requirements and format requirements below.

****Content requirements:****

- (1) The query should be a "wh"-question and keywords in the questions must have synonyms.
- (2) Passage A must always be semantically relevant to the query. Passage B must always be semantically irrelevant to the query.
- (3) Passage A and the query must share at least one overlapping non-stopword keyword. Passage B must not contain any overlapping token with the query.
- (4) Passage A and Passage B should be about similar or related topics, so that the pair forms a hard example (difficult to judge at first glance, but with a unique correct answer).

****Format requirements:****

- (1) Output must be in jsonl format.
- (2) Each entry must include: qid, query, passage_A, passage_B, and output.
- (3) Each qid and pid must be unique and assigned in order.
- (4) Always set "output": "Passage A".

Now, please directly generate 20 new samples that strictly follow the above rules.

Figure 6: GPT-5 prompt used for generating lexical-semantic **non-conflict (TP)** examples.

Prompt 2: Lexical-Semantic Conflict Candidate Generation

Please generate 20 samples in jsonl format for pairwise semantic relevance reranking task. Each sample must follow the content requirements and format requirements below.

****Content requirements:****

- (1) The query should be a "wh"-question and keywords in the questions must have synonyms.
- (2) Passage A must always be semantically relevant to the query. Passage B must always be semantically irrelevant to the query.
- (3) Passage B and the query must share at least one overlapping non-stopword token. ****Passage A**** must not contain any overlapping token with the query.
- (4) Passage A and Passage B should be about similar or related topics, so that the pair forms a hard example (difficult to judge at first glance, but with a unique correct answer).

****Format requirements:****

- (1) Output must be in JSONL format.
- (2) Each entry must include: qid, query, passage_A, passage_B, and output.
- (3) Each qid and pid must be unique and assigned in order.
- (4) Always set "output": "Passage A".

Now, please directly generate 20 new jsonl samples that strictly follow the above rules.

Figure 7: GPT-5 prompt used for generating lexical-semantic **conflict (FP)** examples.

Prompt 3: Lexical-semantic Non-Conflict True Positive Example Perturbation

Please perturb each of the following triples (original examples) used for pairwise semantic relevance reranking. These examples all satisfy the following conditions:

- (1) "gold_output" Passage is always semantically relevant to the query. the other passage is always semantically irrelevant to the query.
- (2) the ****relevant passage**** and the query share at least one overlapping non-stopword token.

****Perturbation requirements:****

- (1) Replace ALL OVERLAPPING TOKENS in the ****Relevant Passage**** that also appears in the query (i.e., all overlapping tokens) with suitable synonyms, while keeping the overall sentence semantics unchanged.
- (2) Do not modify any other part of relevant passage except the overlapping tokens, and make sure all overlapping tokens are replaced. Do not modify irrelevant passage.
- (3) The output must be in JSONL format, consistent with the structure of the original examples.

Following the above instructions, please perturb those original examples provided below and return the results in JSONL format.

Figure 8: GPT-5 prompt used for perturbing lexical-semantic **non-conflict (TP)** examples.

Prompt 4: Lexical-semantic Conflict False Positive Example Perturbation

Please perturb each of the following triples (original examples) used for pairwise semantic relevance reranking. These examples all satisfy the following conditions:

- (1) "gold_output" Passage is always semantically relevant to the query. the other passage is always semantically irrelevant to the query.
- (2) the ****irrelevant passage**** and the query share at least one overlapping non-stopword token.

****Perturbation requirements:****

- (1) Replace all overlapping tokens in ****irrelevant passage**** that also appears in the query (i.e., all overlapping tokens) with suitable synonyms, while keeping the overall sentence semantics unchanged.
- (2) Do not modify any other part of irrelevant passage except the overlapping tokens, and make sure all overlapping tokens are replaced. Do not modify relevant passage.
- (3) The output must be in JSONL format, consistent with the structure of the original examples.

Following the above instructions, please perturb the 20 original examples provided below and return the results in JSONL format.

Figure 9: GPT-5 prompt used for perturbing lexical-semantic **conflict (FP)** examples.

	EN-EN			EN-DE			EN-IT			EN-AR		
	0	[1, 3)	[3, +∞)	0	[1, 3)	[3, +∞)	0	[1, 3)	[3, +∞)	0	[1, 3)	[3, +∞)
Zero-shot	83.1	87.9	83.5	88.4	87.9	85.1	88.2	88.1	90.9	87.2	86.5	86.5
EN-EN-tuned	95.3	95.1	90.3	91.2	91.1	79.3	92.1	89.9	82.6	87.5	86.2	73.0
EN-XX-tuned	96.6	97.4	92.2	93.6	94.0	86.2	93.8	93.3	87.6	89.9	91.0	82.4
XX-XX-tuned	94.6	96.5	94.2	94.0	94.0	93.1	94.5	93.8	90.9	90.7	91.1	83.8

Table 8: Accuracy of pairwise relevance classification on the mMARCO dataset, where models are prompted to judge which of two passages is more relevant to a query. The relevant passage is lexically disjoint from the query, while the irrelevant passage exhibits varying degrees of lexical overlap. Irrelevant passages are grouped into three categories based on their overlap count with the query: 0 (no overlap), [1, 2) (low overlap), and [3, +∞) (high overlap). The table reports classification accuracy across language pairs and overlap levels. **Bold** indicates the overlap group with the lowest accuracy for each model–language-pair pair.

	EN-EN	EN-DE	EN-IT	EN-AR
Zero-shot	32.4	23.1	36.4	70.0
EN-EN-tuned	55.0	50.0	38.1	35.0
EN-XX-tuned	50.0	33.3	46.7	46.2
XX-XX-tuned	50.0	16.7	36.4	25.0

Table 9: Accuracy (recovery rate) of different models on the subset of triple samples where the irrelevant document originally had ≥ 3 lexical overlaps with the query and was incorrectly predicted as relevant. Results shows the proportion of cases in which models correctly identified the relevant document after removing the overlapping tokens.

E Causal Analysis with Word2Vec-based Perturbation

Overlap	EN-EN	EN-DE	EN-IT	EN-AR
0	296	32,157	31,457	53,664
[1, 3)	1,759	7,218	6,262	4,652
[3, +∞)	206	87	121	74

Table 10: Number of pair-wise classification instances extracted from mMARCO, grouped by how many tokens overlap between the query and non-relevant document.

In an earlier version of our causal analysis, we used real examples from the mMARCO dataset and applied word2vec-based perturbations. we first identify triplets $u(q, d_r, d_{nr})$ where the relevant document d_r shares no overlap with the query, while the non-relevant document d_{nr} contains varying degrees of overlap. Inspired by (Litschko et al., 2023a), we partition samples into those where d_{nr} has no overlap (0 tokens), low overlap (1–2 tokens), and high overlap (≥ 3 tokens) with q (see Table 10). For these high-overlap samples, we replaced overlapping tokens in the non-relevant document with their nearest neighbors in the word2vec embedding space and re-evaluated model predictions.

Table 8 shows the classification accuracy of all four models across the four language pairs (dubbed

clean run). Among the 16 combinations of 4 language pairs and 4 models, we observed a consistent pattern: in 12 of these settings, classification accuracy is lowest when the number of overlapping tokens between the query and non-relevant document was greater than or equal to three. For example, for the XX-XX-tuned model on the EN-AR pair, the accuracy falls to 0.838 in the high-overlap group, while reaching 0.907 in the no-overlap group and 0.911 in the low-overlap group. The only exceptions were the zero-shot model applied to the EN-EN and EN-IT language pairs. These drops suggest that models are more likely to over-rely on lexical overlap signals, leading to misclassification when the overlap is misleading.

When comparing models within the same language pair, we find that in cases where the irrelevant document shares at least one token with the query, the models trained on code-switched data generally outperformed the EN-EN-tuned model. For example, for the CLIR pair EN-IT, the EN-XX-tuned and XX-XX-tuned models reach accuracies of 0.876 and 0.909, respectively, exceeding the EN-EN-tuned model’s performance of 0.826.

In the second part of the experiment, we focus on misclassified samples from each language pair in the [3, ∞) group and measure if substituting overlapping tokens causes the predictions to change.

	stopword removal	lemmati- zation	subword tok- enizer	without nega- tives	top-5 nega- tives	top-10 nega- tives	top-20 nega- tives	top-50 nega- tives
MoIR ALOD	0.847	1.083	2.042	2.508	0.902	0.903	0.904	0.904
CLIR ALOD	0.242	0.235	0.460	0.406	0.197	0.197	0.196	0.197

Table 11: Robustness analysis of the ALOD metric under different preprocessing alternatives and varying number of negative documents extracted top the top-k documents in the input ranking.

Table 9 quantifies this recovery effect by reporting the proportion of misclassified high-overlap samples that were corrected after corruption. We observe that all four models show improved accuracy on these modified samples across all language pairs.

However, upon closer inspection, we found that this setup had several limitations. Many overlapping tokens corresponded to named entities or fixed expressions whose substitution could not preserve meaning, and word2vec neighbors sometimes introduced semantic drift. To ensure more controlled perturbations and consistent semantics, we therefore replaced this analysis with the synthetic GPT-5-generated data described in Section 3.3, which allows for precise manipulation of lexical overlap while maintaining contextual coherence.

F ALOD Robustness: Experimental Results

This appendix reports the robustness evaluation results for the ALOD metric, as summarized in Table 11.

Cross-Lingual Knowledge Augmentation for Mitigating Generic Overgeneralization in Multilingual Language Models

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Abstract

Generic statements like “birds fly” or “lions have manes” express generalizations about kinds that allow exceptions, yet language models tend to overgeneralize them to universal claims. While previous work showed that ASCENT KB could reduce this effect in English by 30-40%, the effectiveness of broader knowledge sources and the cross-lingual nature of this phenomenon remain unexplored. We investigate generic overgeneralization across English and four South African languages (isiZulu, isiXhosa, Sepedi, SeSotho), comparing the impact of ConceptNet and DBpedia against the previously used ASCENT KB. Our experiments show that ConceptNet reduces overgeneralization by 45-52% for minority characteristic generics, while DBpedia achieves 48-58% for majority characteristics, with combined knowledge bases reaching 67% reduction. These improvements are consistent across all languages, though Nguni languages show higher baseline overgeneralization than Sotho-Tswana languages, potentially suggesting that morphological features may influence this semantic bias. Our findings demonstrate that commonsense and encyclopedic knowledge provide complementary benefits for multilingual semantic understanding, offering insights for developing NLP systems that capture nuanced semantics in low-resource languages. We release the dataset and code¹

1 Introduction

Generic statements express generalizations about kinds that tolerate exceptions, representing a fundamental aspect of how humans conceptualize and communicate about the world. Statements such as “birds fly” or “lions have manes,” express truths about these categories despite the fact that penguins cannot fly and female lions lack manes. This

linguistic phenomenon poses a significant challenge for natural language understanding systems, as both humans and language models exhibit a bias toward interpreting these statements as universal claims; a phenomenon known as generic overgeneralization (GOG) (Leslie et al., 2011).

The tendency to overgeneralize from generic statements to universal claims reflects cognitive biases in how humans process categorical information. When presented with a true generic like “ducks lay eggs,” people and models tend to incorrectly accept the universal statement “all ducks lay eggs,” despite the obvious fact that only female ducks possess this capability (Khemlani et al., 2007). This effect has been documented in cognitive science literature (Hollander et al., 2002; Cimpian, 2010) and represents an important test case for evaluating whether language models truly understand the nuanced semantics of natural language.

Recent advances in multilingual representation learning have shown notable success in transferring knowledge across languages, yet the interaction between these methods and language-specific phenomena like genericity remains largely unexplored. This gap is more pronounced for morphologically rich, low-resource languages, where both training data and linguistic resources are scarce (Nigatu et al., 2023; Chang et al., 2024; Qin et al., 2025).

Languages such as isiZulu, isiXhosa, Sepedi, and SeSotho face challenges due to limited digital corpora (Eiselen and Gaustad, 2023; Mesham et al., 2021). These languages express genericity and other pragmatic phenomena through morphological mechanisms distinct from English, potentially affecting how generic statements are interpreted and overgeneralized. The analytic tools developed for machine translation and representation (e.g. morphology-aware modeling methods) demonstrate that explicit morphological structure affects performance in these contexts (Nzeyimana,

¹https://github.com/sello-ralethe/Multilingual_Generics

2024), yet empirical work on genericity is lacking.

In this paper, we present an investigation of generic overgeneralization across multiple languages, examining how this phenomenon manifests in typologically diverse languages and whether knowledge enhancement can mitigate its effects. We make several contributions that advance the understanding of this semantic phenomena. First, we demonstrate that generic overgeneralization is indeed a cross-linguistic phenomenon that affects languages with different morphological systems for expressing genericity. Our experiments with four South African languages show patterns in how different language families exhibit this bias, with Nguni languages displaying higher baseline overgeneralization than Sotho-Tswana languages.

Second, we show that knowledge enhancement through carefully selected knowledge bases can reduce overgeneralization effects. By comparing ASCENT KB (Nguyen et al., 2020), ConceptNet (Speer et al., 2016), and DBpedia (Auer et al., 2007) as knowledge sources, we find that different types of knowledge address different aspects of the overgeneralization problem. ConceptNet’s commonsense knowledge proves effective for minority characteristic generics, achieving 45-52% relative reduction in overgeneralization, while DBpedia’s encyclopedic coverage excels at handling majority characteristic generics with 48-58% reduction. The combination of both knowledge types yields even stronger results, reaching up to 67% reduction in overgeneralization.

In this paper, we present the first investigation of generic overgeneralization across morphologically rich, low-resource languages, examining how this phenomenon manifests in typologically diverse settings and whether knowledge enhancement can mitigate its effects across linguistic boundaries. We make several contributions that advance understanding of this semantic phenomenon in multilingual contexts.

First, we demonstrate that generic overgeneralization is indeed a cross-linguistic phenomenon, providing empirical evidence across English and four South African languages (isiZulu, isiXhosa, Sepedi, and SeSotho) which represent two distinct language families. Our experiments reveal systematic patterns in how different language families exhibit this bias, with Nguni languages displaying 4-7% higher baseline overgeneralization than Sotho-Tswana languages, suggesting that morphological features may modulate semantic biases.

Second, we compare three knowledge sources, demonstrating that different types of knowledge address different aspects of the overgeneralization problem. We show that ConceptNet’s commonsense knowledge proves effective for minority characteristic generics, achieving 45-52% relative reduction in overgeneralization, while DBpedia’s encyclopedic coverage excels at handling majority characteristic generics with 48-58% reduction.

The combination of both knowledge types yields even stronger results, reaching up to 67% reduction in overgeneralization. Importantly, these improvements remain consistent across all languages, demonstrating that conceptual knowledge effectively transfers across linguistic boundaries despite significant morphological differences. Our findings thus offer practical insights for developing NLP systems that capture nuanced semantics in low-resource multilingual settings while advancing theoretical understanding of how semantic biases interact with morphological systems.

2 Related Work

2.1 Generic Overgeneralization in Language Models

The distinction between generic statements and universally quantified statements represents a fundamental challenge in natural language semantics that has implications for multilingual NLP. While “tigers have stripes” holds true as a generic despite albino tigers lacking stripes, the universal statement “all tigers have stripes” is demonstrably false. This subtle distinction shows how language encodes conceptual knowledge about categories and their typical properties (pel, 2009).

The generic overgeneralization effect, first documented in cognitive science by Leslie et al. (2011) and Khemlani et al. (2007), demonstrates a human tendency to conflate these two types of statements. This cognitive bias appears to be rooted in humans’ default processing mechanisms, where accepting universal interpretations requires less cognitive effort than maintaining the nuanced understanding that generics admit exceptions (Leslie et al., 2011). Recent work by Ralethe and Buys (2022) extended this investigation to pre-trained language models, showing that when BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019) were asked to predict masked tokens in contexts like “[MASK] lions have manes,” these models showed strong preferences for universal quantifiers like “all” and “every.”

Experiments by [Ralethe and Buys \(2022\)](#) demonstrated that language models not only exhibit human-like overgeneralization patterns but that this bias could be partially mitigated through knowledge injection. By incorporating factual knowledge from ASCENT KB ([Nguyen et al., 2020](#)), they achieved a 30-40% reduction in overgeneralization. However, ASCENT KB’s limitations, including its relatively sparse coverage of approximately 400k animal-related triples and focus on specific factual assertions rather than broader conceptual knowledge, suggests that richer knowledge sources might prove more effective.

2.2 Commonsense vs. Encyclopedic Knowledge

The contrast between different types of knowledge bases indicates complementary approaches to representing world knowledge. ConceptNet ([Speer et al., 2016](#)) encodes commonsense knowledge that people typically know about the world, including relations like “CapableOf,” “HasProperty,” and “PartOf” that capture prototypical information about concepts. This type of knowledge proves valuable for generic reasoning because it encodes default expectations about kinds, including information about typical properties and capabilities that align with how humans conceptualize categories ([Liu and Singh, 2004](#)).

DBpedia ([Auer et al., 2007](#)), extracted from Wikipedia, provides encyclopedic, factual knowledge including specific information about instances, detailed taxonomies, and factual properties. For generic reasoning, DBpedia’s strength lies in its comprehensive coverage of exceptions and variations ([Mendes et al., 2011](#)). It contains information about albino tigers, flightless birds, and other edge cases that violate generic expectations, making it particularly valuable for understanding when universal generalizations fail.

The complementary nature of these knowledge sources becomes apparent when considering their coverage. While ASCENT KB focuses on specific faceted assertions like “young lions do not have manes,” ConceptNet provides broader conceptual knowledge such as “mane is a characteristic feature of male lions,” and DBpedia offers comprehensive factual coverage including specific information about white lions, Barbary lions, and other variations. This suggests that effective mitigation of overgeneralization may require multiple types of knowledge working in concert ([Ilievski et al.,](#)

2020).

2.3 Cross-Lingual Considerations

The expression of genericity varies significantly across languages, raising important questions about whether generic overgeneralization is universal or language-specific ([Dayal, 2004](#); [Chierchia, 1998](#)). English uses bare plurals for generic reference, while other languages use different morphosyntactic strategies. In Nguni languages like isiZulu and isiXhosa, the noun class system inherently pluralizes nouns, with generic reference typically achieved through class prefixes ([Zeller, 2012](#); [Visser, 2008](#)). For example, “amabhumbesi” (lions) in isiZulu uses the class 6 prefix ama-, which inherently indicates plurality. Sotho-Tswana languages like Sepedi and SeSotho use a different noun class system with distinct morphological patterns for expressing genericity ([Mojapelo, 2009](#)).

These typological differences have important implications for how generic overgeneralization might manifest across languages. The obligatory plural marking in Nguni languages may create different baseline expectations about universality compared to languages with optional plural marking ([Demuth, 2000](#)). Furthermore, the morphological complexity of these languages poses additional challenges for knowledge projection and alignment, as the same concept may be realized through different morphological forms depending on the syntactic context ([Kiparsky, 2001](#)).

Previous work on cross-lingual knowledge projection has shown that conceptual knowledge can transfer across languages ([Chen et al., 2016, 2021](#); [Sun et al., 2019](#)), but the interaction with language-specific phenomena like genericity remains largely unexplored. The success of multilingual models like mT5 ([Xue et al., 2021](#)) in capturing cross-lingual semantic similarities suggests that conceptual knowledge about generics might transfer across languages, but this hypothesis requires empirical validation across typologically diverse languages.

While prior work has examined generic overgeneralization in English ([Ralethe and Buys, 2022](#)), our work is the first to: (1) investigate this phenomenon across morphologically rich, low-resource African languages, (2) systematically compare commonsense versus encyclopedic knowledge sources for GOG mitigation, and (3) demonstrate effective cross-lingual knowledge transfer for this semantic task despite typological diversity.

3 Methodology

3.1 Data and Languages

Our investigation encompasses a curated dataset of generic statements and a diverse set of low-resource languages representing different typological features. We utilize the generic overgeneralization datasets from [Ralethe and Buys \(2022\)](#), comprising 5884 minority characteristic generics that express properties true of only a subset of a kind, such as “lions have manes,” and 8750 majority characteristic generics that express prevalent but not universal properties, such as “tigers have stripes.” Additionally, we use 60368 training generics covering diverse generic types to ensure comprehensive coverage of the phenomenon.

For our cross-lingual study, we select English as our baseline and four South African languages representing two distinct language families. The Nguni languages, isiZulu and isiXhosa, share similar morphological structures including extensive noun class systems with obligatory plural marking. The Sotho-Tswana languages, Sepedi and SeSotho, use different noun class systems and morphological patterns. This selection allows us to investigate how typological differences influence generic overgeneralization while controlling for potential areal effects, as all four languages are spoken in South Africa.

3.2 Translation and Quality Validation

To ensure high-quality cross-lingual data, we translated all datasets using the Google Translate API with rigorous quality controls. Our validation process included back-translation verification to identify potential translation errors, entity name validation to ensure proper nouns were correctly handled, and manual checking of quantifier translations.

To quantify translation quality, we conducted manual validation on a random sample of 200 generic statements per language. Each translation was evaluated for semantic accuracy and grammatical correctness. The validation demonstrated high translation quality overall: isiZulu (88%), isiXhosa (89%), Sepedi (91%), and SeSotho (93%). Common translation errors included:

IsiZulu: Incorrect handling of noun class agreement, particularly with complex subjects. For instance, “Young elephants play in water” was incorrectly translated as “Izindlovu ezincane zidlala emanzini” where the class prefix failed to maintain consistency with age modifiers.

IsiXhosa: Confusion between inclusive and exclusive plural forms. The generic “Lions hunt at night” was rendered as “Iingonyama zizingela ebusuku” which could be interpreted as referring to specific lions rather than lions in general.

Sepedi: Misalignment of aspectual markers affecting the generic interpretation. “Birds migrate seasonally” translated to “Dinonyana di huduga ka nako ya sehla” lost the habitual aspect important for generic meaning.

SeSotho: Occasional loss of generic force through inappropriate determiner insertion. “Cats are independent” became “Dikatse tsena di ikemela” where “tsena” (these) inadvertently introduced a deictic element.

These error patterns informed our analysis, particularly regarding how morphological features interact with generic interpretation across language families.

Rationale for Translation Approach We use translation rather than collecting native generic statements because no existing generic overgeneralization datasets exist for these low-resource languages, and creating new datasets would require extensive linguistic validation to ensure consistent generic interpretation across cultures. Translation maintains exact parallel alignment across languages, enabling controlled comparison of how the same conceptual content is processed across different morphological systems. Our high translation quality (88-93% accuracy) and detailed error analysis demonstrate that this approach is sound for investigating cross-linguistic patterns, though we acknowledge translation may introduce some noise.

3.3 Knowledge Sources

Our experimental design compares three distinct knowledge sources, each offering different types and scales of information. Following [Ralethe and Buys \(2022\)](#), we use ASCENT KB as our baseline, which contains approximately 403k animal-related triples with faceted information about properties and subcategories. While ASCENT KB provides valuable specific assertions, its coverage is limited compared to larger knowledge bases.

We extend this baseline by incorporating ConceptNet and DBpedia, both of which offer substantially richer information. ConceptNet provides approximately 220k triples per language after projection into South African languages through LeNS-

Align (Ralethe and Buys, 2025), encoding diverse relation types including taxonomic relations like “male_lion IsA lion,” property relations such as “lion HasProperty mane,” capability relations like “bird CapableOf fly,” and prototype relations such as “tiger HasA stripes.” This commonsense knowledge captures the conceptual structures that underlie generic statements.

DBpedia contributes approximately 450k triples per language after projection (Ralethe and Buys, 2025), offering instance data such as “Cecil_(lion) type Lion,” comprehensive taxonomic information like “White_tiger subClassOf Tiger,” detailed property data including “Albino_tiger colour White,” and extensive geographic and demographic information. This encyclopedic knowledge provides the factual grounding necessary to understand exceptions to generic generalizations.

3.4 Model Architectures

Our experimental framework uses different architectures for English and multilingual experiments to leverage the most appropriate models for each setting. For English experiments, we implement BERT-large and RoBERTa-large augmented with knowledge bases using the KEPLER framework (Wang et al., 2021), following the approach of Ralethe and Buys (2022). KEPLER enables knowledge integration by continuing pre-training on verbalized knowledge triples, where each triple is converted to natural language using templates. This approach allows us to maintain compatibility with the baseline while exploring richer knowledge sources.

For multilingual experiments, we adopt mT5-large as our base model, leveraging its strong multilingual capabilities across all target languages. We follow Ralethe and Buys (2025) in performing knowledge injection of the projected knowledge bases using an adaptation of the QA-GNN framework (Yasunaga et al., 2021).

QA-GNN retrieves relevant subgraphs for each generic statement and uses graph attention networks to reason over the structured knowledge, enabling explicit traversal of knowledge graph connections when interpreting generics across languages. This architecture proves well-suited for working with projected knowledge bases in low-resource languages, as it can leverage the graph structure to compensate for potential noise in the projections (See Appendix B for implementation and training details).

3.5 Evaluation Framework

We use three complementary evaluation tasks to assess model performance and the manifestation of generic overgeneralization. The generic classification task evaluates whether models can distinguish between generic and non-generic statements, with particular focus on universally quantified versions. This task directly tests whether models understand that statements like “all lions have manes” are not true generics despite the truth of the unquantified version.

Following the original work of Ralethe and Buys (2022), the quantifier prediction task provides our primary measure of overgeneralization. By masking the pre-nominal position in statements like “[MASK] lions have manes,” we evaluate how strongly models prefer universal quantifiers. We calculate the Mean Reciprocal Rank (MRR), which measures the inverse of the rank at which the first correct answer appears, averaged across all test instances. For this task, we consider universal quantifiers (all, every, each) as the target predictions, so lower MRR scores indicate better performance as they suggest the model is less likely to predict universal quantifiers. We also compute Precision at 5 (P@5), which measures the proportion of test instances where at least one universal quantifier appears in the top 5 predictions. Lower scores on both metrics indicate less overgeneralization, as models that avoid predicting universal quantifiers demonstrate better understanding of generic semantics.

The quantifier interpretation probing task creates statements with different quantifiers and masks the property position, as in “all lions have [MASK].” Models should assign higher probabilities to the correct property for quantifiers that maintain truth (some, most) than for those that create false universal statements. This task uses MRR to measure how highly models rank the correct property, with higher scores indicating better understanding when the quantifier makes the statement true. This task helps determine whether models genuinely understand the semantic implications of different quantifiers or merely exhibit surface-level patterns.

4 Results

4.1 Comparison with Previous Work: English Results

Table 1 presents a comparison of our results on English with the previous ASCENT KB baseline

from [Ralethe and Buys \(2022\)](#). The improvements achieved by ConceptNet and DBpedia are notable across all evaluation metrics, showing important insights about the types of knowledge most effective for addressing generic overgeneralization.

For minority characteristic generics, ConceptNet demonstrates notable effectiveness, achieving 45-52% relative reduction in overgeneralization compared to 30-34% for using ASCENT KB. This improvement stems from ConceptNet’s richer representation of subcategory relationships and prototypical properties. Where ASCENT KB might only encode “male lions have manes,” ConceptNet additionally provides conceptual relations such as “mane *IsA* male characteristic” and “adult male lion *IsA* lion with mane.” These additional layers of conceptual knowledge help models understand that properties like manes are inherently restricted to subsets of a category.

DBpedia shows its greatest strength with majority characteristic generics, achieving 48-58% reduction versus ASCENT KB’s 40%. This advantage arises from DBpedia’s comprehensive coverage of exceptions and edge cases. While ASCENT KB might note that albino tigers exist, DBpedia provides detailed information about white tigers, melanistic tigers, golden tigers, and numerous specific individuals. This exhaustive coverage of variations gives models concrete evidence against universal generalizations.

The combined ConceptNet+DBpedia approach achieves up to 67% reduction in overgeneralization, nearly doubling ASCENT KB’s best performance. This synergy suggests that commonsense and encyclopedic knowledge provide fundamentally complementary benefits. ConceptNet helps models understand the conceptual structure of categories and why certain properties might be restricted to subsets, while DBpedia provides the specific counterexamples that definitively rule out universal generalizations.

4.2 Cross-Lingual Results

Table 2 presents the results of the quantifier prediction task in all five test languages, demonstrating both universal patterns and language-specific variations in generic overgeneralization across languages. The results show that knowledge enhancement provides consistent benefits across typologically diverse languages, though interesting patterns emerge related to language family and morphological structure.

The most notable finding is the consistency of knowledge enhancement effects across languages. ConceptNet provides 43-47% reduction for minority generics across all languages, while DBpedia achieves 52-56% reduction for majority generics. This suggests that the conceptual knowledge encoded in these resources transfers effectively across languages through the LeNS-Align projection process, despite the significant morphological differences between English and the target languages.

A pattern emerges when comparing language families. Nguni languages (isiZulu and isiXhosa) exhibit higher baseline overgeneralization than Sotho-Tswana languages (Sepedi and SeSotho) and English. The baseline MRR for universal quantifiers is 4-7% higher in Nguni languages. We hypothesize that this may be related to the obligatory plural marking in the Nguni noun class system, which could prime speakers and models toward universal interpretations of generic statements.

The pattern of ConceptNet excelling at minority generics while DBpedia excels at majority generics holds across all languages, confirming that different types of overgeneralization (overgeneralizing from “some” to “all” versus overgeneralizing from “most” to “all”) require different types of knowledge to address effectively. This cross-linguistic consistency suggests that the cognitive and semantic factors underlying generic overgeneralization are largely universal, even as their surface manifestations vary across languages.

4.3 Classification Results

The generic classification results presented in Table 3 provide additional evidence for both the pervasiveness of overgeneralization and the effectiveness of knowledge enhancement. When asked to classify universally quantified statements as generic or non-generic, baseline models fail, achieving only around 10% accuracy. This near-chance performance indicates that without additional knowledge, models treat statements like “all lions have manes” as equivalent to the generic “lions have manes.”

Knowledge enhancement provides improvements, with the combined approach achieving 34-39% accuracy across languages. While still far from perfect, this represents a three- to four-fold improvement over the baseline. This improvement across languages reinforces our finding that knowledge injection helps models develop more nuanced understanding of generic semantics.

Model	Minority		Majority	
	MRR	Reduction	MRR	Reduction
BERT	0.326	-	0.337	-
+ASCENT [†]	0.228	30.1%	0.202	40.1%
+ConceptNet	0.179	45.1%	0.185	45.1%
+DBpedia	0.186	42.9%	0.175	48.1%
+Both KBs	0.142	56.4%	0.138	59.1%
RoBERTa	0.329	-	0.428	-
+ASCENT [†]	0.217	34.0%	0.257	40.0%
+ConceptNet	0.158	52.0%	0.221	48.4%
+DBpedia	0.171	48.0%	0.180	57.9%
+Both KBs	0.108	67.2%	0.141	67.1%

Table 1: English results for the quantifier prediction task comparing knowledge sources (MRR for universal quantifiers - lower is better). [†] indicates results from [Ralethe and Buys \(2022\)](#).

Model	Minority Characteristic Generics					
	English	isiZulu	isiXhosa	Sepedi	SeSotho	Avg Reduction
mT5	0.318	0.347	0.352	0.324	0.319	-
+ConceptNet	0.175	0.189	0.193	0.181	0.177	45.0%
+DBpedia	0.184	0.198	0.201	0.186	0.182	42.1%
+Both KBs	0.139	0.151	0.154	0.144	0.141	55.7%
Model	Majority Characteristic Generics					
	English	isiZulu	isiXhosa	Sepedi	SeSotho	Avg Reduction
mT5	0.412	0.436	0.441	0.411	0.407	-
+ConceptNet	0.216	0.231	0.235	0.218	0.214	47.3%
+DBpedia	0.189	0.201	0.205	0.187	0.184	54.8%
+Both KBs	0.136	0.148	0.152	0.135	0.133	67.0%

Table 2: Cross-lingual results for the quantifier prediction task: MRR for universal quantifiers across all languages (lower is better)

4.4 Probing Experiments

To investigate whether knowledge-enhanced models truly understand the injected knowledge, we conducted two probing experiments adapted from [Ralethe and Buys \(2022\)](#) for our multilingual mT5 setup.

4.4.1 Quantified Statement Classification Probing

We fine-tuned the knowledge-enhanced mT5 on the generic classification task and tested whether quantified statements are correctly classified as non-generic. We quantified minority characteristic generics with “many” and “most,” and majority characteristic generics with “few” and “some” to create false generic statements. For example, “most lions have manes” should be classified as non-generic since only a minority of lions have manes.

Table 4 shows that knowledge injection improves the models’ ability to recognize false quantified statements, though accuracy remains low. The

combined KB approach achieves 21.3% accuracy for minority characteristics and 28.6% for majority characteristics, suggesting that models partially learn the conceptual distinctions but struggle to apply them consistently. Detailed per-language results in Appendix A show that Nguni languages underperform Sotho-Tswana languages in this task, mirroring the overgeneralization patterns.

4.4.2 Quantifier Interpretation Probing

We evaluated whether models correctly interpret different quantifiers by masking the property in quantified statements. For each generic, we created probing instances with four quantifiers (few, some, many, most) and masked the final token. Models should rank the correct property higher for quantifiers that make the statement true.

The results in Table 5 show that knowledge-enhanced models display improved quantifier interpretation. For minority characteristic generics, models correctly assign higher MRR to properties when quantified with “few” or “some” compared to “many” or “most.” The pattern reverses appro-

Model	English	isiZulu	isiXhosa	Sepedi	SeSotho	Average
Baseline	10.8	9.7	8.3	12.1	11.4	10.5
+ConceptNet	23.4	21.2	19.6	24.5	23.7	22.5
+DBpedia	24.9	22.8	21.1	25.3	24.6	23.7
+Both KBs	38.7	36.4	34.2	39.1	38.3	37.3

Table 3: Generic classification accuracy (%) on universally quantified variants

Model	Classification Accuracy (%)	
	Minority	Majority
mT5	8.3	10.1
+ConceptNet	14.7	18.2
+DBpedia	13.9	19.4
+Both KBs	21.3	28.6

Table 4: Accuracy of classifying falsified quantified generics as non-generic (averaged across languages; see Appendix A for per-language results)

privately for majority characteristic generics. The combined KB approach shows the strongest differentiation between appropriate and inappropriate quantifiers, with the gap between true and false quantifiers widening from 0.21 to 0.41 for minority characteristics and from 0.27 to 0.43 for majority characteristics. Per-language analysis (Appendix A) shows that Nguni languages achieve the largest differentiation gaps despite higher baseline overgeneralization.

However, the relatively high MRR scores even for false quantifiers (e.g., 0.31 for “most” with minority generics) indicate that models still struggle with complete understanding. The quantifier “some” proves particularly challenging across all languages (Appendix A), maintaining relatively high scores across both generic types, suggesting models interpret it as a hedge rather than a specific quantity indicator.

5 Discussion

Our results provide several insights into generic overgeneralization, the role of knowledge in addressing it, and the cross-lingual nature of this phenomenon.

5.1 Why ConceptNet and DBpedia Outperform ASCENT KB

The effectiveness of ConceptNet and DBpedia over ASCENT KB reflects their complementary knowledge coverage. ConceptNet’s strength for minority characteristic generics emerges from its encoding of conceptual relationships that help models un-

derstand the logical structure of subset properties. When a model needs to understand that “lions have manes” does not mean “all lions have manes,” ConceptNet provides the conceptual framework: manes are a male characteristic, male lions are a subset of lions, and characteristics can be subset-specific.

DBpedia’s advantage for majority characteristic generics stems from its encyclopedic coverage of exceptions. While ASCENT KB might note that albino tigers exist, DBpedia provides detailed information about white tigers, golden tigers, and stripeless tigers, giving models concrete evidence against universal generalizations.

The combined approach achieving up to 67% reduction demonstrates that generic reasoning requires both conceptual understanding and factual grounding. Neither pure commonsense nor pure factual knowledge alone suffices; models need to understand both the conceptual possibility of exceptions and specific instances of those exceptions.

5.2 Cross-Lingual Universality and Variation

The consistency of knowledge enhancement effects across languages provides evidence that generic overgeneralization reflects a deep semantic challenge rather than a surface linguistic phenomenon. Despite different morphological systems for expressing genericity, all languages benefit similarly from the same types of knowledge, supporting the view that overgeneralization stems from conceptual biases in how categories and properties are related.

However, the higher baseline overgeneralization in Nguni languages could be related to obligatory plural marking creating a stronger bias toward universal interpretation, suggesting that language-specific features can potentially amplify or dampen universal cognitive biases. The fact that knowledge enhancement reduces but does not eliminate these cross-linguistic differences indicates a complex interaction between universal conceptual tendencies and language-specific morphosyntactic features.

Model	Minority Generics				Majority Generics			
	Few	Some	Many	Most	Few	Some	Many	Most
mT5	0.62	0.71	0.48	0.41	0.52	0.68	0.73	0.79
+ConceptNet	0.68	0.74	0.42	0.35	0.48	0.64	0.78	0.83
+DBpedia	0.65	0.72	0.44	0.37	0.45	0.61	0.81	0.85
+Both KBs	0.72	0.77	0.38	0.31	0.41	0.58	0.84	0.88

Table 5: Mean Reciprocal Rank of masked properties under different quantifiers (averaged across languages; see Appendix A for per-language breakdowns). Higher scores for appropriate quantifiers indicate better understanding.

5.3 Implications for Multilingual NLP

Our findings demonstrate that knowledge resources developed for one language can effectively transfer to others when properly projected, suggesting that conceptual knowledge is largely language-independent. However, the type of knowledge matters as much as its quantity; simply adding more factual assertions provides limited benefits compared to incorporating diverse knowledge types. The persistent differences between language families even after knowledge enhancement indicate that effective multilingual systems must account for typological variation while leveraging universal conceptual knowledge. While knowledge enhancement provides consistent benefits, the residual differences between Nguni and Sotho-Tswana languages suggest that language-specific adaptations may be necessary to achieve optimal performance.

6 Conclusion

We demonstrate that generic overgeneralization is a universal semantic challenge that manifests across typologically diverse languages, with language-specific morphological features potentially modulating its expression. Our experiments show that combining ConceptNet’s commonsense knowledge with DBpedia’s encyclopedic coverage achieves up to 67% reduction in overgeneralization. Our cross-lingual analysis uncovers systematic variation between language families, with Nguni languages exhibiting 4-7% higher baseline overgeneralization than Sotho-Tswana languages, possibly due to obligatory plural marking. Manual validation of translations shows that morphological errors directly impact generic interpretation, yet knowledge enhancement partially compensates for these artifacts. These findings advance multilingual NLP by demonstrating that conceptual knowledge transfers effectively across languages while highlighting the need for morphology-aware methods in low-resource settings.

Limitations

While our results demonstrate significant progress in addressing generic overgeneralization, several limitations point toward important future research directions. The classification accuracy on universally quantified statements, while improved, remains below 40% even with comprehensive knowledge enhancement. This suggests that the models still struggle with the fundamental distinction between generic and universal statements, indicating a need for more sophisticated approaches to semantic representation. The reliance on translated generics introduces potential noise and errors that may limit the effectiveness of knowledge enhancement. Our study focuses on four South African languages from two language families, which limits generalizability to other language families and morphological systems.

Acknowledgements

This work is based on research supported in part by the National Research Foundation of South Africa (Grant Number: 129850). Sello Ralethe is supported by the Hasso Plattner Institute for Digital Engineering, through the HPI Research School at the University of Cape Town.

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A Detailed Probing Results by Language

This appendix presents the complete per-language results for our probing experiments, which are averaged in the main text. These detailed breakdowns show language-specific patterns in how models interpret quantifiers and generic statements after knowledge enhancement.

A.1 Quantified Statement Classification Probing

Table 6 shows the accuracy of classifying falsified quantified generics as non-generic for each language. Minority characteristic generics were quantified with “many” and “most” (creating false statements), while majority characteristic generics were quantified with “few” and “some.”

Notably, Nguni languages (isiZulu and isiXhosa) show lower accuracy than Sotho-Tswana languages (Sepedi and SeSotho) and English, mirroring the

overgeneralization patterns in the main results. The gap persists across all knowledge configurations but narrows with knowledge enhancement.

A.2 Quantifier Interpretation Probing

Tables 7 and 8 present the Mean Reciprocal Rank of masked properties under different quantifiers for each language. Models should rank properties higher when paired with appropriate quantifiers (few/some for minority generics, many/most for majority generics).

A.3 Language-Specific Patterns

Several language-specific patterns emerge from the results:

Nguni Languages (isiZulu, isiXhosa): These languages show the strongest differentiation between appropriate and inappropriate quantifiers after knowledge enhancement, despite having higher baseline overgeneralization. For majority generics with combined KBs, the gap between “most” (0.90-0.91) and “few” (0.38-0.39) reaches 0.52-0.53, the largest among all languages.

Sotho-Tswana Languages (Sepedi, SeSotho): These languages demonstrate more balanced improvements across both minority and majority characteristics. They maintain better classification accuracy for falsified generics, suggesting more robust understanding of quantifier semantics.

English: Shows the highest absolute accuracy in classification tasks but moderate MRR differentiation, suggesting that the multilingual model may not fully leverage English’s richer training data when processing generic semantics.

Quantifier “Some”: Across all languages, this quantifier remains problematic, maintaining relatively high MRR scores (0.55-0.61) even for majority characteristic generics where it should receive low scores. This universal challenge suggests a fundamental limitation in how current models process scalar implicatures cross-linguistically.

B Training and Computational Details

All experiments were conducted on a Google Cloud Compute Engine instance with an a2-ultragpu-2g machine type, equipped with 2 x NVIDIA A100 80GB GPUs and 340GB memory.

For English BERT-large and RoBERTa-large experiments, we used the KEPLER framework (Wang et al., 2021) with a batch size of 32, learning rate of 2e-5, and trained for 5 epochs on the knowledge-

Model	Minority Characteristic Generics (%)					
	English	isiZulu	isiXhosa	Sepedi	SeSotho	Avg
mT5	9.2	7.3	6.8	9.7	8.5	8.3
+ConceptNet	16.3	12.8	11.9	16.1	16.4	14.7
+DBpedia	15.4	12.1	11.2	15.3	15.5	13.9
+Both KBs	23.7	18.4	17.2	23.8	23.4	21.3

Model	Majority Characteristic Generics (%)					
	English	isiZulu	isiXhosa	Sepedi	SeSotho	Avg
mT5	11.1	9.2	8.7	11.3	10.2	10.1
+ConceptNet	20.1	16.3	15.8	20.4	18.4	18.2
+DBpedia	21.4	17.5	16.9	21.6	19.6	19.4
+Both KBs	31.6	25.8	24.3	31.2	30.1	28.6

Table 6: Accuracy of classifying falsified quantified generics as non-generic, broken down by language. Higher scores indicate better understanding that inappropriate quantifiers make statements non-generic.

Model	English				isiZulu				isiXhosa				Sepedi				SeSotho			
	Few	Some	Many	Most	Few	Some	Many	Most	Few	Some	Many	Most	Few	Some	Many	Most	Few	Some	Many	Most
mT5	.63	.72	.49	.42	.60	.69	.51	.44	.59	.68	.52	.45	.64	.73	.45	.38	.65	.74	.44	.37
+CN	.69	.75	.43	.36	.66	.72	.45	.38	.65	.71	.46	.39	.70	.76	.39	.32	.71	.77	.38	.31
+DB	.66	.73	.45	.38	.63	.70	.47	.40	.62	.69	.48	.41	.67	.74	.41	.34	.68	.75	.40	.33
+Both	.73	.78	.39	.32	.70	.75	.41	.34	.69	.74	.42	.35	.74	.79	.35	.28	.75	.80	.34	.27

Table 7: MRR for minority characteristic generics under different quantifiers by language. Higher scores for few/some vs. many/most indicate correct interpretation. CN=ConceptNet, DB=DBpedia.

enhanced corpus. Knowledge triples were verbalized using templates such as “X is capable of Y” for ConceptNet’s CapableOf relation and “X has property Y” for DBpedia property assertions, following the approach of [Ralethe and Buys \(2022\)](#).

For multilingual mT5-large experiments, we adopted the QA-GNN framework ([Yasunaga et al., 2021](#)) as adapted by [Ralethe and Buys \(2025\)](#), using batch size 16, learning rate 1e-4, and 10 training epochs. Knowledge graph subgraphs were retrieved using a 2-hop neighborhood around entities mentioned in each generic statement, with graph attention networks processing up to 50 nodes per subgraph. Training time was approximately 8 hours for BERT/RoBERTa models and 12 hours for mT5 models per knowledge configuration.

Model	English				isiZulu				isiXhosa				Sepedi				SeSotho			
	Few	Some	Many	Most	Few	Some	Many	Most	Few	Some	Many	Most	Few	Some	Many	Most	Few	Some	Many	Most
mT5	.53	.69	.72	.78	.50	.66	.75	.81	.49	.65	.76	.82	.54	.70	.71	.77	.55	.71	.70	.76
+CN	.49	.65	.77	.82	.46	.62	.80	.85	.45	.61	.81	.86	.50	.66	.76	.81	.51	.67	.75	.80
+DB	.46	.62	.80	.84	.43	.59	.83	.87	.42	.58	.84	.88	.47	.63	.79	.83	.48	.64	.78	.82
+Both	.42	.59	.83	.87	.39	.56	.86	.90	.38	.55	.87	.91	.43	.60	.82	.86	.44	.61	.81	.85

Table 8: MRR for majority characteristic generics under different quantifiers by language. Higher scores for many/most vs. few/some indicate correct interpretation. CN=ConceptNet, DB=DBpedia.

What if I ask in *alia lingua*? Measuring Functional Similarity Across Languages

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Abstract

How similar are model outputs across languages? In this work, we study this question using a recently proposed model similarity metric— κ_p —applied to 20 languages and 47 subjects in GlobalMMLU. Our analysis reveals that a model’s responses become increasingly consistent across languages as its size and capability grow. Interestingly, models exhibit greater cross-lingual consistency within themselves than agreement with other models prompted in the same language. These results highlight not only the value of κ_p as a practical tool for evaluating multilingual reliability, but also its potential to guide the development of more consistent multilingual systems.

1 Introduction

Users interact with large language models (LLMs) in a variety of languages across families and resource availabilities (Nicholas and Bhatia, 2023). As such, there is a need for LLMs to perform well across languages. These models should provide consistent responses—if switching languages results in incorrect answers to the same question, it could potentially mislead users, especially in critical areas like medical advice or legal interpretation. However, current evaluations primarily focus on per-language accuracy, with little attention to consistency across languages (Koto et al., 2024; Romanou et al., 2024; Singh et al., 2024).

To quantify this consistency, we study the functional similarity of model outputs. We use Chance Adjusted Probabilistic Agreement (CAPA or κ_p), a metric recently proposed by (Goel et al., 2025), which incorporates model accuracy on a given benchmark. We extend it to measure how similar the mistakes are across different languages, giving a view of multilingual functional similarity.

^{*} These authors contributed equally
Please find our code here: [GitHub](#)

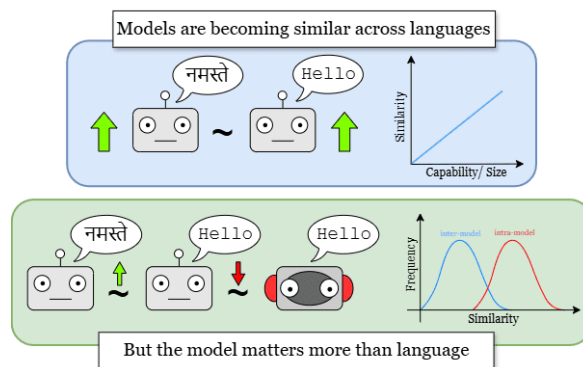


Figure 1: **Our Main Findings:** We use functional similarity to measure the consistency of model outputs across different languages. We find: (1) as language models get bigger and more capable, their outputs become more similar across languages; (2) models tend to be more self-consistent across languages than when comparing different models in a common language.

We use GlobalMMLU (Singh et al., 2024) - a carefully translated version of MMLU across multiple languages - as our benchmark. It tests the factual QA capabilities of models across a variety of subjects, ranging from mathematics to philosophy, in a multiple-choice format. Our choice of this benchmark is motivated by its parallel nature, which allows us to test whether models behave consistently across languages on factual tasks.

Our study encompasses two dimensions of functional similarity: intra-model (consistency across languages for a given model) and inter-model (consistency across models for a given language). When considering intra-model similarity, we find that with increasing size and accuracy, models are becoming more functionally similar across languages. Notably, we observe that all models are more consistent with themselves across languages than they are with other LLMs for the same language, indicating that intra-model similarity exceeds inter-model similarity for our task. Interestingly, multilingual similarity further varies by

domain and resource levels of the languages.

Primarily, we show that κ_p , a chance-adjusted functional similarity metric, provides a powerful lens for analyzing multilingual consistency of LLMs. We explore cross-lingual patterns that accuracy and representational similarity alone cannot capture, by combining the output behavior and performance of the LLM. We find interesting patterns about multilingual model behavior, including effects of scale, domain, and resources.

2 Related Work

Similarity Metrics: Prior work on model similarity falls broadly into two classes: *representational similarity* and *functional similarity*. Representational similarity metrics (Huh et al., 2024; Klabunde et al., 2025) focus on the internal states of models such as weights and activations, whereas functional similarity metrics (Goel et al., 2025) evaluate models based on their input–output behavior, making them applicable across architectures. Importantly, functional similarity better reflects the user experience, since what ultimately matters is whether models behave consistently across inputs, rather than how their internal representations align.

Multilingual Evaluations: In representational studies, researchers have identified language-specific neurons (Tang et al., 2024) and language-agnostic “semantic hubs” (Wu et al., 2024), and even used steering interventions to demonstrate their causal effects. While such work sheds light on cross-lingual representations, it does not establish quantitative trends in cross-lingual *output* consistency as models scale. On the functional side, prior work on multilingual factual consistency (Qi et al., 2023), as well as classical agreement metrics (Scott, 1955; Cohen, 1960), do not account for model accuracy and can overestimate similarity. This leaves a gap for metrics such as κ_p , which explicitly account for error consistency with agreement to provide a more realistic view of multilinguality.

3 Methodology

The accuracy of LLMs differ greatly across languages and their performance is particularly in low-resource languages (Li et al., 2025). This can artificially inflate similarity scores for some languages as high performance leaves little room for disagreement (as explained further in Appendix A). Given that κ_p addresses these issues, we use it to compare similarity of model outputs in light of variable

performance across languages. Our work complements studies on representational similarity across languages such as (Wu et al., 2024).

κ_p computes observed agreement c_{obs}^p as the proportion with which the same option is selected across samples. To account for agreement by chance, κ_p introduces an expected agreement c_{exp}^p , derived from the marginal distribution of each set of predictions. The κ_p score is given by:

$$\kappa_p = \frac{c_{\text{obs}}^p - c_{\text{exp}}^p}{1 - c_{\text{exp}}^p},$$

We use the discrete variant of κ_p as described in (Goel et al., 2025). As κ_p increases, models make more similar mistakes, and their errors become more correlated, making them functionally more similar. Henceforth, we compute the average κ_p using micro-averaging by concatenating all datasets in the group and then computing the κ_p across the combined set. Since κ_p is non-linear, the technique of micro-averaging is preferred as it smooths out extremes and operates directly at the per-sample level to better understand κ_p across a dataset.

We use Gemma-3 (1B, 4B and 12B variants) (Team et al., 2025) and Qwen-3 (1.7B, 4B, 8B and 14B variants) (Yang et al., 2025) in our experiments, as they are some of the latest models as of August 2025 which have undergone multilingual pretraining. We also use the older Gemma-7B (Team et al., 2024) as a sanity check. We evaluate these models on a subset of 20 languages of the GlobalMMLU dataset (Singh et al., 2024) with our choice of languages justified in Appendix B. Building on our evaluation methodology, we leverage the LM Evaluation Harness (Gao et al., 2024), a unified framework for testing generative language models on a wide variety of benchmarks known for its reproducibility and extensive adoption.

4 Experimentation

4.1 Intra-Model Multilingual Similarity

RQ1: Are LLMs becoming similar across languages? Motivated by the findings of (Huh et al., 2024) which shows that model representations tend to converge with an increase in size and performance of models, we investigate whether a similar convergence occurs in the output space across languages. A clear trend is observed — as the model size increases, the average κ_p score across languages also increases. κ_p also positively correlates with model accuracy. These findings suggest

that outputs become more consistent across languages for larger and more accurate LLMs. The statistically significant results are illustrated in Figure 2. A possible reason for this could be that bigger models are trained on a greater volume of data including from low resource languages allowing for greater similarity. But it is not possible to confirm this hypothesis as we do not have access to their exact training data.

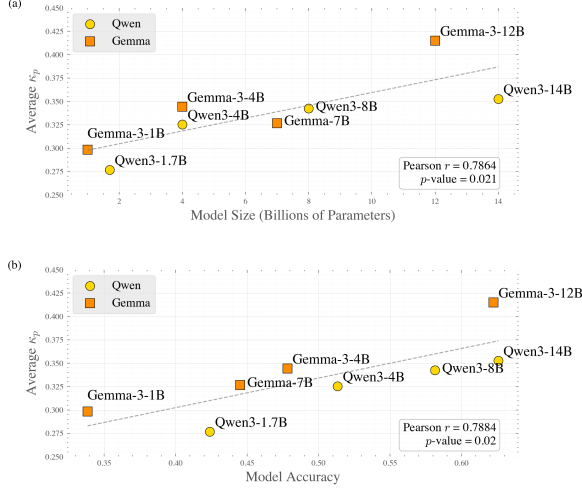


Figure 2: κ_p correlates positively with model size and accuracy. (a) κ_p averaged over languages positively correlates with model size (b) Similarly, κ_p averaged over languages positively correlates with model performance. This indicates that models grow similar across languages with their capability and size.

RQ2: Does the domain of questions asked matter? Prior work shows that the language of prompting shapes LLM outputs, influencing both cultural preferences and ethical judgments (Vida et al., 2024; Agarwal et al., 2024; Aksoy, 2025). We thus hypothesize that models will be more inconsistent for subjects like ethics, morality, and sociology, which tend to be heavily influenced by sociocultural norms, as opposed to topics with relatively fewer cultural priors, such as mathematics and computer science. The questions in GlobalMMLU are divided into four domains- *STEM*, *Humanities*, *Social Sciences* and *Other*. We further subdivide these categories to provide a more detailed analysis. κ_p tends to be greater for *STEM* in all the models as opposed to the other subjects (see Figure 3). This affirms our hypothesis about language sensitivity for culturally sensitive domains. Looking at the fine-grained categories (refer Table 6) in Figure 4 we continue to see a substantial difference between κ_p of the subjects.

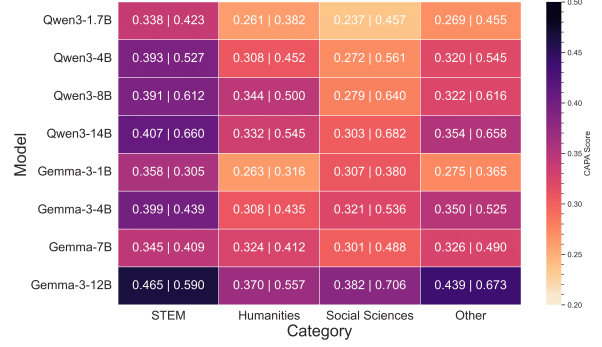


Figure 3: Models answer more similarly across languages for STEM than other domains. Each heatmap cell represents the κ_p and accuracy averaged over languages. For example, a cell value of (0.3 | 0.4) for a given model and category would represent an average κ_p of 0.3 and an average accuracy of 40%, both averaged over all the languages.

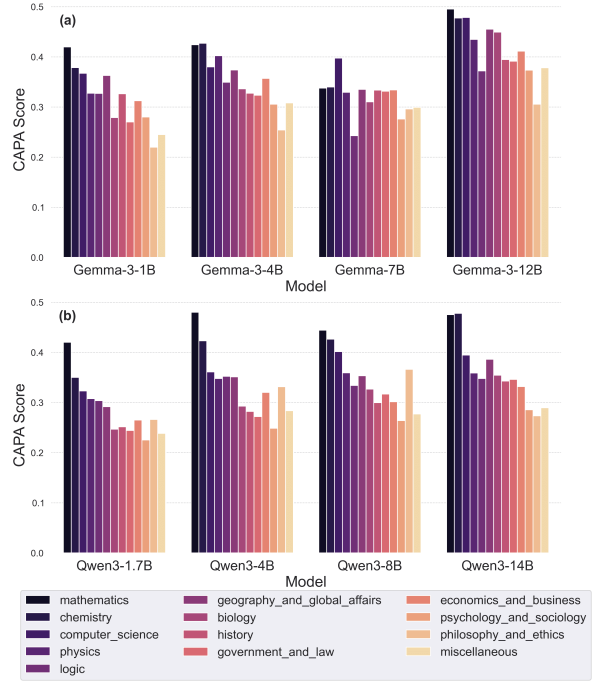


Figure 4: Intra-model κ_p scores are higher for categories belonging to STEM (Mathematics, Physics, Computer Science) than the Humanities (Philosophy, Psychology, Sociology). (a) Family of Gemma models (b) Family of Qwen Models.

4.2 Inter-Model Multilingual Similarity

RQ3: Do models agree more on high-resource languages? When we average the κ_p scores for a given language across all unique model pairs - a clear trend emerges - high-resource languages tend to have greater inter-model functional similarity, implying that the results are more consistent for languages like English than Amharic across all the

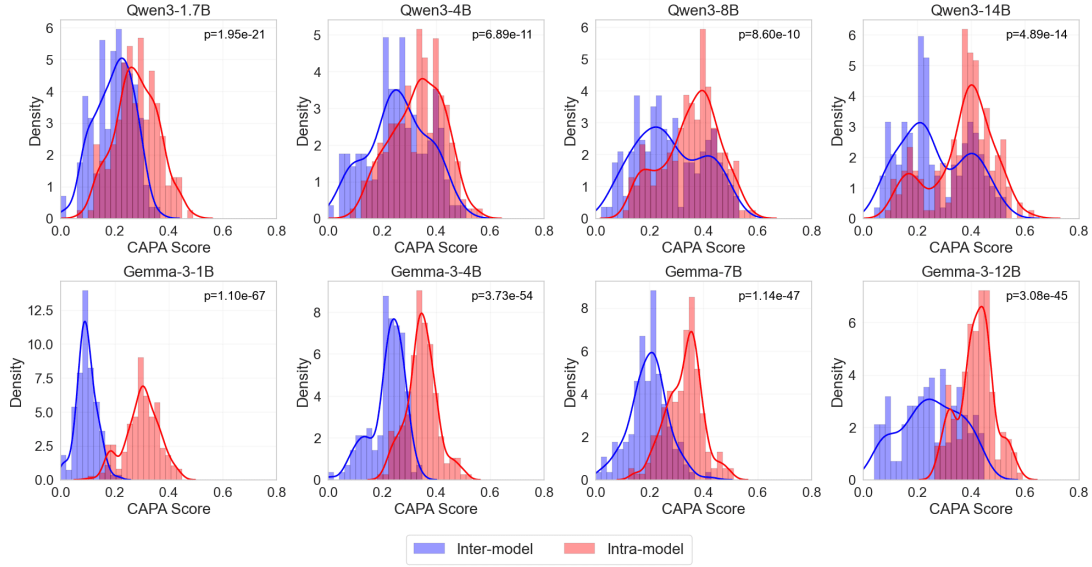


Figure 5: Frequency density distribution of the intra-model (across 20 language pairs) and inter-model (1 model vs remaining 7) κ_p scores along with the p-values of the Mann-Whitney U Test. Intra-Model similarity is greater for all models than Inter-Model similarity with high significance.

models. We confirm this by using the number of Wikipedia articles for a given language as a proxy for their resource availability. Figure 6 indicates a significant positive correlation between the count of Wikipedia articles and inter-model functional similarity κ_p score.

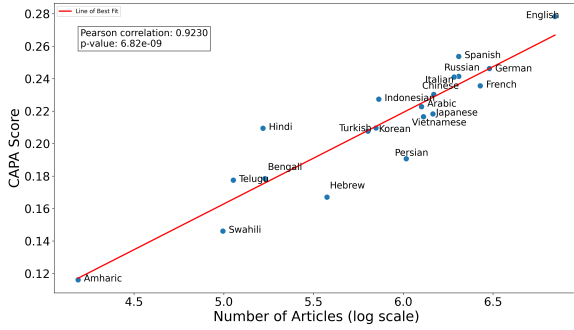


Figure 6: Higher-resource languages exhibit more model agreement. We observe a high correlation between κ_p and number of wiki articles (*Pearson correlation* = 0.923).

RQ4: Is cross-lingual similarity within the same model stronger than cross-model similarity in the same language? For each model, we find the distribution of the κ_p scores for two cases- Intra-Model (across all unique language pairs) and Inter-Model (across all models for each language). For the most part, models tend to be more similar to themselves for different languages than other models for the same language (see Figure 5). We employ the Mann-Whitney U test (Nachar et al.,

2008) - a non-parametric statistical test commonly used to compare two independent samples - for this purpose. The null hypothesis of this test is that randomly selected values from two populations have the same distribution. The p-values (< 0.001) indicate that all tests are statistically significant, confirming that the intra-model and inter-model similarity distributions are significantly different, with intra-model scores tending to be higher. We further conduct an ablation using English, the highest-resource language, as a pivot. The results (see Appendix D) remain consistent: intra-model similarity scores are higher than inter-model similarity scores, reinforcing our main findings. Additionally, we find that the functional and representational similarity correlate to a certain degree in Appendix E.

5 Conclusion

We introduced κ_p as a functional similarity metric for evaluating multilingual consistency in LLMs. Across GlobalMMLU, we found that larger and more capable models are more consistent across languages, with intra-model similarity exceeding inter-model similarity. Consistency also varies by domain — being higher in STEM than in culturally sensitive subjects — and by resource availability, with high-resource languages showing stronger inter-model agreement. Together, these results establish κ_p as a practical tool for analyzing multilingual functional behavior beyond accuracy alone.

6 Future Work

We advocate for κ_p to be used as a tool for analyzing multilinguality. We find interesting observations on the GlobalMMLU dataset, and feel that using this approach would be beneficial to the field of multilingual NLP in addition to the substantial work already being done in the representational space. There is also a great scope to explore if the two notions of similarity have any fundamental connection.

Although we hypothesize that having more data could help in improving multilingual consistency, it is also possible that it is inherently easier to learn one language from a greater capacity in another language if their underlying structures are similar. Is the cause of high functional similarity between two languages a function of their training (multilingual or parallel corpus), a natural alignment or a common syntactic structure of the two languages, or something different altogether? Establishing causality to our observations using interpretability techniques would be challenging but worthwhile.

Besides our current use case, we can see it being valuable in several applications. Higher functional similarity between two languages can have consequences on downstream tasks. For example, if a model with high κ_p between Hindi and English exists, it might become easier to translate between the two languages. Furthermore, it might allow such models to interpret Hindi-English code mixed text samples more easily than another pair with a lower score.

7 Limitations

Although our findings establish statistically significant correlations across languages and models, we cannot establish causality for the observed phenomena as this would require extensive mechanistic interventions. κ_p is limited to multiple-choice benchmarks, and there is a lack of free-form functional similarity metrics that take error consistency into account. This restricts our study to multilingual MCQ benchmarks. Additionally, there is also a lack of parallel multilingual MCQ benchmarks, and most existing ones, such as (Xuan et al., 2025), are variants of MMLU. Hence, we limit our analysis to the largest of these, GlobalMMLU.

Acknowledgments

The authors of the paper would like to thank Srija Mukhopadhyay, Hemang Jain, Sweta Jena, Monish

Singhal and other members of IIITH’s Precog lab for their valuable feedback and support. We thank Eleuther AI as their tool, lm-evaluation-harness (Gao et al., 2024), was instrumental in our experimentation.

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A κ_p vs Other Metrics

We choose κ_p as it has clear advantages over other metrics which have been theoretically and empirically validated in (Goel et al., 2025). κ_p metric is chance-adjusted, meaning it is not inflated when model accuracy is high. An example to help understand this is A model with 95% accuracy in English and Spanish answers 95/100 questions correctly in both. Raw agreement appears high, but this is trivial—it reflects correctness. κ_p down-weighs such expected agreement. In contrast, with 50% accuracy in two low-resource languages, if the model makes similar mistakes, κ_p captures this meaningful functional similarity as agreement beyond chance. When we compare it to other metrics Cohen’s κ and Scott’s π , we observe the difference in inflation due to accuracy.

Note that in our analysis we are using the discrete variant of κ_p which converts probability logits to their softmax labels. Consider two raters with predictions [0, 0, 0, 1, 2, 1] and [0, 0, 0, 1, 2, 0] respectively with ground truths [0, 0, 0, 1, 2, 2].

• Cohen’s κ

$$\begin{aligned}\kappa &= \frac{P_o - P_e}{1 - P_e} = \frac{\frac{5}{6} - \frac{15}{36}}{1 - \frac{15}{36}} \\ &= \frac{0.833 - 0.417}{0.583} \approx 0.714\end{aligned}$$

• Scott’s π

$$\pi = \frac{P_o - P_e}{1 - P_e}$$

$$\text{where } P_o = \frac{5}{6} = 0.833,$$

$$\begin{aligned}P_e &= (0.583)^2 + (0.250)^2 + (0.167)^2 \\ &= 0.431\end{aligned}$$

thus

$$\pi = \frac{0.833 - 0.431}{1 - 0.431} \approx 0.707$$

• κ_p

$$\kappa_p = \frac{c_{\text{obs}}^{E,M} - c_{\text{exp}}^{E,M}}{1 - c_{\text{exp}}^{E,M}}$$

$$\text{where } c_{\text{obs}}^{E,M} = \frac{5}{6},$$

$$c_{\text{exp}}^{E,M} = \text{acc}_1 \times \text{acc}_2 = \frac{5}{6} \times \frac{5}{6} = \frac{25}{36}$$

thus

$$\kappa_p \approx 0.45$$

Since both models are highly accurate (83.3%), the similarity scores as measured by traditional metrics are inflated. This is not the case with κ_p as it takes model accuracy into account.

All the results we have presented for remains consistent for other metrics. These results substantiate our findings, indicating their robustness and generalizability beyond the confines of the κ_p metric. Computed values are in tables 2, 3 and 4.

Here we showcase a numerical example of the advantage of probabilistic κ_p over RankC (Qi et al., 2023). Consider two raters with probabilistic predictions

$$R_1 = \begin{bmatrix} 0.50 & 0.45 & 0.05 \\ 0.50 & 0.05 & 0.45 \\ 0.05 & 0.45 & 0.50 \end{bmatrix}$$

$$R_2 = \begin{bmatrix} 0.50 & 0.05 & 0.45 \\ 0.50 & 0.45 & 0.05 \\ 0.45 & 0.05 & 0.50 \end{bmatrix}.$$

Finding the maximum probabilities from R_1 and R_2 , the hard labels are

$$r_1 = [0, 0, 2], \quad r_2 = [0, 0, 2].$$

Thus $P_o = 1$.

• **Cohen's κ**

$$\text{Rater marginals: } p^{(1)} = p^{(2)} = \left[\frac{2}{3}, 0, \frac{1}{3}\right],$$

$$P_e = \sum_i p_i^{(1)} p_i^{(2)} = \left(\frac{2}{3}\right)^2 + 0^2 + \left(\frac{1}{3}\right)^2 = \frac{5}{9},$$

$$\kappa = \frac{P_o - P_e}{1 - P_e} = \frac{1 - \frac{5}{9}}{1 - \frac{5}{9}} = 1.0.$$

• **Scott's π**

Pooled counts over both raters: $[4, 0, 2]$

$$p = \left[\frac{2}{3}, 0, \frac{1}{3}\right],$$

$$P_e = \sum_i p_i^2 = \left(\frac{2}{3}\right)^2 + 0^2 + \left(\frac{1}{3}\right)^2 = \frac{5}{9},$$

$$\pi = \frac{P_o - P_e}{1 - P_e} = \frac{1 - \frac{5}{9}}{1 - \frac{5}{9}} = 1.0.$$

• **RankC**

For each item, let $r^{(1)}, r^{(2)}$ be class rankings from R_1, R_2 . For $j = 1, 2, 3$

$$P@j = \frac{|\text{Top-}j(r^{(1)}) \cap \text{Top-}j(r^{(2)})|}{j}$$

$$\text{Weights: } w_j = \frac{e^{3-j}}{\sum_{\ell=1}^3 e^{3-\ell}}$$

$$\Rightarrow (w_1, w_2, w_3) \approx (0.665, 0.245, 0.090).$$

From the matrices:

$$(P@1, P@2, P@3) = (1, 0.5, 1).$$

$$\Rightarrow \text{item score} = \sum_{j=1}^3 w_j \cdot P@j$$

$$= 0.665 \cdot 1 + 0.245 \cdot 0.5 + 0.090 \cdot 1$$

$$\approx 0.878.$$

Averaging over all three items (identical here) gives

$$\text{RankC} \approx 0.878.$$

• κ_p

$$\kappa_p = \frac{c_{\text{obs}}^p - c_{\text{exp}}^p}{1 - c_{\text{exp}}^p}$$

$$\text{where } c_{\text{obs}}^p = \frac{1}{N} \sum_{i=1}^N \sum_{c=1}^C p_{i,c}^{(1)} p_{i,c}^{(2)} = 0.295$$

$$c_{\text{exp}}^p = \bar{p}^{(1)} \bar{p}^{(2)} + \frac{(1 - \bar{p}^{(1)}) (1 - \bar{p}^{(2)})}{C - 1}$$

$$= 0.375$$

thus

$$\kappa_p = -0.128.$$

Collapsing to hard labels yields perfect agreement ($\kappa = \pi = 1.0$). RankC, which compares top- j sets from the probability rankings, shows high but non-perfect agreement (≈ 0.878). κ_p , which directly

evaluates the full probability distributions, detects conflicting uncertainty allocations across classes and therefore yields a *negative* chance-corrected agreement (-0.128). This is intuitive, as when the models are incorrect, they give very different (and in fact, opposite) predictions which is not captured by the other metrics.

B Choice of Languages Used

We choose to do our analysis over twenty languages as listed in Table 1. The languages chosen belong to a wide range of groups, including the Afro-Asiatic (Amharic, Arabic, Hebrew), Dravidian (Telugu), Germanic (English, German), and Indo-Iranian (Persian, Hindi, Bengali) language families/branches, among others. The subset of GlobalMMLU was curated to represent a spectrum of resource availability, where high-resource languages refer to those with abundant linguistic data, such as large corpora, annotated datasets, and digital tools (e.g., English, Spanish), while low-resource languages lack such resources and infrastructure (e.g., Amharic, Telugu). This selection allows us to assess model behavior across typologically and resource-diverse settings. All the languages have an equal number of questions, and we have chosen the subset among these which have consistent answers among all the languages leading to a total of 13844 questions in each language.

C Sub-Categorization of GlobalMMLU

We sub-categorized the existing categories of GlobalMMLU to make better and fine-grained inferences. We follow the standard GlobalMMLU setup in lm-evaluation-harness (Gao et al., 2024) to conduct the evaluations. The tables 5 and 6 show the categorization based on the four domains and further split 14 categories, respectively. The tables also show the distribution of the samples for each category. Each numerical value in the Samples columns of the table corresponds to the number of resulting samples for a given model for a given language.

D Ablations for Inter-model vs Intra-model Similarity

We explore an alternate way to plot inter-model similarity by removing potential confounders from cross-size comparisons. Initially, the computation for the inter-model similarity was plotting the distribution of the computed κ_p values for each model

with the remaining seven models across 20 languages. For intra-model similarity, we compute, for each model, the distribution of κ_p values across 20 unique language pairs. For this ablation, we compute the κ_p values for inter-model similarity to be a single κ_p value for each model with the model of the other family with the closest number of parameters (model size). We then plot two distributions for intra-model similarity. In Figure 8a, the intra-model similarity computation remains the same, calculation κ_p across 20 unique language pairs. In Figure 8b, the intramodel similarity distribution has been revised to include only pairs of English-non-English languages ($en - \{lang\}$). The results remain consistent with previous results, showing that intra-model similarity is still greater than inter-model similarity.

E Some Correlation Between Functional and Representational Similarity

Following the procedure in (Wu et al., 2024), we compute the representation cosine similarity and use the last token position as the sentence representation over a subset of the translation dataset, FLORES-101 (Goyal et al., 2022). We subtract these scores by a baseline of non-matching sentences and find that when two languages have a greater κ_p score, i.e. they have high functional similarity, they also tend to have a greater representational similarity as measured by the increase over the baseline. We do it over limited layers of the Qwen model (Qwen3-4B and Qwen3-8B) due to compute constraints. This experiment is carried out to establish some degree of correlation between the two notions of similarity, the existence of which has been debated before in (Klabunde et al., 2025).

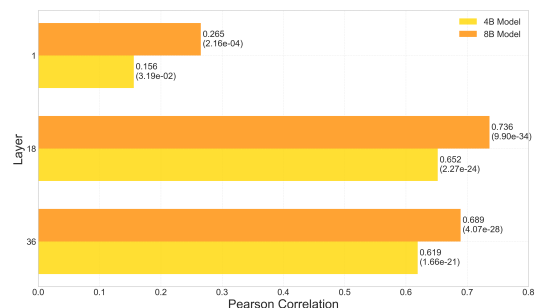
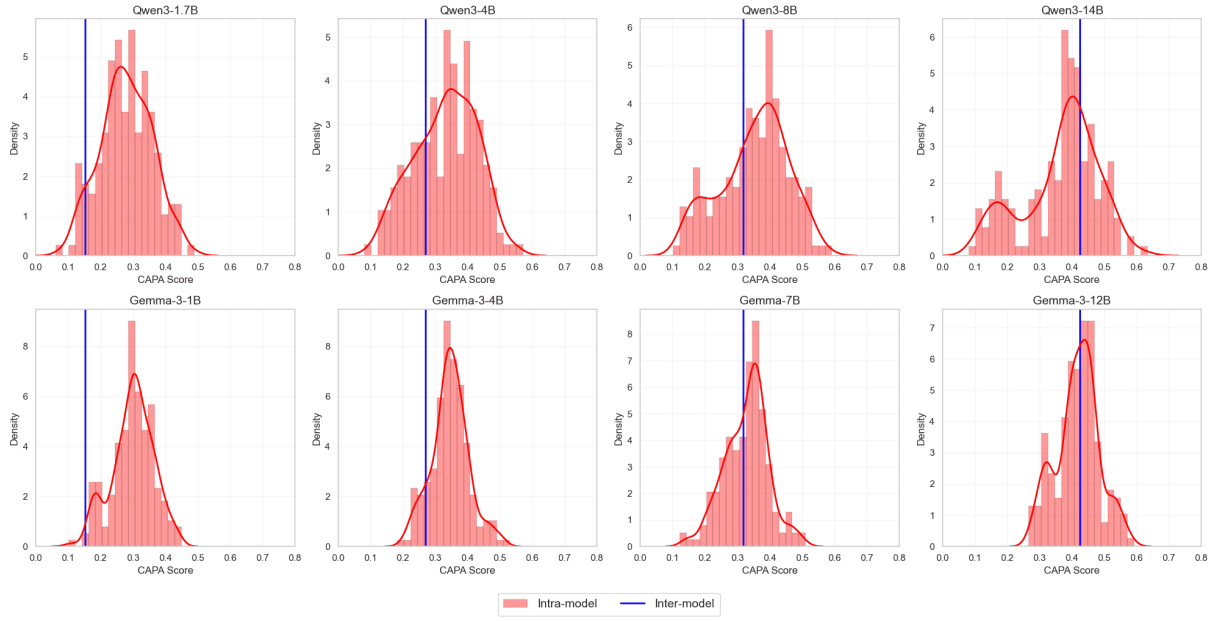


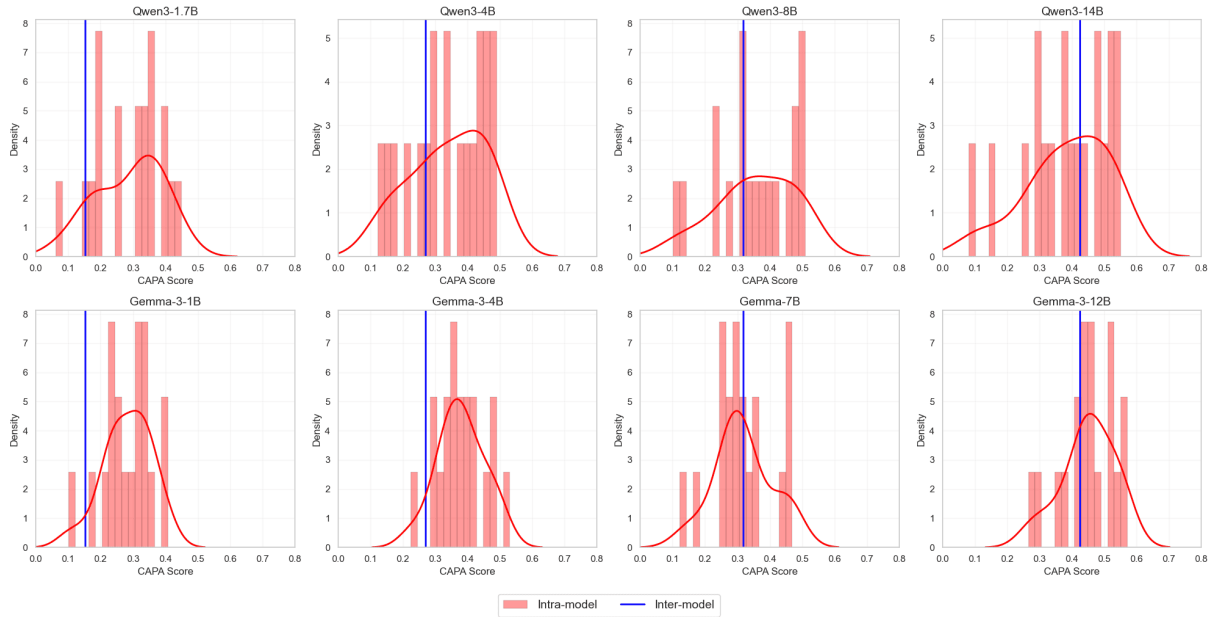
Figure 7: Languages with higher functional similarity (κ_p) also exhibit greater representational similarity. Representation cosine similarity is computed using the last token position from FLORES-101 sentence pairs. Scores are baseline-adjusted using non-matching sentence pairs.

Code	Language	Code	Language	Code	Language	Code	Language
am	Amharic	fr	French	it	Italian	es	Spanish
ar	Arabic	de	German	ja	Japanese	sw	Swahili
bn	Bengali	he	Hebrew	ko	Korean	te	Telugu
zh	Chinese	hi	Hindi	fa	Persian	tr	Turkish
en	English	id	Indonesian	ru	Russian	vi	Vietnamese

Table 1: Language codes and their corresponding language names used in our experiments.



(a) Frequency distribution of the intra-model (across 20 language pairs) and inter-model (1 model vs closest family model).



(b) Frequency distribution of the intra-model (across English-non-English pairs) and inter-model (1 model vs closest family model).

Metric	Pearson correlation for Size	Pearson correlation for Accuracy	Pearson correlation for Resource (log no. of Articles)
κ_p	0.7864 (0.02062)	0.7884 (0.02009)	0.9230 (6.82e-09)
Cohen's κ	0.8862 (0.003376)	0.9714 (5.694e-05)	0.9321 (2.28e-09)
Scott's π	0.8861 (0.003385)	0.9714 (5.728e-05)	0.9313 (2.53e-09)

Table 2: Pearson correlation coefficients (top) with p-values in parentheses (bottom).

Metric	Qwen3-1.7B	Qwen3-4B	Qwen3-8B	Qwen3-14B
κ_p	12150 (1.95e-21)	16686 (6.89e-11)	17278 (8.60e-10)	15148 (4.89e-14)
Cohen's κ	23750 (6.08e-02)	21710 (1.29e-03)	17992 (1.48e-08)	14766 (6.90e-15)
Scott's π	22358 (5.26e-03)	21644 (1.11e-03)	17542 (2.53e-09)	14460 (1.38e-15)

Table 3: Mann–Whitney U statistics for Qwen models (p-values in parentheses).

Metric	gemma-3-1b-it	gemma-3-4b-it	gemma-7b	gemma-3-12b-it
κ_p	180 (1.10e-67)	3050 (3.73e-54)	4556 (1.14e-47)	5148 (3.08e-45)
Cohen's κ	5660 (3.46e-43)	11650 (7.83e-23)	16394 (1.88e-11)	7316 (6.87e-37)
Scott's π	4364 (1.79e-48)	11176 (3.37e-24)	15598 (4.53e-13)	7228 (3.27e-37)

Table 4: Mann–Whitney U statistics for Gemma models (p-values in parentheses).

Domain	Subjects	# Samples
STEM	College Chemistry, High School Computer Science, College Biology, Abstract Algebra, High School Mathematics, Computer Security, Machine Learning, College Physics, Conceptual Physics, Astronomy, High School Biology, High School Physics, Anatomy, College Mathematics, Electrical Engineering, College Computer Science, High School Chemistry, High School Statistics, Elementary Mathematics	3153
Humanities	Philosophy, World Religions, Professional Law, Moral Scenarios, High School European History, Moral Disputes, Jurisprudence, Formal Logic, High School US History, Prehistory, High School World History, International Law, Logical Fallacies	4511
Social Sciences	High School Microeconomics, High School Geography, US Foreign Policy, Professional Psychology, Security Studies, High School Government and Politics, High School Psychology, Econometrics, Sociology, High School Macroeconomics, Public Relations, Human Sexuality	3076
Other	Professional Accounting, Professional Medicine, College Medicine, Marketing, Nutrition, Global Facts, Clinical Knowledge, Human Aging, Virology, Miscellaneous, Business Ethics, Management, Medical Genetics	3104

Table 5: Original Grouping of GlobalMMLU subjects into 4 domains with corresponding sample counts.

Category	Subjects	# Samples
Mathematics	Abstract Algebra, College Mathematics, Elementary Mathematics High School Mathematics, High School Statistics, Formal Logic Logical Fallacies	1064
Logic	Formal Logic, Logical Fallacies	289
Physics	College Physics, Conceptual Physics, High School Physics, Astronomy	640
Biology	College Biology, High School Biology, Human Aging Human Sexuality, Virology	971
Chemistry	College Chemistry, High School Chemistry	303
Medicine	Anatomy, Clinical Knowledge, College Medicine Medical Genetics, Nutrition, Professional Medicine	1251
Computer Science	College Computer Science, High School Computer Science Computer Security, Machine Learning	412
Economics and Business	Econometrics, High School Macroeconomics, High School Microeconomics Business Ethics, Management, Marketing Professional Accounting	1461
Psychology and Sociology	High School Psychology, Professional Psychology, Sociology	1358
Geography and Global Affairs	Global Facts, High School Geography, US Foreign Policy Security Studies	643
History	High School US History, High School European History High School World History, Prehistory	741
Government and Law	High School Government and Politics, International Law, Jurisprudence Professional Law	1951
Philosophy and Ethics	Philosophy, Moral Disputes, Moral Scenarios	1552
Miscellaneous	World Religions, Public Relations, Electrical Engineering, Miscellaneous	1208

Table 6: Fine-grained categorization of GlobalMMLU subjects used in our ablation.

Multilingual Learning Strategies in Multilingual Large Language Models

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Abstract

Despite the effective performance of multilingual large language models (LLMs), the mechanisms underlying their multilingual capabilities remain unclear. This study examines the intermediate representations of multilingual LLMs to determine if these models utilize human-like second language acquisition strategies: coordinate, sub-coordinate, or compound learning. Our investigations into the discriminative and generative aspects of these models indicate that coordinate learning is the dominant mechanism, with decoder-only models progressively developing distinct feature spaces for each language, while encoder-only models exhibit a mixture of coordinate and compound learning in their middle layers. We find little evidence for sub-coordinate learning. Moreover, the role of training data coverage in shaping multilingual representations is reflected in the fact that languages present in a model’s training data consistently exhibit stronger separation than those absent from it.

1 Introduction

Large language models (LLMs) have exhibited impressive performance across multiple languages in a wide range of tasks (Shi et al., 2023). However, the underlying mechanisms that enable their multilingual capabilities remain largely unexplored. Recent studies suggest that these capabilities may stem from a combination of implicit translation into a dominant language like English and internally adopted language-specific processing strategies (Zhang et al., 2023; Wendler et al., 2024).

However, these studies primarily base their hypotheses on the generative capabilities of language models, leaving the explicit exploration of their internal mechanisms unaddressed. We fill this gap by providing a granular perspective on the internal mechanisms underlying multilingualism in multilingual large language models. Specifically, we examine the intermediate representations (activations)

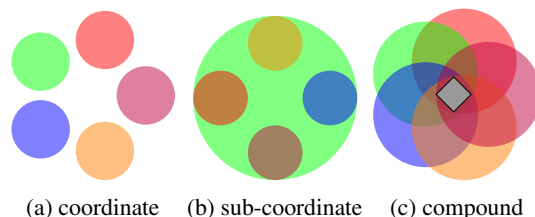


Figure 1: A conceptual visualization of feature spaces corresponding to human bilingualism. Each circle represents a feature space for a language. The gray diamond in compound learning refers to a universal space formed by the intersection of all language spaces.

of LLMs to identify the presence of multilingual information that supports each of the three types of bilingualism in human language learners: coordinate, sub-coordinate, and compound learning (D’Acierno, 1990). We generalize human bilingualism into multilingualism and conceptualize it in terms of the vector representation of linguistic units formed in the intermediate activations of an LLM. Figure 1 illustrates this conceptualization.

Coordinate learners acquire languages in distinct environments, such as home and school, leading them to process each language independently through separate cognitive systems. In other words, coordinate learners tend to develop language-specific feature spaces, where each language is encoded in its own dedicated representational structure with minimal cross-linguistic influence. From a language model perspective, coordinate learning manifests as distinct language clusters in the intermediate representations.

Sub-coordinate learners, however, interpret languages through the lens of a dominant language by implicitly translating non-dominant languages into the dominant one. This typically occurs in late acquisition, low proficiency, or non-immersive settings, where the learner relies on mental translation rather than direct comprehension. From the perspective of a language model, this translates to the

existence of a broad feature space for the dominant language, which includes other languages.

In contrast, compound human learners develop a core, universal understanding of language, where linguistic units such as word categories and concepts are partially shared across different languages and expressed through varying verbal forms. These learners acquire multiple languages simultaneously within the same environment and tend to abstract away language-specific properties. In a language model’s feature space, this translates into the existence of feature spaces shared across all languages.

The training environment of multilingual language models resembles that of coordinate and compound learners, as their training data are sampled from multiple language sources, but each segment primarily consists of a pragmatically complete text (i.e., coherent and self-contained segments, such as articles or conversational exchanges) in a single language, with limited language mixing. Accordingly, we hypothesize that multilingual language models primarily adopt a coordinate learning strategy with some degree of compound learning, while sub-coordinate learning, if present, is likely restricted to unseen languages.

We employ two complementary strategies to investigate this hypothesis based on the intermediate activations of language models. The first is a discriminative approach, quantifying language-specific and universal information in intermediate feature activations. The second examines the models’ generation process by analyzing the contribution of intermediate features to token generation.

Our findings across different LLM architectures strongly support the view that multilingual processing in these models aligns primarily with coordinate learning, with partial evidence of compound learning. Decoder-only models such as mGPT (Shliazhko et al., 2024) and BLOOM (Scao et al., 2023) predominantly rely on coordinate learning, whereas encoder-only models like mBERT (Devlin et al., 2019) and XLM-R (Conneau et al., 2020) exhibit a more complex interplay of coordinate and compound strategies. Evidence for sub-coordinate learning is limited, as none of the models show a strong dependence on a dominant language to process others.

2 Previous Work

Zhang et al. (2023) systematically investigate the multilingual capabilities of LLMs across three di-

mensions: reasoning, knowledge access, and articulation. Their analysis of ChatGPT-generated text shows that LLMs perform better when prompted in English, excel in tasks that allow direct translation, and exhibit a mix of coordinate and sub-coordinate bilingual processing. Our findings strongly support Zhang et al. (2023)’s conclusion that LLMs function as coordinate learners. However, we find clear contradictions with their claim that LLMs also exhibit sub-coordinate bilingualism based on their behavioral analysis of language models. Since their study relies on a different methodology and uses a commercial model (ChatGPT), which does not provide access to internal representations, directly validating their results within our experimental setup remains infeasible.

Wendler et al. (2024) take a different approach to examining the origins of multilingual capabilities in language models primarily trained on English text. They apply the logit lens technique, which projects intermediate representations into the vocabulary space using the model’s final token projection layer. Through this method, they argue that a translational shift in intermediate representations is indicative of sub-coordinate learning. However, Belrose et al. (2025) highlight key limitations of the logit lens, showing that it fails to yield meaningful insights for modern language models, including BLOOM (Scao et al., 2023). In particular, they demonstrate that the logit lens often predicts the input token itself as the top output and disproportionately allocates probability mass to tokens that diverge from those emphasized in the model’s true output distribution.

When it comes to implications of compound learning, previous studies have suggested the existence of partially shared subspaces between languages in mBERT (Shliazhko et al., 2024). Specifically, Pires et al. (2019) attribute mBERT’s cross-lingual capabilities to its language-independent tokenization, while Chi et al. (2020) demonstrate that the model shares portions of its representations across languages, suggesting that compound learning supports cross-lingual transfer through overlapping representational subspaces. Yet, whether these subspaces reflect universal linguistic features or artifacts of training remains an open question that our analysis investigates.

This paper extends previous research by examining multilingualism in open-source LLMs trained on multiple languages and architectures, in contrast to Wendler et al. (2024), which focus on English-

centric models. In addition, we propose novel methods for probing interactions across languages at the level of neural activations, enabling deeper insights into multilingual processing than output-based analyses, a line of inquiry recently criticized for its limitations (Zhao et al., 2025).

3 Methodology

Let us consider a sentence $s = t_1, \dots, t_n$ drawn from a language, and define A as an $l \times n \times d$ tensor representing the intermediate activations of a language model as it processes s . Here, l denotes the number of layers, and d represents the number of features, i.e., embedding dimension. In this setup, A provides l distinct representations, each residing in a separate d -dimensional space, for every token. We extend this formulation to multiple aligned sentences across different languages, where each token is annotated with relevant linguistic labels (e.g., language identification or POS tag). This results in a large tensor of size $l \times N \times d$, where N is the total number of tokens across all sentences.

To facilitate efficient visualization, reduce noise, and retain the most informative features of the activation space, we apply principal component analysis (PCA) to each of the l views independently, reducing their dimensionality to \tilde{d} while preserving at least 95% of the activation variance. This results in a tensor \tilde{H} of size $l \times N \times \tilde{d}$, which, together with H , serves as the foundation for our analysis.

We adopt two approaches to examine the generative and discriminative aspects of intermediate representations. The first adopts an information-theoretic procedure to quantify the amount of \mathcal{V} -usable information (Xu et al., 2020) encoded in intermediate representations that discriminates between language-specific and universal features. The \mathcal{V} -usable information in a random variable X for predicting a category Y is defined as the difference in conditional entropy between predictions based on X and a baseline prediction where no input features are provided (i.e., Φ):

$$I_v(Y; X) = H(Y|\Phi) - H(Y|X)$$

A high value of $I_v(Y; X)$ indicates that X is highly effective at reducing the uncertainty in predicting Y , though this does not necessarily translate to better task performance. In order to make the usable information comparable across tasks, we normalize them by the marginal task entropy and refer to it as the normalized usable information or usable

information for short.

$$I_{nv}(Y; X) = 1 - \frac{H(Y|X)}{H(Y|\Phi)} \quad (1)$$

Our motivation for using this metric is twofold. First, its discriminative nature makes it applicable to both encoder-only and decoder-only architectures. Second, it allows for a direct comparison of the effectiveness of feature vectors across different tasks defined over the same feature space X (Ethayarajh et al., 2022). Such a comparison would not be possible if the analysis were based solely on task-specific metrics (e.g., F_1 -score and accuracy), as these metrics are not directly comparable across different tasks. Additional details regarding the implementation of this metric are in Appendix A.

The second approach examines the generation capability of the decoder-only models. It utilizes saliency maps to examine how individual intermediate features contribute to token generation (Hou and Castanon, 2023). By examining the gradients of next-token predictions with respect to intermediate activations, we identify the features that play a key role in encoding language-specific and universal properties. We use Gradient-weighted Class Activation Mapping to measure the importance of a feature h_i^k at a layer k to the prediction of a token by computing the product of the feature value for an input token (i.e., $h_i^k(t_j)$) and the gradient of the prediction (before softmax) with respect to that feature (i.e., $\frac{\partial f(t_{j+1})}{\partial h_i^k(t_j)}$). This product undergoes a ReLU activation to ignore negative contributions:

$$c_i^k(t_j) = \text{ReLU}(h_i^k(t_j) \cdot \frac{\partial f(t_{j+1})}{\partial h_i^k(t_j)})$$

where $h_i^k(t_j)$ corresponds to the element (k, j, i) in H , and $f(t_{j+1})$ is the logit for t_{j+1} .

To assess the significance of c_i^k for a group of tokens (e.g., tokens belonging to a particular language), we conduct a two-tailed t-test with a significance level of 0.01. We refer to features with significant contribution to the generation of a particular token group as differentiating features for the group. Accordingly, we define the *differentiating rate* of layer k as the ratio of differentiating features to the total features in the layer:

$$D_k = \frac{\sum_{i=1}^d \mathbb{I}(p\text{-value}(c_i^k) < 0.01)}{d} \quad (2)$$

where \mathbb{I} is an indication function.

In addition to the aforementioned metrics, which are designed to assess coordinate and compound learning, we introduce another approach in Section 8 to assess sub-coordinate learning based on the proximity of intermediate activations to those of a dominant language.

4 Experiment Setup

We leverage the Parallel Universal Dependencies (PUD) treebanks (Zeman et al., 2017; Nivre et al., 2016) which comprise aligned sentences from news sources and Wikipedia, annotated for both morphological and syntactic structures. The cross-lingual alignment of sentences ensures that our findings are not skewed by domain-specific variations or differences in syntactic and semantic structures in certain languages. Additionally, the availability of syntactic annotations allows us to effectively assess compound learning within LLMs.

Our experiments are based on 1000 sentences from each of the 21 topologically different languages in PUD. A summary of the dataset is available in Table 1. The analyses are based on three publicly available multilingual language models with different architectures and language coverages: BLOOM (Scao et al., 2023) and mGPT (Shliazhko et al., 2024) are decoder-only models, and mBERT (Devlin et al., 2019) and XLMR (Conneau et al., 2020) (base and large) are encoder-only models. More information about the models’ size and language coverage is provided in Table 2.

To assess the generalizability of information to unseen languages, we consider two experimental scenarios based on whether a test language is included in a model’s pre-training data. The **Seen** setting contains only languages present during pre-training, while the **Unseen** setting includes those absent from it. For mBERT and XLM-R, the Unseen set is empty, as all test languages are covered in their pre-training data.

5 Coordinate Learning

We investigate coordinate learning by analyzing the separability of intermediate representations across input languages through the usable information for language identification and the feature differentiation rate for language processing. The underlying principle is that coordinate learners construct distinct processing systems for each language.

Language	ISO	Family	Size	A	B	C	D
Arabic	ar	Afro-Asiatic	20K	✓	✓	✓	✓
Chinese	zh	Sino-Tibetan	21K	✓	✗	✓	✓
Czech	cs	IE Slavic	18K	✓	✗	✗	✓
English	en	IE Germanic	21K	✓	✓	✓	✓
Finnish	fi	Uralic	15K	✓	✓	✗	✓
French	fr	IE Romance	25K	✓	✓	✓	✓
Galician	gl	IE Romance	25K	✓	✗	✗	✓
German	de	IE Germanic	21K	✓	✓	✗	✓
Hindi	hi	IE Indo-Aryan	23K	✓	✓	✓	✓
Icelandic	is	IE Germanic	18K	✓	✗	✗	✓
Indonesian	id	Austronesian	19K	✓	✓	✓	✓
Italian	it	IE Romance	25K	✓	✓	✗	✓
Japanese	ja	Japonic	28K	✓	✓	✗	✓
Korean	ko	Koreanic	16K	✓	✓	✗	✓
Polish	pl	IE Slavic	18K	✓	✓	✗	✓
Portuguese	pt	IE Romance	24K	✓	✓	✓	✓
Russian	ru	IE Slavic	19K	✓	✓	✗	✓
Spanish	es	IE Romance	23K	✓	✓	✓	✓
Swedish	sv	IE Germanic	19K	✓	✓	✗	✓
Thai	th	Kra-Dai	22K	✓	✓	✗	✓
Turkish	tr	Turkic	17K	✓	✓	✗	✓

Table 1: Selected languages. IE: Indo-European. A: mBERT, B: mGPT, C: BLOOM, D: XLMR.

LLM	Size	l	d	LD	LC
BLOOM	1.7B	24	1536	46	17%
mGPT	1.3B	24	2048	61	28%
mBERT	172M	12	768	104	100%
XLMR-base	270M	12	768	100	100%
XLMR-large	550M	24	1024	100	100%

Table 2: Language Models. l and d: number of layers and features LD: Language Diversity – number of training languages; LC: Language Coverage – The ratio of test languages to training languages.

5.1 Usable Information

Figure 2 presents the layer-wise variation in usable information for predicting the source language from activation vectors. The consistent upward trends in the decoder-only models indicate that the activation vectors progressively encode more information about the processing language in deeper layers. The presence of this trend in the Unseen settings suggests that the language-specific information captured by the models generalizes beyond the languages seen during training. However, the overall level of usable information is substantially lower for unseen languages than for seen ones, highlighting the influence of pre-training data coverage on the emergence of coordinate learning.

The encoder-only models, on the other hand, show a different pattern. The decreasing trajectory after the second layer indicates that these models quickly encode language-specific information in their lower layers but gradually lose it until the top

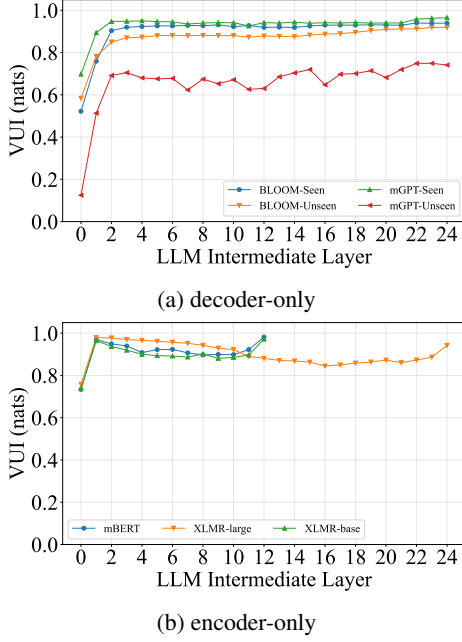


Figure 2: Usable information for language identification.

layers, where reconstruction begins. This pattern holds regardless of the model size, as we see for both the XLMR-base and XLMR-large.

Overall, the results from both architectures support our hypothesis that encoder- and decoder-only models tend to take a coordinate learning, as their primary multilingual learning strategy, which in the case of the decoder-only models develops increasingly through the layers, while being conflated with other learning strategies in the middle layers of encoder-only models.

The progression of coordinate learning is further illustrated by the t-SNE visualization of activation vectors in Figure 3. In both mBERT (encoder-only) and BLOOM (decoder-only), the lower layers show substantial cross-lingual overlap, with limited language separation. In BLOOM, the language overlap diminishes in the upper layers, where language representations become almost entirely separated into distinct feature spaces. The formation of such language-specific feature spaces is also evident for languages not included in the models’ pre-training data. Notably, BLOOM tends to develop distinct feature spaces for unseen languages such as German, Finnish, and Swedish. In contrast, mBERT exhibits more substantial cross-lingual overlap in its middle layers, with representations becoming relatively more separable at the second and last layers. Both models show some degree of coordinate learning in their lower layers, limited to typologically

logically distant languages such as Arabic, Czech, Finnish, German, Hindi, Korean, and Russian, occupying separate regions in the feature space.

5.2 Language Differentiating Features

By computing layer differentiation rates in decoder-only models, we identify language-specific features crucial for token generation in each language. The features are identified through their contribution to token prediction in each of the Seen and Unseen settings based on Equation 2. For each language, we estimate feature contributions to next-token prediction and compare them across languages using statistical tests. The proportion of features that differ significantly at each layer defines its differentiation rate, providing a layer-wise measure of language-specific processing. The experiment is detailed in Appendix B and the results are summarized in Figure 4. High differentiation rates indicate distinct feature spaces for each language group, supporting coordinate learning.

The results show that both models tend to dedicate a substantial number of features to differentiate between languages. These features are significantly higher for Seen languages than Unseen ones. The upward trend in mGPT indicates that the model progressively isolates languages into increasingly distinct feature spaces across all layers, regardless of whether the languages were part of its training data. BLOOM, however, follows a different strategy. For Unseen languages, the differentiation rate remains relatively stable around 40-50%, while for Seen languages, it takes a smooth downward trend, implying that BLOOM tends to share some features between languages at the top layers, although it still processes languages through a set of significantly isolated features for each language.

6 Compound Learning

Compound learning involves constructing universal feature spaces shared among languages. Our analysis of compound learning examines the existence of such shared spaces at the syntax level for Universal Part-Of-Speech tags (UPOS). We probe this phenomenon through the usable information for UPOS tagging and the joint differentiation rate of features for languages and syntactic categories.

6.1 Usable Information for UPOS Tagging

Figure 5 illustrates the variation of usable information in the models’ intermediate activations for

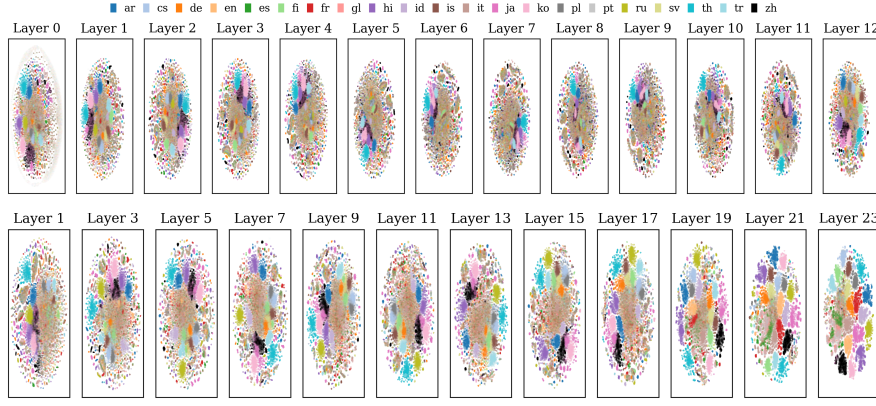


Figure 3: tSNE visualization of activation vectors. Top: mBERT, bottom: BLOOM.

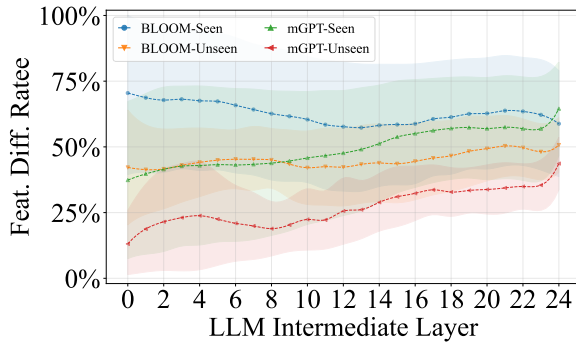
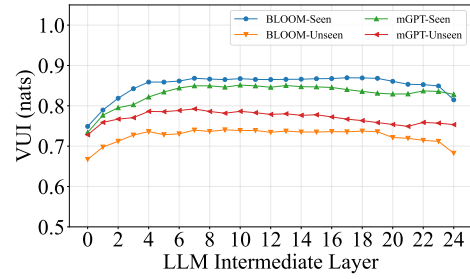


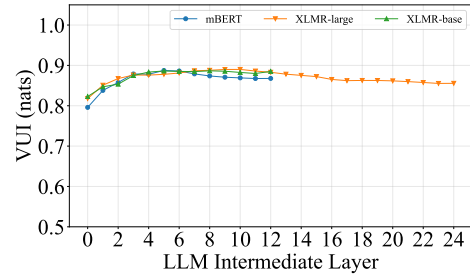
Figure 4: Language differentiation rates across layers. Shaded areas show variation across languages; solid lines show the mean.

predicting UPOS tags. The results show a consistent pattern across all models: usable information for UPOS prediction is low in early layers, peaks around the middle layers, and declines in the upper layers. This trend holds irrespective of architecture and aligns with prior findings on syntactic localization in transformers (Tenney et al., 2019).

Comparing Seen and Unseen languages reveals that the decoder-only models encode more UPOS information for languages included in their training data. To examine whether models encode universal syntax through shared representations or within language-specific spaces, we measure usable information for the joint prediction of UPOS tags and languages. As shown in Figure 6, decoder-only models exhibit a clear upward trend, indicating that higher layers become increasingly informative for the joint task. This pattern is also observable in tSNE visualization of BLOOM’s activation vectors in Figure 7, where the UPOS activations are clustered within the feature space of languages formed at the top layers of the model. This indicates that



(a) decoder-only



(b) encoder-only

Figure 5: Usable information for UPOS identification.

decoder-only models such as BLOOM represent universal syntax within language-specific feature spaces, reducing the likelihood of compound learning, particularly in the upper layers.

However, the process appears more complex in the encoder-only models. The increasing trends in the initial and top layers support coordinate learning, while the decreasing patterns in the middle layers indicate an additional mechanism, likely linked to compound learning. Still, the fairly high values of the usable information for the joint language and UPOS identification are more in support of coordinate learning, which suggests that the models tend to process universal syntactic properties of the languages within language-specific feature spaces.

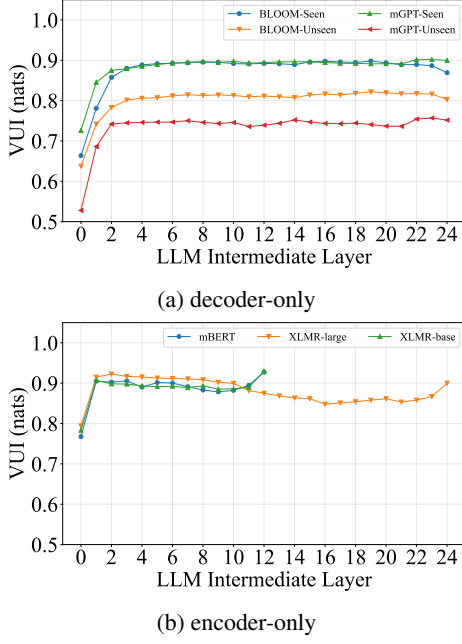


Figure 6: Usable information for joint prediction of UPOS tags and languages.

7 Language-UPOS Differentiating Features

To further examine how UPOS tags are processed within language-specific feature spaces, we measure layer differentiation rates based on the prediction of words belonging to a given syntactic category in a target language. By testing whether the same syntactic tag is processed differently across languages, we compute a joint differentiation rate that quantifies the extent to which syntactic categories are represented in language-specific versus shared feature spaces. The details of this experiment are provided in Appendix C.

Figure 8 shows that decoder-only models allocate a subset of features to distinguishing syntactic categories within each language, irrespective of whether the language was included in pre-training. The absolute values of the differentiation rates, however, are consistently higher for Seen languages, suggesting that universal syntactic categories are more strongly encoded in language-specific feature spaces when the language is represented in training. In mGPT, the modest upward trend for Seen languages further indicates that these differentiating features become increasingly effective in the top layers.

8 Sub-coordinate Learning

Sub-coordinate learning implies a shift in intermediate feature vectors towards a dominant language that filters and influences the representations of other languages. The dominant language, which is more represented in the pre-training data of our test language models, is English.

If a language model employs sub-coordinate learning internally, we would expect the representations of non-English languages to be enveloped by or significantly overlap with English representations. To examine this, we measure the proximity of language-specific activation vectors by computing the Kullback-Leibler (KL) divergence between the distribution of each non-English language and English. If language models employ internal filtering mechanisms consistent with sub-coordinate learning, we expect a reduction in KL divergence, indicating that representations of different languages become more aligned with English.

Figure 9 presents the KL divergence between the feature space of each language and English. For decoder-only models, divergence begins relatively small in the lower layers and peaks in the middle layers, reflecting increased separation from English. At the top layers, BLOOM shows a sharp divergence, whereas mGPT instead converges strongly toward English. These trends are consistent across both Seen and Unseen settings: BLOOM’s behavior suggests a weakening of sub-coordinate learning, while mGPT’s sharp convergence in the top layers provides stronger evidence. Nevertheless, because sub-coordinate learning is expected to manifest primarily in the middle layers, the decrease observed at the top layers of mGPT is less likely to be explained by this mechanism alone.

The encoder-only models display a different pattern. mBERT and XLM-R show only a modest shift toward English, while in XLM-R-large, this turns into a growing divergence after the middle layers. Moreover, the absolute divergence values are substantially smaller than in decoder-only models, peaking at around 80 compared to several thousand, indicating that encoder-only feature spaces are generally denser. The modest reduction in divergence may reflect weak sub-coordinate learning, or, in line with our earlier discussion, could instead result from weak compound learning effects in the middle layers.

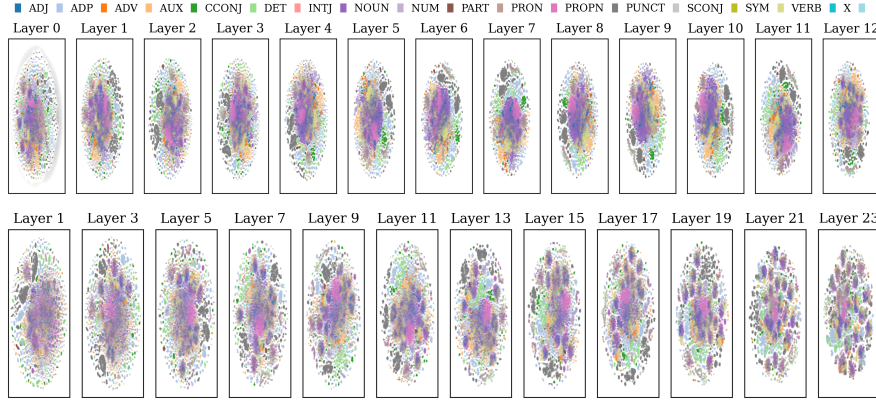


Figure 7: tSNE visualization of activation vectors. Top: mBERT, bottom: BLOOM.

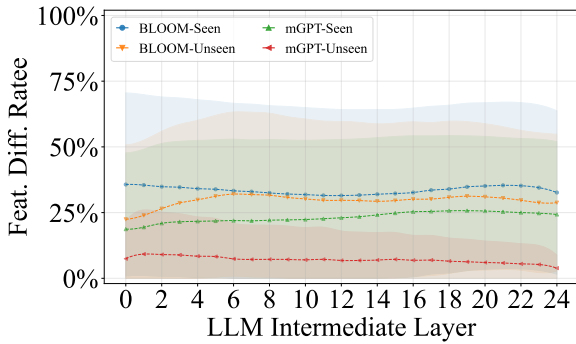


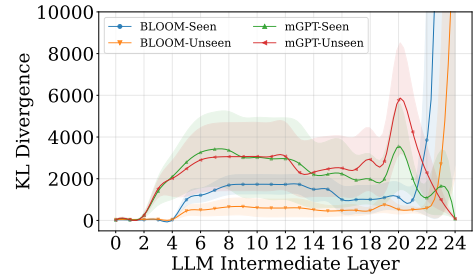
Figure 8: Joint Language-UPOS differentiation rates across layers. Shaded areas show variation across languages; solid lines show the mean.

9 Conclusion

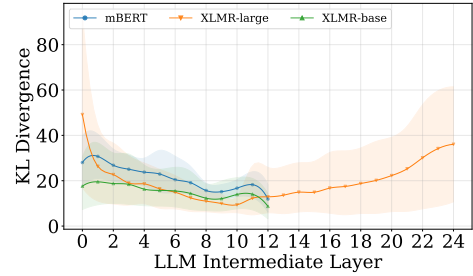
Our analysis of multilingual large language models reveals differences in how encoder-only and decoder-only architectures handle multilingual representation. We examined the intermediate representations of these models to determine whether they follow coordinate, sub-coordinate, or compound learning strategies.

We show that coordinate learning is the dominant mechanism, with decoder-only models developing strongly separated feature spaces for each language, while encoder-only models exhibit a more complex interplay of coordinate and compound learning in their middle layers. Sub-coordinate learning plays little to no role. Moreover, training data coverage substantially affects the strength of language separation, with Seen languages consistently exhibiting higher usable information and differentiation rates.

Our findings show that both architecture and pre-training data shape multilingual representations in LLMs. Decoder-only models appear better suited



(a) decoder-only



(b) encoder-only

Figure 9: KL Divergence between English and non-English activation vectors. Shaded areas show variation across languages; solid lines show the mean.

for tasks that require maintaining clear language-specific boundaries, while encoder-only models may be more advantageous for cross-lingual transfer, as their denser and partially shared representations facilitate knowledge sharing. More broadly, our results suggest that multilingual generalization in LLMs is not a single mechanism but a balance between language separation and cross-lingual sharing, which emerges differently across architectures and training regimes.

In future work, we will extend the analysis of compound learning to a broader set of cross-linguistic features, including semantic and pragmatic aspects. Additionally, we aim to explore the

impact of training data diversity from a linguistic typology perspective on the balance between coordinate and compound learning, as well as how language models generalize to unseen and low-resource languages. Expanding our study to a wider range of language models will help assess the influence of model scale on multilingual processing strategies.

Limitations

The limitations of this study are as follows: First, our analysis of compound learning primarily focuses on Universal POS (UPOS) tags, which restricts the exploration of higher-level linguistic properties such as syntax, semantics, and pragmatics. Second, we evaluate a limited set of language models, mBERT, XLMR, mGPT, and BLOOM, potentially constraining the generalizability of our findings to larger or differently trained models. Third, the influence of pre-training data availability may introduce biases in our cross-linguistic comparisons, as certain languages are underrepresented. Fourth, while we draw parallels between LLM multilingualism and human language acquisition, our study lacks direct psycholinguistic evaluations to substantiate these comparisons. Finally, our experiments focus on next-token prediction and language identification, leaving other multilingual tasks, such as cross-lingual transfer and code-switching, unexplored.

Acknowledgments

We thank the anonymous reviewers for their valuable feedback on this paper. We are also grateful to Bolette Sandford Pedersen, Costanza Navarretta, Joakim Nivre, and Patrizia Paggio for their insightful comments. Additionally, we acknowledge the Danish e-Infrastructure Consortium (DeiC) for providing computational resources through UCloud, supported under the Linguistic Universals in Language Models project.

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A The Implementation of Usable Information

To compute \mathcal{V} -usable information for a given function family \mathcal{V} , we estimate the conditional entropy terms $H(Y|\Phi)$ and $H(Y|X)$ using a simple classifier to prevent overfitting, following Xu et al. (2020). The classifier is a two-layer perceptron with Layer Normalization applied after each linear layer, a ReLU activation between layers, and a softmax activation at the output. For a given task $X \rightarrow Y$, we compute $H(Y|X)$ as the cross-entropy loss of a classifier trained on real samples X and Y , and $H(Y|\Phi)$ is estimated using a separate classifier that predicts Y based only on a zero vector Φ .

In our experiments, Y corresponds to one of the following: UPOS tags, language IDs, or a combination of UPOS tags and language IDs, and X represents a set of hidden activations. Accordingly, for each task and a language model with l layers, we train l classifiers to estimate $H(Y|X)$, along with an additional classifier to compute $H(Y|\Phi)$. The classifiers are trained on the PCA-reduced representations in \tilde{H} for one epoch, using an 80/20% split for training and testing. We employ the Adam optimizer with a learning rate of 0.01 to minimize the cross-entropy loss. The reported \mathcal{V} -usable information values in this paper are based on the test split.

B Layer Differentiation Rates for Languages

For language differentiation, we extract the hidden activations and logit gradients for predicting the next token while processing sentences from a target language through a language model. Feature contributions are then estimated by computing the element-wise product of the activation and gradient tensors, followed by a ReLU activation. This results in a contribution tensor of size $l \times n \times d$ for a target language, where l and d are the number of layers and features of the language model, and n is the number of tokens in the language.

To assess differentiation, we repeat this process for all other languages present in the pre-training data of the language model (Seen languages), resulting in a set of contribution tensors. A two-tailed statistical test is applied to compare corresponding elements in the contribution tensors of the target language and each of the other languages. Specifically, we perform the test on the arrays $[i, :, j]$ extracted from each tensor to measure the differentiating rate of feature j at the layer i . This results in a binary tensor of size $l \times d$ for each language pair (i.e., a target language paired by each of the Seen languages), where each element indicates whether the corresponding feature in each layer contributes differently across the two languages.

To identify differentiating features for the target language, we apply a logical AND operation across all binary tensors, producing a final tensor of size $l \times d$. The mean value of this tensor along the second dimension (d) represents the language differentiation rate of each layer.

This procedure is applied to all languages, treating each as the target language in each of the Seen and Unseen settings in turn. By doing so, we obtain a comprehensive measure of how distinctively the model processes each language relative to the others.

C Layer Differentiation Rate for Joint Language and UPOS Tags

For joint language–UPOS differentiation, we extend the procedure described in Appendix B to account for universal syntactic categories within languages. For a given language and UPOS tag, we compile contribution tensors for all tokens assigned to the tag. Each tensor, of size $l \times n \times d$, encodes the contribution of each feature to next-token prediction for words in that language–UPOS category, where l is the number of layers, n the number of tokens, and d the number of features.

We then assess feature-wise differences across languages for each UPOS tag. Specifically, for a feature j in layer i , we perform a two-tailed t-test comparing the contribution arrays $[i, :, j]$ from the target language–UPOS pair with the corresponding arrays from the same UPOS tag in other languages. The target language may be any language under the Seen or Unseen setting, while the comparison is always made against Seen languages.

The resulting binary decisions are aggregated to estimate the proportion of differentiating features

at each layer, yielding the *layer differentiation rate* for the joint language–UPOS category. A high differentiation rate indicates that the model processes tokens of a given UPOS tag in distinct, language-specific feature spaces, rather than in a universal syntactic space.

Sub-1B Language Models for Low-Resource Languages: Training Strategies and Insights for Basque

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Abstract

This work investigates the effectiveness of small autoregressive language models (SLMs) with up to one billion parameters (sub-1B) for natural language processing (NLP) tasks in low-resource languages, focusing on Basque. We analyze optimal training strategies by comparing training from scratch and continual pre-training using state-of-the-art SLM architectures. Our analysis considers factors such as model size and the extent of Basque presence in the pre-training corpus. To assess linguistic capabilities, models are evaluated on 12 NLP tasks using the Harness framework. We also conduct a manual evaluation of fine-tuned models on three downstream natural language generation (NLG) tasks: question answering (QA), summarization, and machine translation (MT). Our findings indicate that continual pre-training on a multilingual SLM substantially enhances linguistic performance compared to training from scratch, particularly in low-resource language settings where available corpora typically contain fewer than one billion words. Additionally, the presence of Basque during the pre-training and larger model sizes contribute positively to performance in NLG tasks.

1 Introduction

In recent years, we have witnessed a growing interest in small language models (SLMs) that can run efficiently on-device with low energy and memory consumption, as well as fast response times, such as MobiLlama (Thawakar et al., 2024), OpenELM (Mehta et al., 2024) or SmolLM2 (Allal et al., 2025). Leading research labs are also releasing smaller versions of their flagship models, namely Llama3.2 1B (Dubey et al., 2024), DeepSeek-R1 1.5B (DeepSeek-AI et al., 2025) and Qwen3-5 0.6B (Qwen-Team, 2025), to reach users and use cases with computational constraints.

This work focuses on SLMs with up to one billion parameters (sub-1B), specifically exploring

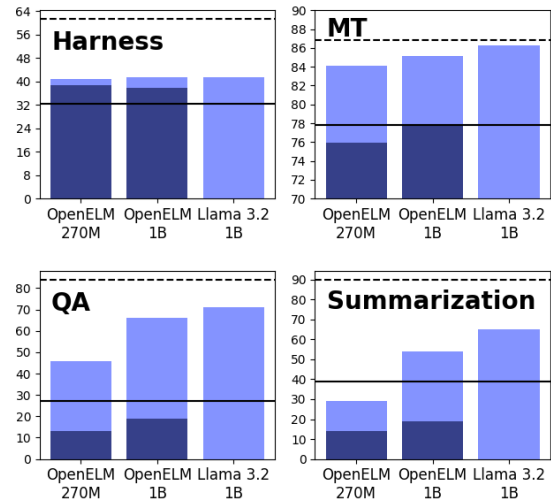


Figure 1: Comparison of from-scratch (dark blue) and continual-trained (light blue) models across 12 tasks in the Harness framework and NLG downstream tasks (QA, MT and summarization). Upperlines (dashed black) show Llama-eus-8B scores, and baselines (solid black) include random guessing for Harness, BART for QA and summarization, and a Transformer-based model for MT. Metrics: accuracy for Harness, correct answers for QA, correct/partially correct for summarisation, and COMET22 for MT.

their effectiveness for performing NLP tasks in low-resource languages, which struggle to collect over 1B word datasets¹, with Basque (see Appendix A for details about the language) as a primary case study. We aim to identify the most effective training strategy for these models. To address this, we investigate several key aspects of the training process using state-of-the-art SLM architectures (Mehta et al., 2024; Dubey et al., 2024): Is it more efficient to train models from scratch, or should we start with pre-trained models from other languages? Does prior exposure to the target language during

¹FineWeb 2 (Penedo et al., 2024b) covers over 1,000 languages, though only 57 exceed one billion words.

pre-training provide any advantages? And how does model size influence performance?

The results of our experiments show the following (see summary in Figure 1):

- When working with limited corpora ($\sim 500\text{M}$ words), continuing training an SLM pre-trained in other languages allows for models with much better linguistic capabilities than those trained from scratch.
- When fine-tuned for Question & Answering (QA), summarization, and machine translation (MT) tasks, continual pre-trained sub-1B models perform notably better than robust baselines based on BART (Lewis, 2019) and Transformer-based sequence-to-sequence models. This advantage is even more remarked if the pre-trained base model has been exposed, even minimally, to Basque.
- The performance gap in NLG tasks between sub-1B continual pre-trained models and the state-of-the-art Llama-eus-8B (Corral et al., 2025) is smallest in MT, followed by QA, and is most pronounced in summarization—reflecting the increasing linguistic complexity required by each task.

As part of the experimentation, the first sub-1B models² for Basque have been created, along with fine-tuned versions for QA, summarization, and MT tasks. Furthermore, two new Basque datasets have been developed for QA and summarization tasks, namely CloseBookQA-eu³ and SAMSUM-eu⁴.

2 Model Training

We selected two competitive English-centric models: OpenELM (Mehta et al., 2024) and Llama3.2 (Dubey et al., 2024). Specifically, we included OpenELM-270M, OpenELM-1B, and Llama3.2-1B. This selection enables comparisons between two model sizes (270M vs 1B) and across models with varying levels of exposure to Basque during the pre-training phase (see Table 1).

To determine the most effective training strategy for sub-1B SLMs, we explored two approaches: training models from scratch (Liu et al., 2023; Tonja et al., 2024) and continual pre-training of

multilingual models (Cui et al., 2023; Fujii et al., 2024; Kuulmets et al., 2024; Etxaniz et al., 2024; Corral et al., 2025).

From-scratch models—applied exclusively to the OpenELM architecture—were pre-trained on ZelaiHandi (San Vicente et al., 2024), the largest freely available Basque text corpus, comprising 521 million words. Continual models were trained using an 80-20 mix of ZelaiHandi and a FineWeb (Penedo et al., 2024a) subset, following prior works (Fujii et al., 2024; Kuulmets et al., 2024; Corral et al., 2025) to avoid catastrophic forgetting, as English results reported in Appendix F indicate. For full pre-training detail see Appendix C.

Continual pre-trained models retained their base model’s tokenizer, while from-scratch models used a native 32K Llama3 tokenizer trained on ZelaiHandi, resulting in a 50% reduction in the tokens-per-word ratio and a tokenization scheme more closely aligned with the morphological structure of Basque (for a more in-depth analysis of the tokenizers see Section 4.3).

3 Analysis of Language Priors in SLMs

In this section, we examine the extent to which the models described in Section 2 were exposed to Basque during pre-training. To this end, we compare the base and continual 1B versions of Llama-3.2-1B and OpenELM-1B.

Following previous work (Wang et al., 2024), we sampled 512 generations per model using only the beginning-of-sequence token as input. To examine how language priors shift with stronger language cues, we also assessed model generations when provided with partial prompts of varying lengths in Basque⁵. Each generation had a maximum length of 300 tokens and was produced with a temperature of 1.0. The primary language of each generated sequence was determined automatically using FastText (Joulin et al., 2016).

Table 1 presents the results of our analysis of language priors in SLMs. Our findings show that both of the base versions of Llama-3.2-1B and OpenELM-1B exhibit a strong bias toward English in their zero-word cue generations, with English accounting for over 90% of outputs. When given a Basque word as a cue, these models still generate predominantly English text, with only a slight increase in Basque output in the

²[hf.co/collections/orai-nlp/slm-for-basque](https://huggingface.co/collections/orai-nlp/slm-for-basque)

³[hf.co/datasets/orai-nlp/ClosedBookQA-eu](https://huggingface.co/datasets/orai-nlp/ClosedBookQA-eu)

⁴[hf.co/datasets/orai-nlp/SAMSUM-eu](https://huggingface.co/datasets/orai-nlp/SAMSUM-eu)

⁵Document beginnings from the ZelaiHandi validation set up to 2 words.

Model	EU Cue	EN	EU	Oth
Llama 1B base	0-words	94.1	0.0	5.9
	1-words	87.3	4.7	8.0
	2-words	62.9	21.7	15.4
OpenELM 1B base	0-words	90.2	0.0	9.8
	1-words	94.9	0.0	5.1
	2-words	79.1	1.4	19.5
Llama 1B cont.	0-words	13.5	85.5	1.0
	1-words	7.7	89.6	2.7
	2-words	5.5	91.4	3.1
OpenELM 1B cont.	0-words	8.6	91.0	0.4
	1-words	2.9	96.3	0.8
	2-words	2.9	94.9	2.1

Table 1: Analysis of language priors in SLMs (base and continual), showing the percentage of generations classified as English (EN), Basque (EU), or others.

case of Llama-3.2-1B. As more words are added to the prompt, Basque output increases, though OpenELM-1B remains notably less responsive to Basque cues than Llama-3.2-1B. These results highlight that OpenELM-1B has been exposed to less Basque data during pre-training, which likely contributes to its lower responsiveness to Basque cues. This suggests that, in theory, Llama-3.2-1B is a more suitable candidate for continual pre-training, as its initial exposure to Basque provides a stronger foundation for further adaptation.

In contrast, the continually pre-trained models exhibit a strong bias (over 85%) toward Basque in the zero-word cue generations, which further increases when Basque cue words are provided.

4 Evaluation

We conducted an intrinsic evaluation of the linguistic competences of both from-scratch and continual pre-trained models and compared them to the original model using the Harness evaluation framework. While Harness offers an automatic and cost-effective method for assessing the potential linguistic performance of SLMs, it does not fully reflect real-world performance, as the scores are based on the system selecting the most appropriate answers from multiple-choice questions. To better evaluate the models in realistic settings, we also fine-tuned and manually evaluated them on downstream NLG tasks. In addition, we explore how native tokenizers contribute to more efficient and linguistically aligned from-scratch models.

4.1 Intrinsic Evaluation of Linguistic Abilities

To evaluate models’ linguistic competences in Basque, we employed a variety of existing benchmarks including language proficiency, reading comprehension, general knowledge and commonsense reasoning tasks: ARC_eu, Winogrande_eu, MMLU_eu and HellaSwag_eu (Corral et al., 2025); BL2MP (Urbizu et al., 2024); BasqueGLUE (Urbizu et al., 2022); Belebele (Bandarkar et al., 2024); X-StoryCloze (Lin et al., 2021a); EusProficiency, EusReading, EusExams, and EusTrivia (Etxaniz et al., 2024). Evaluations were carried out with the LM Evaluation Harness framework (Gao et al., 2024), following an in-context few-shot setup as in previous work (Etxaniz et al., 2024; Corral et al., 2025). Results are shown in Table 2.

The OpenELM base models perform below random chance, likely due to limited exposure to Basque data during pretraining. The Llama-3.2-1B base model performs slightly better than random, indicating that its exposure to Basque data, though minimal, offers some advantage (see Section 3).

When trained from scratch, all OpenELM models outperform their base counterparts. However, these from-scratch models often perform at random levels across many tasks. Notably, the OpenELM-270M from-scratch model achieves the highest overall performance, which might indicate that a 1B model could struggle to generalize effectively with a modest 521M-word Basque training dataset due to its larger parameter size.

Substantial improvements are observed with continual pre-training across all models, with the 1B-parameter models performing comparably, while the 270M model lags behind. Continual pre-training consistently outperforms from-scratch pre-training, especially in the 1B model, suggesting that the available Basque training data—similar to other low-resource languages—is insufficient for from-scratch pre-training and leveraging multilingual pre-training through continual training proves to be more effective.

While there remains a performance gap of approximately 20 points between the continual pre-trained variants and Llama-eus-8B, the results are consistent with expectations from scaling laws (Hoffmann et al., 2022), highlighting the strong capabilities of smaller models given their size.

Model		BL2mp	Arc	WnGr.	Mmlu	HSwg	Beleb.	XStrC.	Exams	Prof.	Read.	Trivia	BGlue	Avg.
<i>Random</i>		50.0	25.0	50.0	25.0	25.0	25.0	50.0	25.0	25.0	25.8	26.6	37.5	32.5
OpenELM 270M	base	44.7†	26.0	47.6†	25.6	28.0	26.0	50.1	25.3	25.0	22.4†	26.2†	36.2†	31.9†
	scratch	88.1	32.0	47.2†	27.8	40.0	27.9	55.7	24.9†	24.0†	25.3†	27.4	38.6	38.2
	continual	89.9	33.6	53.2	23.3†	45.2	27.9	55.3	25.0	24.7†	30.4	27.1	41.0	39.7
OpenELM 1B	base	46.2†	24.4†	41.2†	25.2	27.6	28.1	49.8†	25.7	24.8†	23.3†	26.4†	37.8	31.7†
	scratch	87.2	28.8	47.6†	25.2	40.4	25.4	54.1	24.5†	24.1†	24.2†	26.2†	37.9	37.1
	continual	90.4	42.0	55.6	25.9	48.0	26.3	60.4	26.2†	24.4†	28.7	26.2	42.7	41.4
Llama 1B	base	49.1†	29.6	52.0	26.7	24.4†	27.9	50.0	26.5	23.8†	25.3†	28.6	38.4	33.5
	continual	88.9	42.0	56.8	28.5	46.4	27.9	60.2	27.1	25.5	23.3†	28.2	41.4	41.4
<i>Llama-eus 8B</i>		89.2	55.2	67.2	53.3	63.6	73.4	65.7	52.5	48.4	54.6	56.2	55.3	61.2

Table 2: Results from the intrinsic evaluation of linguistic abilities, conducted using 5 in-context examples for most tasks, except for HellaSwag (10-shot), ARC (25-shot), BL2MP (0-shot), X-StoryCloze (0-shot), and EusReading (1-shot). The best-performing model is highlighted in bold, and † denotes models performing below random guess.

4.2 Downstream NLG Tasks Evaluation

We further assessed our models by fine-tuning them on three downstream NLG tasks of varying difficulty—ordered from most to least challenging: summarization, QA (including both hard and factoid questions), and English-to-Basque MT. Fine-tuning details are provided in Appendix D.

To address the lack of task-specific Basque datasets, we constructed training data for the QA and summarization tasks. For QA, we constructed CloseBookQA-eu based on the Belebele-eus MCQA dataset (Bandarkar et al., 2024), and enriched it with translated examples from the MCTest MCQA dataset (Richardson et al., 2013) as well as semi-automatically generated factoid questions derived from news articles. For summarization, we automatically translated the SAMSUM dataset (Gliwa et al., 2019). In the case of the MT task, we compiled a 2M-sentence English-Basque parallel dataset from OPUS (Tiedemann, 2009). Appendix D.1 offers further details on dataset creation.

Evaluation methodologies varied by task. For QA-easy (factoid questions), QA-hard and summarization, a native Basque speaker from our team manually evaluated a random test set of 100 examples per task. QA responses were deemed correct or incorrect, while summarization outputs were rated correct, partially correct, or incorrect. For MT, evaluation was performed by computing the COMET22 (Rei et al., 2022) metric on the Flores-200 benchmark (Team et al., 2024).

Regarding baselines, we fine-tuned a monolingual BART for the QA and summarization tasks, and trained a Transformer-based model for MT (see Appendix B for further details). Additionally, we fine-tuned Llama-eus-8B (Corral

et al., 2025) on downstream tasks to establish the upper bound performance for each task.

Model		QA	Sum	MT
Baseline		42 12	19 (39)	77.8
OpenELM 270M	scratch	17 09	06 (14)	75.9
	continual	64 28	14 (29)	84.1
OpenELM 1B	scratch	31 07	06 (19)	77.8
	continual	84 48	37 (54)	85.1
Llama 1B	continual	88 54	39 (65)	86.3
<i>Llama-eus 8B</i>		95 73	60 (90)	86.8

Table 3: Results on the downstream NLG tasks of QA, Summarization and MT). The QA task is formed by two datasets of different difficulty (QA-easy|QA-hard). Scores in parentheses for the summarization task indicate the sum of correct and partially correct outputs.

Table 3 presents the results of the fine-tuned models on downstream tasks. For the continual pre-trained models, performance differences across architectures and sizes align with the level of language understanding required by each task, with larger gaps observed in more complex tasks—ordered from most to least complex: QA-hard, summarization, QA-easy, and machine translation. Notably, Llama 1B consistently outperforms OpenELM 1B, highlighting the benefits of Basque-specific priors discussed in Section 3. In line with scaling laws (Hoffmann et al., 2022), performance improves with model size, with 1B models outperforming their 270M counterparts and the 8B model achieving the highest overall gains.

Following the trend in Section 4.1, from-scratch models fail to surpass continual pre-trained ones, reinforcing the importance of leveraging prior linguistic knowledge through continual pre-training. Despite the potential benefits of a

Tokenizer	Vocab.	TPW	Morph.
OpenELM	32K	3.23	0.12
Llama3	128K	2.95	0.20
Native	32K	1.60	0.41

Table 4: Vocabulary size, tokens-per-word (TPW) ratio and morphological alignment score of different tokenizers used by our models.

native Basque tokenizer, the results indicate it does not offer a significant advantage in making from-scratch models competitive. Section 4.3 analyzes the impact of native tokenizers and shows that, although they improve the tokens-per-word ratio and better align with Basque morphology, they do not lead to a significant improvement in linguistic performance.

4.3 Impact of Native Tokenizers

One potential advantage of training a model from scratch is the ability to use a native tokenizer fully adapted to the target language. This results in a lower tokens-per-word ratio, which implies shorter sequence lengths to process the same word sequence, leading to faster and more memory-efficient models.

As stated in Section 2, continually pre-trained models retain their base’s tokenizer. In contrast, our from-scratch models use a new native 32K Llama3 tokenizer trained on ZelaiHandi (San Vicente et al., 2024), resulting in a 50% reduction in the tokens-per-word ratio⁶, as shown in Table 4.

Furthermore, a native tokenizer is expected to align more closely with morpheme boundaries, which might be beneficial for morphologically rich languages like Basque. To evaluate this morphological alignment, we compare the tokenized subwords with the expected lemma-morpheme boundaries. A score of 1 is assigned if the first subword matches the lemma.

We conduct this evaluation using a dataset of 100K sentences (over 1M words), which have been automatically annotated⁷ with lemma and morpheme boundaries—e.g., *Brasil da aurtēn|go herrialde gonbidatu|a*—extracted from the 5M-word Basque corpus defined by Urbizu et al. (2024). This corpus comprises news articles and Wikipedia articles, offering a representative sample of real-world Basque usage.

⁶Calculated on the ZelaiHandi validation set.

⁷Using an Apertium-based custom implementation.

Tokenizer	Vocab.	TPW	Morph.	Harness Avg.
Original	128K	2.90	0.20	35.49
Native	128K	1.43	0.56	35.04

Table 5: Vocabulary size, tokens-per-word (TPW) ratio and morphological alignment score for each tokenizer of equal size, with average results for from-scratch llama3.2 1B models on the Harness evaluation.

As shown in Table 4, native tokenizers achieve higher morphological alignment scores. However, results from Sections 4.1 and 4.2 indicate that this alignment advantage does not yield sufficient performance gains for scratch-trained models to match those continually pre-trained with suboptimal multilingual tokenizers. The performance gap is especially pronounced in downstream NLG tasks.

To more precisely assess the impact of using a native tokenizer versus the English-centric tokenizer, we trained two additional Llama 3.2-1B models from scratch: one using the original 128k-token vocabulary and the other using a native tokenizer of equivalent size⁸.

Table 5 shows the Harness evaluation results for models trained from scratch. Although the native tokenizer provides better morphological alignment and achieves greater compression—as evidenced by a lower tokens-per-word ratio—it does not lead to improved linguistic performance compared to the original tokenizer. This suggests that, for Basque and with a training corpus of around 500 million words, a native tokenizer does not necessarily enhance the model’s linguistic competence. This finding holds despite Basque’s morphological complexity, particularly its rich system of case endings, and is consistent with the results reported by Urbizu et al. (2024).

5 Conclusions

This work examines the effectiveness of SLMs with up to 1B parameters for NLP tasks in low-resource languages, focusing on Basque. Our findings show that continual pre-training of a multilingual SLM notably improves performance compared to training from scratch, with larger model sizes and the presence of Basque during pre-training further enhancing the performance on NLG tasks.

⁸With same training procedure of the native 32K tokenizer.

Limitations

Basque has been chosen as a case study, as it is an isolated language with complex morphology, and a corpus of 521 million words has been used for training. We consider this scenario to be representative of a significant number of low-resource languages. However, extending these conclusions to other languages may require additional experiments that account for their specific linguistic characteristics and level of digital development.

For the construction of the SLMs, we explored training strategies both from scratch and based on continual pre-training. In some languages, developing SLMs using knowledge distillation strategies could be of interest, and we leave this analysis for future work.

The evaluation of SLMs on downstream tasks has been limited to three representative tasks: QA, summarization, and MT. Training for these tasks was conducted using datasets of a fixed size. In future work, we aim to extend this study to additional downstream tasks and analyze the impact of dataset size on the fine-tuning process for each task.

Ethical Concerns

The outputs of the SLMs trained for this work may show undesired biases and produce offensive language. Although the Basque text sources gathered to pre-train the SLMs were selected by hand, they contain bad words from fictional sources and social biases that were not handled here. These aspects must be analyzed and treated before building applications that interact with final users.

Acknowledgments

This work has been partially funded by the Basque Government (ICL4LANG project, grant no. KK-2023/00094) and the European Union (EFA 104/01-LINGUATEC IA project, INTERREG POCTEFA 2021-2027 program). Pre-training and fine-tuning of SLMs were conducted using the Hyperion system at the Donostia International Physics Center (DIPC). We also acknowledge the support of Google’s TFRC program for pre-training the BART baseline on TPUs. Finally, we thank Idoia Davila Uzkudun for her contributions to manual data curation and evaluation.

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A Basque Language

Basque is a language with roughly 810K fluent speakers in the region of the Basque Country, spanning northern Spain and southwestern France. It is currently classified as vulnerable according to The UNESCO Atlas of the World’s Languages in Danger (Moseley, 2010). Basque is a language isolate (unrelated to any other known languages) and uses the Latin script. It is a morphologically rich language, with a flexible word order and follows an ergative–absolutive syntactic alignment. Despite being low-resource in terms of corpora (< 1B words), Basque does have annotated datasets for a number of NLU and NLG tasks, thanks to the effort of a strong local NLP community.

B Baselines

B.1 BART

The monolingual BART base model (139M parameters), used as a baseline for question

answering (QA) and summarization tasks, was pre-trained on the ZelaiHandi corpus (San Vicente et al., 2024). It employs a Byte-Pair Encoding (BPE) tokenizer with a 50K token vocabulary, which was also trained on ZelaiHandi.

The model was trained for 154 epochs (equivalent to 1,460K steps) with a batch size of 32, a learning rate of 1e-4, and a sequence length of 512 tokens. The final checkpoint was retained as it achieved the best performance based on validation loss. We used the Flax implementation of BART from the Hugging Face Transformers library (Wolf et al., 2020) and pre-trained the model on a single TPUv3-8 node for one week.

B.2 MT Baseline

The Baseline MT system was trained using the sequence-to-sequence Transformer architecture (Vaswani et al., 2017) as implemented in the Eole Toolkit⁹ with the default configuration (6 layers, 1024 size vectors). We apply BPE tokenization (Sennrich et al., 2016) learned on 32,000 merge operations on the joint training parallel data. The training corpus comprises of 2.2M parallel sentences gathered from various sources from the Opus collection (Tiedemann, 2009). The model was trained for 230K steps (early stopping after 10 validation steps, validating each 10K steps). Validation is done over 8K parallel sentences composed of the Flores benchmark validation dataset and 5K sentences excluded from the training data. Training was carried out on a single Nvidia RTX A5000 GPU.

C Pre-Training Details

From-scratch models were pre-trained for up to 25 epochs, while continual models were further pre-trained for up to 5 epochs. In both cases, we selected the best-performing checkpoint according to validation loss for the final model. Our OpenELM and Llama models, based on the architectures of OpenELM¹⁰ (Mehta et al., 2024) and Llama3.2¹¹ (Dubey et al., 2024), have a maximum sequence length of 2048 and 4096, respectively. OpenELM models were pre-trained with a cosine learning rate of 3e-5 and an effective batch size of around 4M following the configuration of OpenELM-270M (Mehta et al.,

⁹<https://eole-nlp.github.io/eole/>

¹⁰Licensed under Apple Sample Code License

¹¹Licensed under Llama3.2 Community License Agreement

Model	Size	GPU time	kgCO ₂ eq
OE270M-s	270M	282h	30.46
OE270M-c	270M	138h	14.90
OE1B-s	1.1B	571h	61.67
OE1B-c	1.1B	290h	31.32
LL1B-c	1B	122h	13.18

Table 6: Carbon footprint of pre-training our models. Llama3-1B is more efficient and emitted less CO₂ due to the available flash attention implementation. OE = OpenELM, LL = LLama3. s = scratch. c = continual.

2024). Llama3-1B was further trained with a cosine learning rate of 1e-4 and an effective batch size of around 2M following the configuration of LLama-eus-8B (Corral et al., 2025).

Pre-training LMs involves computationally intensive experiments that contribute significantly to carbon emissions. For efficient large-scale pre-training, we opted for the Hugging Face Transformers (Wolf et al., 2020) library, alongside DeepSpeed ZeRO (Rajbhandari et al., 2020) and Accelerate (Gugger et al., 2022). Flash Attention (Dao et al., 2022) was only available for Llama3 models since OpenELM does not have it implemented on Transformers.

The training was conducted on NVIDIA A100 80GB GPUs (1-8). We provide details on model size, compute hours, and carbon emissions for our experiments in Table 6. Carbon emissions were estimated using the Machine Learning Impact calculator¹² (Lacoste et al., 2019).

D Fine-Tuning Details

Each foundational model was fine-tuned for up to five epochs, independently on each task (QA, summarization, and MT). To ensure optimal performance, we selected the checkpoint with the lowest validation loss.

We used a batch size of 32 and a learning rate of 3e-5. However, for certain models where the validation loss curve showed instability—collapsing before completing the first epoch—we reran fine-tunings, reducing the learning rate until achieving a run with a stable validation loss trajectory.

We fine-tuned the BART model on QA and summarization with the same batch size, learning rate and epochs as the rest of the models, selecting the best-performing checkpoint on validation loss.

¹²<https://mlco2.github.io/impact#compute>

The transformer baseline on MT was trained from scratch (see Appendix B.2).

D.1 Downstream Datasets

ClosedBookQA. For question answering (QA), we constructed ClosedBookQA-eu, a closed-book QA dataset derived from three sources: the MCQA Belebele-eus dataset¹³ (Bandarkar et al., 2024), the MCTest dataset¹⁴ (Richardson et al., 2013), and semi-automatically generated examples based on news content.

Belebele is a multiple-choice QA (MCQA) dataset that includes a passage (context), a question, and four possible answers. Although a Basque version of Belebele is available, it only provides a test set of 900 examples. To adapt it for a generative QA setting, we extracted passage-question-answer triplets and discarded examples that were unanswerable¹⁵ without the full set of answer choices. After filtering, we retained 573 usable examples, which we split into 423 for training, 50 for validation, and 100 for the QA-hard test set.

To further expand the training data, we incorporated MCTest, which contains 2,000 MCQA examples. These were translated into Basque using a proprietary document-level machine translation system based on Llama-eus-8B (Corral et al., 2025). After manually filtering out translation errors, 1,962 examples were retained. The final training set thus comprised 2,385 examples.

In addition to the QA-hard test set derived from Belebele, we created a complementary QA-easy test set of 100 simpler factoid questions. This set was generated using GPT-4o (OpenAI, 2024) in a two-step process: first, selecting passages from 100 Basque news articles not included in ZelaiHandi, and second, generating corresponding questions and answers. All examples were manually reviewed, corrected, and refined by a native Basque speaker to ensure both linguistic quality and appropriate difficulty.

Summarization. For summarization, there is no publicly available summarization dataset in Basque. To address this, we automatically translated SAMSum¹⁶ (Gliwa et al., 2019), a

¹³Licensed under CC-BY-SA 4.0

¹⁴Licensed under Microsoft Research License

¹⁵E.g., “Which of these is true?” or “Which option is not mentioned?”

¹⁶Licensed under CC-BY-NC-ND 4.0

human-annotated dialogue dataset for abstractive summarization, using a proprietary document-level MT system based on Llama-eus-8B. We then filtered out examples with incomplete translations or non-Basque outputs.

The translated test set was further refined by a native speaker to obtain 100 high-quality, manually curated test examples. In total, we obtained 11,313 training examples, 636 validation examples, and 100 manually curated test examples for evaluation.

Machine translation. In the case of the MT task, we compiled an English-Basque dataset gathered from various sources in OPUS¹⁷ (Tiedemann, 2009). The final corpus contains a 2.2M parallel sentences, obtained after applying rule-based cleaning, and used BiCleaner (Ramírez-Sánchez et al., 2020) with a threshold of 0.9.

E Harness Benchmarks for Basque

To assess our model’s performance in Basque, we utilized a range of existing benchmarks:

- **ARC_HT_eu_sample** (Corral et al., 2025): A subset of 250 samples manually translated to Basque from the ARC dataset (Clark et al., 2018). The ARC dataset consists of genuine grade-school level, multiple-choice science questions.
- **Winogrande_HT_eu_sample** (Corral et al., 2025): A subset of 250 samples manually translated to Basque from the WinoGrande dataset (Sakaguchi et al., 2020). WinoGrande is a dataset of 44k problems specifically designed to test commonsense reasoning.
- **MMLU_HT_eu_sample** (Corral et al., 2025): A subset of 270 samples manually translated to Basque from the MMLU dataset (Hendrycks et al., 2021). The MMLU dataset is a massive multitask test consisting of multiple-choice questions from various branches of knowledge. The test spans subjects in the humanities, social sciences, hard sciences, and other areas that are important for some people to learn.
- **HellaSwag_HT_eu_sample** (Corral et al., 2025): A subset of 250 samples manually translated to Basque from the HellaSwag dataset (Zellers et al., 2019). The HellaSwag

dataset commonsense NLI evaluation benchmark.

- **BL2MP** (Urbizu et al., 2024): The BL2MP test set is designed to assess the grammatical knowledge of language models in the Basque language, inspired by the BLiMP (Warstadt et al., 2020) benchmark.
- **BasqueGLUE** (Urbizu et al., 2022): BasqueGLUE is an NLU benchmark for Basque, which has been elaborated from previously existing datasets and following similar criteria to those used for the construction of GLUE and SuperGLUE.
- **Belebele** (Bandarkar et al., 2024): Belebele is a multiple-choice machine reading comprehension dataset spanning 122 language variants.
- **X-StoryCloze** (Lin et al., 2021b): XStoryCloze consists of the professionally translated version of the English StoryCloze dataset to 10 non-English languages. It is a commonsense reasoning framework for evaluating story understanding, story generation, and script learning.
- **EusProficiency, EusReading, EusExams, and EusTrivia** (Etxaniz et al., 2024): Basque-specific benchmarks covering proficiency tests based on past EGA exams (C1 level Basque), reading comprehension, public service exam preparation, and trivia questions, respectively.

This comprehensive evaluation approach enables us to measure the model’s capabilities across various tasks, providing a thorough understanding of its formal and functional competencies in Basque.

F English Results on Harness

The continual models were trained using an 80-20 mix of ZelaiHandi and a FineWeb (Penedo et al., 2024a) subset, following prior works (Fujii et al., 2024; Kuulmets et al., 2024; Corral et al., 2025) to avoid catastrophic forgetting. Thus, they are expected to retain some English knowledge from the pretraining. To measure English linguistic abilities of the continual models and see if they are kept from the base model, we evaluated base and continual versions of OpenELM-1B and Llama-1B

¹⁷Includes data licensed under various open licenses.

Model		Arc	WnGr.	Mmlu	HSwg	Beleb.	XStrC.	Avg.
<i>Random</i>		25.0	50.0	25.0	25.0	25.0	50.0	32.5
OpenELM-1B	base	53.2	70.8	30.7	67.6	27.7	72.1	53.2
	continual	45.6	58.0	24.4	56.8	27.2	68.6	46.8
Llama 1B	base	52.8	68.4	28.1	45.2	34.7	71.3	50.5
	continual	53.6	66.4	23.7	64.8	30.4	71.1	51.7

Table 7: Results from the intrinsic evaluation of linguistic abilities on the English counterparts of the datasets used for Basque, conducted using 5 in-context examples for most tasks, except for HellaSwag (10-shot), ARC (25-shot) and X-StoryCloze (0-shot). The best-performing model is highlighted in bold.

in the English versions of the subsets of several NLU tasks used to evaluate the models in Basque in Section 4.1, described in Appendix E.

The results for English are shown in Table 7. It shows that the results of the base models hold after continual training for Basque, with a few exceptions, proving that models kept most of their English linguistic abilities, and the 80-20 corpora approach is successful at avoiding catastrophic forgetting. When we compare both architectures, while Llama 1B holds its results in overall, there is a small drop in the case of OpenELM, which might be caused by the lack of prior exposure to Basque.

jina-embeddings-v4: Universal Embeddings for Multimodal Multilingual Retrieval

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Abstract

We introduce *jina-embeddings-v4*, a 3.8 billion parameter embedding model that unifies text and image representations, with a novel architecture supporting both single-vector and multi-vector embeddings. It achieves high performance on both single-modal and cross-modal retrieval tasks, and is particularly strong in processing visually rich content such as tables, charts, diagrams, and mixed-media formats that incorporate both image and textual information. We also introduce JVDR, a novel benchmark for visually rich document retrieval that includes more diverse materials and query types than previous efforts. We use JVDR to show that *jina-embeddings-v4* greatly improves on state-of-the-art performance for these kinds of tasks.

1 Introduction

We present *jina-embeddings-v4*, a multimodal embedding model capable of processing text and image data to produce single- and multi-vector embeddings, with modular LoRA adapters (Hu et al., 2022) for information retrieval and semantic text similarity. An adapter is also provided for programming language embeddings, technical question-answering, and natural language code retrieval.

This model supports dual-mode output, producing both single-vector outputs suitable for conventional embeddings-based applications and multi-vector embeddings for "late interaction" applications along the lines of ColBERT (Khattab and Zaharia, 2020) and ColPali (Faysse et al., 2025). This single-model approach entails significant savings in practical use cases when compared to deploying multiple AI models for different tasks and modalities.

A major contribution of this model is introducing new functionality for processing "visually rich" documents: mixed textual and visual media like

tables, charts, diagrams, screenshots, web page captures, and similar images. (Ding et al., 2024) We have devised a new diversified benchmark, JVDR, for measuring performance on visually rich materials and show that *jina-embeddings-v4* far outpaces comparable models on this type of media.

2 Related Work

Late interaction models generally have higher precision than traditional embedding models. (Khattab and Zaharia, 2020; Faysse et al., 2025) These models produce multi-vector outputs that consist of sequences of context-sensitive token embeddings. Similarity is calculated using a form of chamfer distance adapted to the task: Given two sequences of token embeddings, a query and a document, sum the maximum cosine similarity values of each query token embedding to any of the document token embeddings.

Faysse et al. (2025) train a late-interaction embedding model to search document screenshots using text queries, performing significantly better than traditional approaches involving OCR and CLIP-style models trained on image captions. To show this, they introduce the *ViDoRe* (Vision Document Retrieval) benchmark. However, this benchmark is limited to question-answering tasks in English and French involving only charts, tables, and pages from PDF documents. Xiao et al. (2025) extend this benchmark to create MIEB (Massive Image Embedding Benchmark) by rendering the texts from existing semantic textual similarity tasks as images.

The principal purpose of multimodal embedding models is to project objects from multiple modalities into the same semantic embedding space. Bimodal image-text models derived from OpenAI's CLIP architecture (Radford et al., 2021) consist of one model for each modality, typically trained with bimodal contrastive pairs to produce embeddings in a common semantic space. The *Vision-Language*

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Model (VLM) is an alternate architecture with a single processing path for both images and texts, significantly improving performance on bimodal text-image tasks. (Chen et al.; Bai et al., 2025)

Previous work has shed light on the so-called *modality gap* in this kind of model. (Liang et al., 2022; Schrodi et al., 2025; Eslami and de Melo, 2025) Good semantic matches across modalities tend to lie considerably further apart in the embedding space than comparable or even worse matches of the same modality, i.e., texts in CLIP-style models are more similar to semantically unrelated texts than to semantically similar images. Bai et al. (2025) demonstrate that VLMs have less of a modality gap than CLIP-style dual encoder architectures.

3 Model Architecture

The architecture of `jina-embeddings-v4`, schematized in Figure 1, is a VLM built on a Qwen2.5-VL-3B-Instruct¹ backbone. Text and image inputs are processed through a shared pathway: Images are first converted to token sequences via a vision encoder, then both modalities are jointly processed by the language model decoder with contextual attention layers.

As shown in Figure 1, this architecture supports single- and multi-vector output. Additionally, three task-specific LoRA adapters, each with 60M parameters, provide specialized task optimization without modifying the frozen backbone weights.

The core specifications of `jina-embeddings-v4` are summarized in Table 1.

`jina-embeddings-v4` differs from CLIP-style dual-encoder models in offering a single processing path for both text and image input. For text input, it behaves like other Transformer-based embedding models: The text is tokenized, each token is replaced with a vector representation from a lookup table, and then these vectors are stacked and become the input vector to a Transformer-based language model.

For images, a Transformer-based image model acts as a preprocessor to the language model: The image is divided into patches and the image model processes it as if each patch were a token given to a language model. The output is a multi-vector embedding which becomes the input to the language model, as if it were a stacked set of tokenized text vectors.

Users can choose between traditional single

Feature	Value
Parameters	3.8 billion (3.8×10^9) plus 60M per LoRA
Text input	Up to 32,768 tokens
Image input	All images resized to 20 megapixels
Single-vector embedding	2048 dimensions, truncatable down to 128
Multi-vector embedding	128 dimensions per token

Table 1: Basic specifications of `jina-embeddings-v4`

(dense) vector embeddings and ColBERT-style multi-vector embeddings. Single-vector embeddings are the result of mean-pooling the final layer of the base model to 2048 dimensions. `jina-embeddings-v4` has been trained with Matryoshka Representation Learning (Kusupati et al., 2022), so its single-vector embeddings can be truncated to as few as 128 dimensions with minimal loss of precision. An additional layer projects the output of the base model into multi-vector embeddings comparable to ColBERT (Khattab and Zaharia, 2020) and ColPali (Faysse et al., 2025) outputs. Single-vector embeddings offer fast, memory-efficient retrieval ideal for large-scale or first-stage search, while multi-vector late-interaction approaches are more costly but achieve higher accuracy by capturing fine-grained interactions, as shown in the evaluation results in Table 2. Multi-vector embeddings are best used to re-rank first-stage retrieval results on a smaller set of candidates or for technically challenging matching scenarios where single-vector approaches perform poorly, such as scanned technical documents.

We have implemented three task-specific LoRA adapters for different information retrieval use cases described in Section 4.2. Each LoRA adapter has only 60M parameters, so keeping all three in memory adds less than 2% to the memory footprint of `jina-embeddings-v4`. See Section 6 for performance information about these adapters. We employ PEFT (Mangrulkar et al., 2022) to support LoRA and dynamically switch between adapters based on the intended task for each batch, without significant runtime overhead. We used a standard LoRA configuration with rank 32 and a scaling factor of 1, parameterizing all linear layers in the backbone LLM.

¹<https://huggingface.co/Qwen/Qwen2.5-VL-3B-Instruct>

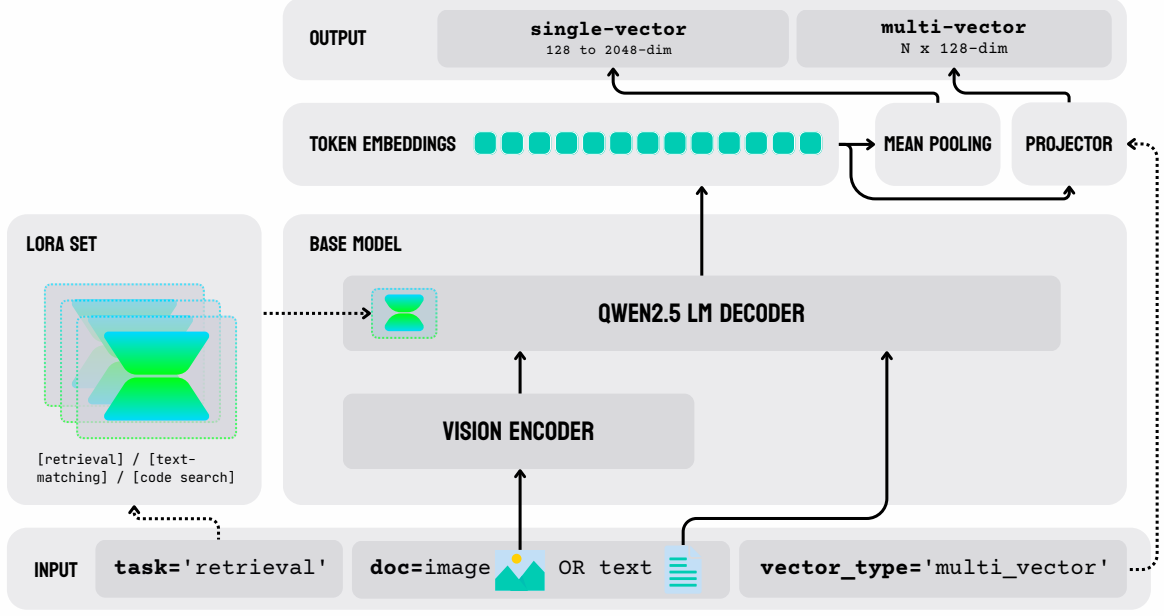


Figure 1: Architecture of `jina-embeddings-v4`.

4 Training Method

Before training, model weights are initialized to match Qwen/Qwen2.5-VL-3B-Instruct. The multi-vector projection layer and LoRA adapters are randomly initialized. Only the LoRA adapters are trained, the base model and projection layer remain as initialized.

In all phases of training, we apply Matryoshka loss (Kusupati et al., 2022) to our base loss function so that single-vector embeddings from `jina-embeddings-v4` are truncatable.

4.1 LoRA pre-training

We pre-train a single LoRA adapter using pair data and the contrastive InfoNCE (van den Oord et al., 2018) loss function. There is no task-specific training in the pre-training phase.

The training data consists of text-text and text-image pairs from more than 300 sources. Text-text pairs are selected and filtered as described in Sturua et al. (2024). Text-image pairs have been curated from a variety of sources following a more eclectic strategy than previous work on training text-image embedding models. We have also created images from website screenshots, rendered Markdown files, charts, tables, and other kinds of materials "found in the wild." Queries primarily consist of questions, keywords, key phrases, long descriptions, and statements of fact.

In each training step, we sample two different

batches of training data:

- A batch \mathcal{B}_{text} of text pairs.
- A batch \mathcal{B}_{multi} of multimodal pairs containing a text and a related image.

We generate normalized single-vector and multi-vector embeddings for all texts and images in the selected pairs. We then construct a matrix of similarity values $\mathbf{S}_{dense}(\mathcal{B})$ by calculating the cosine similarity of all combinations of single-vector embeddings \mathbf{q}_i and \mathbf{p}_j in \mathcal{B} . We construct an analogous matrix \mathbf{S}_{chamf} for each \mathcal{B} for the multi-vector embeddings using a normalized version of the chamfer distance metric described by Khattab and Zaharia (2020) for the ColBERT late interaction model. Our choice of loss function requires a normalized score, so we divide the chamfer distance by the number of tokens in the query.

The result is four matrices of normalized similarity scores for each batch:

- Cosine similarity of single-vector embeddings for text-text pairs.
- Chamfer similarity of multi-vector embeddings for text-text pairs.
- Cosine similarity of single-vector embeddings for text-image pairs.
- Chamfer similarity of multi-vector embeddings for text-image pairs.

Then, we apply the contrastive InfoNCE loss function \mathcal{L}_{NCE} (van den Oord et al., 2018) to each of the four matrices to calculate the training loss.

Following Hinton et al. (2014), we compensate for differences in error distributions between the single-vector and multi-vector similarity scores by adding the Kullback–Leibler divergence (D_{KL}) of the two sets of softmax-normalized similarity scores. This enables us to train for the single-vector and multi-vector outputs simultaneously, even though the multi-vector/late interaction scores have much less error.

Given $\mathbf{S}_{\text{dense}}(\mathcal{B})$ as the softmax of a matrix of single-vector cosine similarity scores for batch \mathcal{B} , and $\mathbf{S}_{\text{chamf}}(\mathcal{B})$ as the softmax of a matrix of multi-vector chamfer similarity scores for batch \mathcal{B} , define the added term $\mathcal{L}_D(\mathcal{B})$

$$\mathcal{L}_D(\mathcal{B}) := D_{KL}(\mathbf{S}_{\text{dense}}(\mathcal{B}) \parallel \mathbf{S}_{\text{chamf}}(\mathcal{B}))$$

The resulting joint loss function, which we use in training, is defined as:

$$\begin{aligned} \mathcal{L}_{\text{joint}}(\mathcal{B}_{\text{text}}, \mathcal{B}_{\text{multi}}) := & \\ & w_1 \mathcal{L}_{\text{NCE}}(\mathbf{S}_{\text{dense}}(\mathcal{B}_{\text{text}}),) \\ & + w_2 \mathcal{L}_{\text{NCE}}(\mathbf{S}_{\text{chamf}}(\mathcal{B}_{\text{text}})) + w_3 \mathcal{L}_D(\mathcal{B}_{\text{text}}) \\ & + w_4 \mathcal{L}_{\text{NCE}}(\mathbf{S}_{\text{dense}}(\mathcal{B}_{\text{multi}})) \\ & + w_5 \mathcal{L}_{\text{NCE}}(\mathbf{S}_{\text{chamf}}(\mathcal{B}_{\text{multi}})) + w_6 \mathcal{L}_D(\mathcal{B}_{\text{multi}}) \end{aligned}$$

The weights w_1, \dots, w_6 are training hyperparameters.

4.2 Task-Specific Training

We instantiate three copies of the pre-trained LoRA adapter and give each task-specific training.

4.2.1 Asymmetric Retrieval Adapter

We used the prefix method described by Wang et al. (2022) to generate different query and document embeddings in `jina-embeddings-v4`.

Our training data consists of *hard negatives*. (Wang et al., 2022; Li et al., 2023) For every pair $(q_i, p_i) \in \mathcal{B}$ in a batch, p_i is intended to be a good match for q_i , and we presume that for all $(q_j, p_j) \in \mathcal{B}$ where $j \neq i$, p_j is a hard negative for q_i . We incorporate those negatives into the training process via an extended version of the \mathcal{L}_{NCE} loss described in Günther et al. (2023).

We used existing datasets to create multimodal pairs for training, including Wiki-SS (Ma et al.,

2024) and VDR multilingual,² but we also mined hard negatives from curated multimodal datasets.

4.2.2 Text Matching Adapter

We find that for symmetric semantic similarity tasks like text matching, training data with ground truth similarity values works best. As discussed in Sturua et al. (2024), we use the CoSENT³ loss function \mathcal{L}_{co} from Li and Li (2024), which operates on two pairs of text values with known ground truth similarity.

We used data from semantic textual similarity training datasets such as STS12 (Agirre et al., 2012) and SICK (Marelli et al., 2014), where ground truth similarity values are available. However, the amount of data in this format is very limited, so we enhanced our training data with pairs that do not have known similarity scores. For these pairs, we use the standard InfoNCE loss in place of the CoSENT loss.

4.2.3 Code Adapter

Code embeddings in `jina-embeddings-v4` are designed for natural language-to-code retrieval, code-to-code similarity search, and technical question answering. Because code embeddings do not involve image processing, the vision portion of `jina-embeddings-v4` is not affected by training the code retrieval LoRA adapter. Qwen2.5-VL-3B-Instruct was pre-trained on data including the StackExchangeQA⁴ and the CodeSearchNet (Husain et al., 2020) datasets, giving it some capacity to support code embeddings before further adaptation.

Our LoRA training used the same method described in Section 4.2.1. Training triplets are derived from a variety of sources, including CodeSearchNet, CodeFeedback (Zheng et al., 2024), APPS (Hendrycks et al., 2021), and the CornStack dataset (Suresh et al., 2025).

5 JVDR: Visually Rich Document Retrieval Benchmark

To evaluate the performance of `jina-embeddings-v4` across a broad range of visually rich document retrieval tasks, we have produced a new benchmark collection and released it to the public.⁵

²<https://huggingface.co/datasets/llamaindex/vdr-multilingual-train>

³<https://github.com/bojone/CoSENT>

⁴<https://github.com/laituan245/StackExchangeQA>

⁵<https://huggingface.co/collections/jinaai/jinavdr-visual-document-retrieval->

This new collection extends the ViDoRe benchmark by adding more than 30 additional tests designed to be compatible with ViDoRe. They span a broad range of domains (e.g. legal texts, historic documents, marketing materials), cover a variety of material types (e.g. charts, tables, manuals, printed text, maps) and query types (e.g. questions, facts, descriptions), and use up to 20 languages. These tests include re-purposed existing datasets, new manually-annotated data, and generated synthetic data. We employed LLM-based filtering to ensure all queries are relevant and reflective of realistic usage.⁶

We have adapted a number of existing VQA (visual question answering) and OCR datasets, modifying and restructuring them into appropriate query-document pairs. For some datasets, we used structured templates and generative language models to formulate text queries to match their contents. We also created benchmarks from available data to use unconventional querying techniques. We drew heavily on Wikimedia materials and other public data sources. For example, some datasets contain encyclopedia article fragments and image descriptions as queries to match with charts and maps. We obtained multilingual documents from Wikipedia and paired them with paragraphs that reference them. We used GitHub README files to create rendered images from Markdown-formatted rich texts and paired them with LLM-generated natural language descriptions in 17 languages.

We have also curated a number of human-annotated resources to better reflect real-world use cases. These include educational materials like lecture slides, commercial catalogs, marketing materials, and institutional documents. We paired these documents with human-written queries.

We have been attentive, in constructing JVDR, to the lack of diversity that often plagues information retrieval benchmarks. We cannot commission human-annotated datasets for everything and have had recourse to generative AI to fill in the gaps.

We obtained a number of datasets from primarily European sources containing scans of historical, legal, and journalistic documents in German, French, Spanish, Italian, and Dutch, and public service documents and commercial catalogs in Hindi, Russian, and other often underrepresented languages. We used Qwen2⁷ to generate queries for

these documents. In several cases, we introduced cross-language queries synthesized using advanced multilingual LLMs, in order to better measure cross-language retrieval.

For a comprehensive overview of the individual benchmarks, see Appendix A.3.

6 Evaluation

Table 2 provides an overview of benchmark averages for `jina-embeddings-v4` and other embedding models.

6.1 Text Retrieval

For MTEB and MMTEB benchmarks (Enevoldsen et al., 2025), we used the asymmetric retrieval adapter except for some symmetric retrieval tasks like ArguAna,⁸ where we used the text matching adapter instead. We evaluated our model on retrieval tasks that involve long text documents using the *LongEmbed* benchmark (Zhu et al., 2024). We also tested the text matching adapter on MTEB STS and MMTEB STS benchmarks.

Results for these benchmarks are tabulated in Appendix A.1. The performance of `jina-embeddings-v4` is broadly comparable with the state-of-the-art. For long document performance, `jina-embeddings-v4` significantly outpaces competing models except voyage-3.

6.2 Code Retrieval

To assess performance on code retrieval, we evaluated the model on the MTEB-CoIR benchmark (Li et al., 2025). The results are reported in Table A6. `jina-embeddings-v4` is competitive with the state-of-the-art in general-purpose embedding models, but the specialized voyage-code model has somewhat better benchmark performance.

6.3 CLIP Benchmark

To evaluate the model’s performance on typical text-to-image search tasks, we used the CLIP Benchmark.⁹ The results are tabulated in Appendix A.2.

`jina-embeddings-v4` generally outperforms CLIP-style models on these benchmarks, although nllb-siglip-large performs somewhat higher on the Crossmodal3600 benchmark (Thapliyal et al., 2022) (see Table A8) because it supports low-resource languages not included in training the Qwen2.5-VL-3B-Instruct backbone model.

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⁶See A.5 for the specific prompts.

⁷<https://huggingface.co/collections/Qwen/qwen2-6659360b33528ced941e557f>

⁸<https://huggingface.co/datasets/mteb/arguana>

⁹https://github.com/LAION-AI/CLIP_benchmark

Model	JVDR	ViDoRe	CLIPB	MMTEB	MTEB-en	COIR	LEMB	STS-m	STS-en
jina-embeddings-v4 (single)	73.98	84.11	84.11	66.49	55.97	71.59	67.11	72.70	85.89
jina-embeddings-v4 (multi)	80.55	90.17							
text-embedding-3-large	—	—	—	59.27	57.98	62.36	52.42	70.17	81.44
bge-m3	—	—	—	55.36			58.73		
multilingual-e5-large-instruct	—	—	—	57.12	53.47		41.76		
jina-embeddings-v3	47.82	26.02	—	58.58	54.33	55.07	55.66	75.77	85.82
voyage-3	—	—	—	66.13	53.46	67.23	74.06	68.33	78.59
gemini-embedding-001	—	—	—	67.71	64.35	73.11		78.35	85.29
jina-embeddings-v2-code	—	—	—			52.24			
voyage-code	—	—	—			77.33			
nllb-clip-large-siglip			83.19						
jina-clip-v2	40.52	53.61	81.12						
colpali-v1.2 (late)	63.80	83.90							
dse-qwen2-2b-mrl-v1 (dense)	67.25	85.80							
voyage-multimodal-v3 (dense)		84.24							

Table 2: Average Retrieval Scores of Embedding Models on Various Benchmarks.

Task Acronyms: ViDoRe = ViDoRe, CLIPB = CLIP Benchmark, MMTEB = MTEB(Multilingual, v2) Retrieval Tasks, MTEB-EN = MTEB(eng, v2) Retrieval Tasks, COIR = CoIR Code Retrieval, LEMB = LongEmbed, STS-m = MTEB(Multilingual, v2) Semantic Textual Similarity Tasks, STS-en = MTEB(eng, v2) Semantic Textual Similarity Tasks

Average Calculation: For JVDR and ViDoRe, we calculate the average for the multilingual tasks first and consider this as a single score before calculating the average across all tasks. Scores are nDCG@5 for JVDR and ViDoRe, Recall@5 for CLIPB, nDCG@10 for MMTEB, MTEB-en, COIR, and LEMB, and Spearman coefficient for STS-m and STS-en.

Evaluation of Text Retrieval Models on JVDR: For evaluating text retrieval models on JVDR, we used EasyOCR (<https://github.com/JaidedAI/EasyOCR>) and the provided extracted texts from the original ViDoRe datasets.

6.4 Visually Rich Document Benchmarks

Appendix A.4 tabulates the results of evaluating [jina-embeddings-v4](#) on our new JVDR benchmark. Table A12 provides a comparison with other models. [jina-embeddings-v4](#) excels at visually rich document tasks, and is currently the state-of-the-art in both single- and multi-vector mode. These results suggest that other models underperform on visually rich document tasks that do not closely resemble the ones in the ViDoRe benchmark.

6.5 Modality Gap

The so-called *modality gap* is dramatically reduced with [jina-embeddings-v4](#) because of its cross-modal encoder. We measure the cross-modal alignment score of a multimodal embedding model as the average of cosine similarities of matching pairs of image and text embeddings. Table A10 displays this score for [jina-embeddings-v4](#) and CLIP-style models for data sampled from the Flickr30K,¹⁰ MSCOCO, (Lin et al., 2014) and CIFAR-100¹¹ datasets. These results confirm that [jina-embeddings-v4](#) generates a far better aligned cross-modal embedding space than

CLIP-style models, as can be seen in Figure 2 in the appendix.

7 Conclusion

We present [jina-embeddings-v4](#), a state-of-the-art multimodal and multilingual embedding model designed for a wide range of tasks, including semantic text retrieval, text-to-image retrieval, text-to-visually-rich document retrieval, and code search. The model achieves strong performance using single-vector representations and demonstrates even greater effectiveness with multi-vector representations, particularly in visually rich document retrieval. [jina-embeddings-v4](#) aligns representations across modalities into a single, shared semantic space, sharply reducing structural gaps between modalities compared to CLIP-style dual-tower models, enabling more effective cross-modal retrieval.

We also present JVDR, a novel benchmark for visually rich documents that dramatically extends the ViDoRe benchmark by including much more diverse data types, more languages, and more kinds of queries and semantic similarity tests. We have made this benchmark available to the public for future work.

¹⁰<https://www.kaggle.com/datasets/adityajn105/flickr30k>

¹¹<https://www.kaggle.com/datasets/fedesoriano/cifar100>

Limitations

`jina-embeddings-v4` is a model that extends Qwen2.5-VL-3B-Instruct and is limited by its original training. As a result, its performance on many languages is not comparable to the state-of-the-art and it may not perform well on materials too far outside of its training. Furthermore, highly domain-specialized models may have significantly better performance at specific tasks.

Although this model is theoretically capable of embedding text and image input together, it has not been trained for such input. It has also not been trained for image-image retrieval or semantic similarity, and may underperform on those tasks.

JVDR is not a rigorously representative data collection. It is a significant expansion over previous related benchmarks, but this is a new area for embeddings research, and JVDR undoubtedly has gaps and shortcomings that usage will reveal.

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A Appendix

A.1 MTEB and MMTEB

Table A1: Evaluation Results on MTEB Retrieval Tasks (nDCG@10%)

Model	Arg	CQG	CQU	CFHN	FEV	FiQA	HPQA	SCI	TREC	TOU	AVG
jina-embeddings-v4†	67.07	57.59	42.95	34.57	87.16	46.51	69.01	21.47	80.36	52.41	55.91
jina-embeddings-v3†	54.33	58.02	43.52	43.14	89.90	47.35	64.70	19.92	77.74	55.28	55.39
jina-embeddings-v2-base-en	44.18	56.52	38.66	23.77	73.41	41.58	63.24	19.86	65.91	63.35	49.05
jina-embedding-l-en-v1	48.30	51.68	38.66	25.93	71.16	41.02	57.26	18.54	60.34	62.34	47.52
multilingual-e5-large	54.36	58.70	39.89	26.00	83.79	43.82	70.55	17.45	71.15	49.59	51.53
e5-mistral-7b-instruct	61.65	63.52	46.75	28.50	86.99	56.81	73.21	16.32	87.03	55.44	57.62
text-embedding-3-large	57.99	65.40	50.02	30.10	88.53	55.00	71.66	23.07	79.56	58.42	57.98
gemini-embedding-001	86.44	70.68	53.69	31.06	88.98	61.78	87.01	25.15	86.32	52.39	64.35

†using the text-matching adapter

Tasks: Arg: ArguAna, CQG: CQADupstackGamingRetrieval, CQU: CQADupstackUnixRetrieval, CFHN: ClimateFEVERHardNegatives, FEV: FEVERHardNegatives, FiQA: FiQA2018, HPQA: HotpotQAHardNegatives, SCI: SCIDOCS, TREC: TRECCOVID, TOU: Touche2020Retrieval.v3

Table A2: Evaluation Results on MMTEB Retrieval Tasks (nDCG@10%)

Model	Avg	AI	Arg	Bel	Cov	Hag	PK	LB	MIR	ML	SD	SQA	SO	TC	STC	TR	TW	Wiki	WG
JinaV4	66.5	50.2	67.1	74.3	80.2	98.8	69.8	94.8	61.2	74.9	21.5	30.2	91.9	80.4	59.5	1.3	84.4	88.5	67.3
JinaV3	58.6	32.8	54.3	73.4	78.6	98.7	38.0	93.4	62.6	73.4	19.8	0.7	90.8	77.7	39.2	0.6	73.0	89.1	18.6
BGE-M3	55.4	29.0	54.0	78.2	77.5	98.8	59.0	90.3	69.6	74.8	16.3	7.5	80.6	54.9	21.9	1.0	37.8	89.9	41.7
CohV3	59.2	29.7	55.1	81.1	77.1	98.8	38.2	93.8	68.0	76.1	19.3	4.7	89.4	83.4	24.2	0.9	75.8	90.9	58.4
Gem001	68.1	48.8	86.4	90.7	79.1	99.3	38.5	96.0	70.4	84.2	25.2	10.3	96.7	86.3	51.1	3.0	98.0	94.2	60.5
TE3L	61.1	42.0	58.0	68.8	68.4	99.1	69.8	95.2	56.9	73.2	23.1	7.4	92.4	79.6	31.1	2.1	81.4	89.2	29.1
Voy3	66.0	42.5	61.0	76.5	88.5	98.6	94.8	94.5	57.7	75.7	21.4	10.7	94.3	80.5	49.2	1.2	85.7	89.7	67.7
VoyM2	–	45.0	61.8	–	–	98.9	97.0	95.9	–	–	22.5	10.2	–	80.1	–	1.4	87.3	–	39.1

Model abbreviations: JinaV4: jina-embeddings-v4, JinaV3: jina-embeddings-v3, BGE-M3: bge-m3, CohV3: cohere-embed-multilingual-v3, Gem001: gemini-embedding-001, TE3L: text-embedding-3-large, Voy3: voyage-3, VoyM2: voyage-multilingual-2.

Tasks: Avg: Mean nDCG@10% for all tasks, AI: AILAStatutes, Arg: ArguAna, Bel: BelebeleRetrieval, Cov: CovidRetrieval, Hag: HagridRetrieval, PK: LEMBPaskeyRetrieval, LB: LegalBenchCorporateLobbying, MIR: MIRACLRetrievalHardNegatives, ML: MLQARetrieval, SD: SCIDOCS, SQA: SpartQA, SO: StackOverflowQA, TC: TREC-COVID, STC: StatcanDialogueDatasetRetrieval, TR: TempReasonL1, TW: TwitterHjerneRetrieval, Wiki: WikipediaRetrievalMultilingual, WG: WinoGrande

Table A3: Retrieval performance on MTEB LongEmbed (nDCG@10%)

Model	Avg	NaQA	Needle	Passkey	QMSum	SummScreen	Wikim
jina-embeddings-v4	67.11	57.52	51.75	65.50	46.49	96.30	85.08
jina-embeddings-v3	55.66	34.30	64.00	38.00	39.34	92.33	66.02
multilingual-e5-large	40.44	24.22	28.00	38.25	24.26	71.12	56.80
multilingual-e5-large-instruct	41.76	26.71	29.50	37.75	26.08	72.75	57.79
bge-m3	58.73	45.76	40.25	59.00	35.54	94.09	77.73
cohere-embed-english-v3	42.11	25.04	30.50	38.50	23.82	75.77	59.03
text-embedding-3-large	52.42	44.09	29.25	69.75	32.49	84.80	54.16
voyage-3	74.07	54.12	57.75	94.75	51.05	97.82	88.90
voyage-3-lite	71.41	51.67	54.00	84.75	53.01	96.71	88.34
voyage-multilingual-2	79.17	64.69	75.25	97.00	51.50	99.11	87.49

Tasks: Avg: Mean nDCG@10% for all tasks, NaQA: LEMBNAQA, Needle: LEMBNeedleRetrieval, Passkey: LEMBPaskeyRetrieval, QMSum: LEMBQMSumRetrieval, SummScreen: LEMBSummScreenFDRetrieval, Wikim: LEMBWikimQARetrieval

Table A4: STS performance on MTEB v2 (Spearman correlation %).

Model	Avg	BIO	SICK-R	STS12	STS13	STS14	STS15	STS17	STS22	STSB
jina-embeddings-v4	85.89	89.21	89.23	83.50	88.61	84.77	89.69	88.71	70.71	88.58
jina-embeddings-v3	85.82	88.69	89.62	82.44	89.49	84.95	89.32	90.01	68.45	89.43
multilingual-e5-large	81.39	84.57	80.23	80.02	81.55	77.72	89.31	88.12	63.66	87.29
bge-m3	80.61	–	79.72	78.73	79.60	79.00	87.81	87.13	67.99	84.87
cohere-embed-English-3	82.40	83.50	81.27	74.37	85.20	80.98	89.23	90.34	68.18	88.55
cohere-embed-multilingual-v3	83.05	85.01	82.18	77.62	85.16	80.02	88.92	90.09	69.63	88.79
gemini-embedding-001	85.29	88.97	82.75	81.55	89.89	85.41	90.44	91.61	67.97	89.08
text-embedding-3-large	81.44	84.68	79.00	72.84	86.10	81.15	88.49	90.22	66.89	83.56
voyage-3	78.59	87.92	79.63	69.52	80.56	73.33	80.39	86.81	69.60	79.53
voyage-large-2	82.63	89.13	79.78	72.94	83.11	77.21	85.30	88.77	–	84.78
voyage-multilingual-v2	76.98	87.11	78.97	67.30	80.09	71.98	78.07	86.52	67.02	75.79

Tasks: Avg: Mean Spearman Correlation % for all tasks, BIO: BIOSSES, STS22: STS22v2, STSB: STSBenchmark

Table A5: STS performance on MMTEB v2 (Spearman correlation %).

Model	Avg	Faro	FinP	Ind	JSCK	SKCR	STS12	STS13	STS14	STS15	STS17	STS22	STSB	STSES	Sem
JinaV4	72.7	72.3	14.4	35.2	80.3	89.2	83.5	88.6	84.8	89.7	88.7	70.7	88.6	75.3	56.5
JinaV3	75.8	80.8	22.4	54.7	78.2	89.6	82.4	89.5	84.9	89.3	85.9	71.1	89.4	77.9	64.6
BGE-M3	73.0	77.8	30.4	52.1	79.2	79.7	78.7	79.6	79.0	87.8	79.7	70.0	84.9	77.5	65.4
CohV3	73.8	76.0	28.2	46.7	77.2	82.2	77.6	85.2	80.0	88.9	90.1	69.4	88.8	78.8	63.8
Gem001	78.3	86.1	28.6	62.9	85.0	82.8	81.5	89.9	85.4	90.4	88.6	71.7	89.1	81.8	73.1
TE3L	70.2	75.0	23.5	12.6	81.2	79.0	72.8	86.1	81.2	88.5	90.2	69.3	83.6	74.2	65.2
Voy3	68.3	72.5	22.5	41.6	71.8	79.6	69.5	80.6	73.3	80.4	76.2	71.9	79.5	72.5	64.7
VoyM2	68.0	74.4	27.1	35.0	75.9	79.0	67.3	80.1	72.0	78.1	77.1	69.0	75.8	76.7	64.9

Model abbreviations: JinaV4: jina-embeddings-v4, JinaV3: jina-embeddings-v3, BGE-M3: bge-m3, CohV3: cohere-embed-multilingual-v3, Gem001: gemini-embedding-001, TE3L: text-embedding-3-large, Voy3: voyage-3, VoyM2: voyage-multilingual-2.

Tasks: Avg: Mean Spearman Correlation % for all tasks, Faro: FaroeseSTS, FinP: FinParaSTS, Ind: IndicCrosslingualSTS, JSCK: JSICK, SKCR: SICK-R, STS22: STS22v2, STSB: STSBenchmark, Sem: SemRel24STS

Table A6: Performance on MTEB Code Information Retrieval (MTEB-CoIR) (nDCG@10%).

Model	Avg	AppsR	CCSN	CodeMT	CodeST	CodeSN	CodeTO	CodeTD	CosQA	StackO	SynSQL
jina-embeddings-v4	71.59	76.08	84.05	70.60	85.06	83.69	89.34	44.19	31.48	93.45	70.45
jina-embeddings-v3	55.07	29.01	–	59.67	78.14	53.18	77.37	30.91	35.34	90.79	41.27
jina-embeddings-v2-code	52.24	16.37	83.97	44.40	68.66	59.62	75.68	27.25	41.92	89.26	46.99
cohere-embed-English-3	51.36	13.72	–	47.02	74.82	52.81	65.28	31.38	30.65	89.35	57.20
cohere-embed-mult.-v3	54.31	31.91	–	42.91	74.19	57.57	70.25	30.14	32.58	89.42	59.79
gemini-embedding-001	73.11	93.75	81.06	56.28	85.33	84.69	89.53	31.47	50.24	96.71	69.96
text-embedding-3-large	62.36	28.37	–	68.92	80.42	73.18	84.25	34.23	31.00	92.44	68.45
voyage-3	67.23	73.03	–	66.69	83.02	77.87	89.92	33.92	28.70	94.34	57.56
voyage-code-3	77.33	93.62	89.35	93.58	90.67	90.09	94.96	38.57	34.45	97.17	62.87

Tasks: Avg: Mean nDCG@10% for all tasks, AppsR: AppsRetrieval, COIR: COIRCodeSearchNetRetrieval, CodeMT: CodeFeedbackMT, CodeST: CodeFeedbackST, CodeSN: CodeSearchNetCCRetrieval, CodeTO: CodeTransOceanContest, CodeTD: CodeTransOceanDL, StackO: StackOverflowQA, SynSQL: SyntheticText2SQL

A.2 CLIP

Table A7: Cross-modal (Text-to-image) retrieval performance (Recall@5%) on the CLIP benchmark.

Model	Avg	flickr30k	mscoco_captions	crossmodal3600	xtd10
nllb-clip-large-siglip	83.19	92.24	70.84	82.07	87.60
jina-clip-v2	81.12	89.84	68.35	81.43	84.87
jina-embeddings-v4	84.11	91.36	76.18	79.42	89.46

Avg: Mean Recall@5% over all 4 tasks.

Table A8: Text-to-image retrieval performance (Recall@5%) on **crossmodal3600** for all supported languages.

Language	jina-embeddings-v4	jina-clip-v2	nllb-clip-large-siglip
average	79.42	81.43	82.07
ar	75.75	73.56	78.92
bn	57.97	63.78	75.19
da	80.47	85.39	87.14
de	91.75	91.25	89.56
el	66.50	75.03	77.83
en	76.47	75.83	73.11
es	83.64	83.64	82.64
fi	66.67	82.83	86.42
fr	88.69	88.78	87.86
hi	47.81	55.25	60.31
id	87.41	84.22	86.31
it	87.97	88.33	85.94
ja	91.22	87.03	86.06
ko	82.19	78.81	78.75
nl	81.00	82.56	81.69
no	71.94	81.08	82.69
pl	80.86	84.00	82.72
pt	81.42	82.42	82.69
ro	84.33	89.36	90.03
ru	90.28	88.97	86.44
sv	72.58	78.06	79.33
th	83.36	81.61	81.14
tr	73.08	81.31	83.47
uk	86.28	88.56	85.44
vi	88.81	86.64	85.56
zh	86.67	78.97	76.56

Table A9: Text-to-image retrieval performance (Recall@5%) on **xtd10** for all supported languages.

Language	jina-embeddings-v4	jina-clip-v2	nllb-clip-large-siglip
average	89.46	84.87	87.60
de	92.10	85.70	88.30
en	93.10	89.40	89.40
es	91.50	85.90	88.20
fr	91.30	85.10	87.70
it	92.20	85.80	89.30
ko	86.30	82.10	85.20
pl	89.10	86.50	89.40
ru	91.50	81.10	83.40
tr	84.70	83.70	88.30
zh	82.80	83.40	86.80

Table A10: Comparison of cross-modal alignment scores on 1K of random samples from each dataset.

Model	Flickr30K	MSCOCO	CIFAR-100
OpenAI-CLIP	0.15	0.14	0.20
jina-clip-v2	0.38	0.37	0.32
jina-embeddings-v4	0.71	0.72	0.56

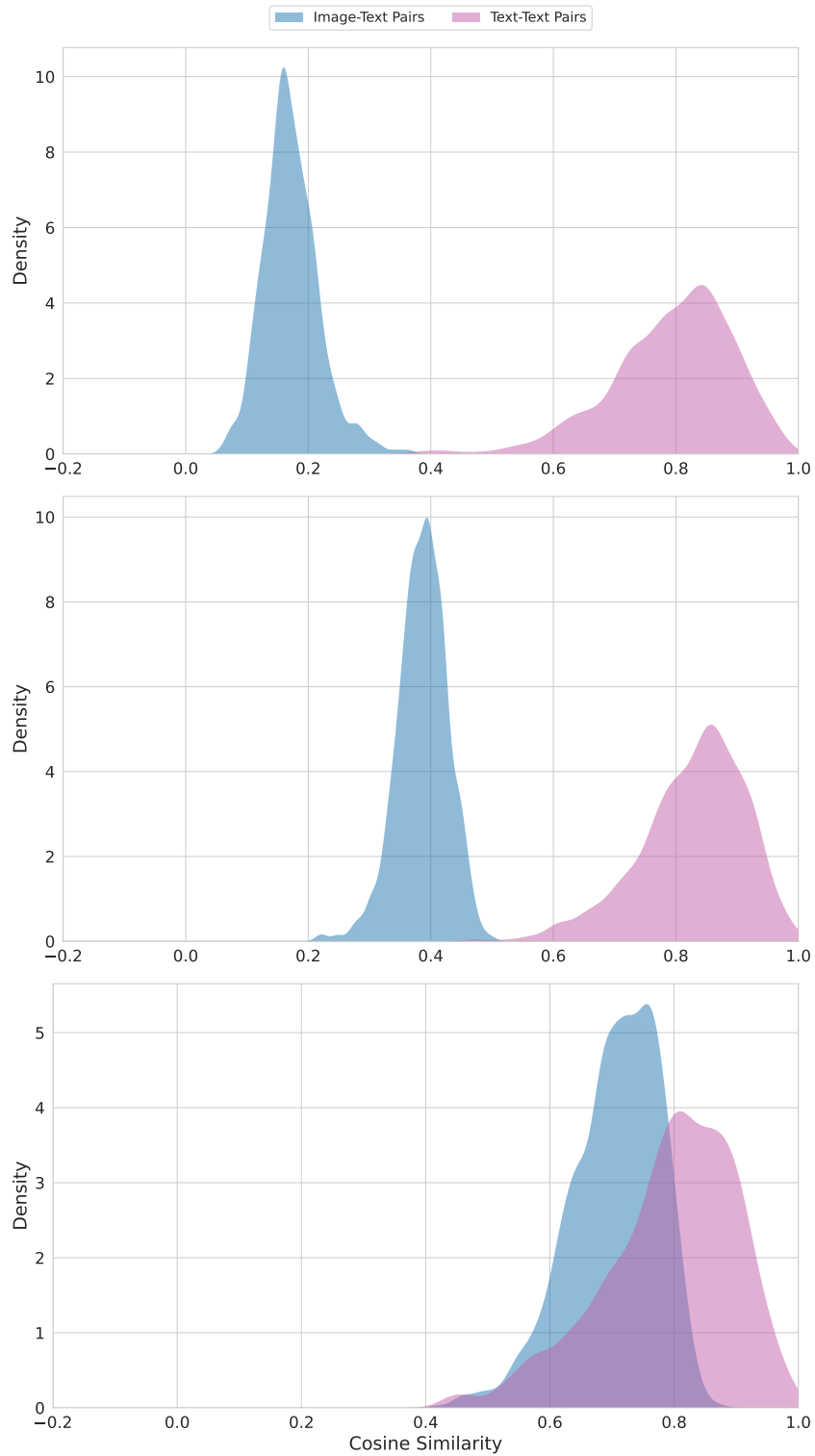


Figure 2: Distribution of the cosine similarities of the paired image-text embeddings versus paired text-text embeddings from the Flickr8K dataset. **Top:** OpenAI CLIP, **Middle:** [jina-clip-v2](#), **Bottom:** [jina-embeddings-v4](#)

A.3 Datasets in the JVDR Benchmark

Table A11: Overview of the Dataset Collection

Dataset Name	Domain	Document Format	Query Format	Number of Queries / Documents	Languages
airbnb-synthetic-retrieval†	Housing	Tables	Instruction	4953 / 10000	ar, de, en, es, fr, hi, hu, ja, ru, zh
arabic_chartqa_ar	Mixed	Charts	Question	745 / 342	ar
arabic_infographicsvqa_ar	Mixed	Illustrations	Question	120 / 40	ar
automobile_catalogue_jp	Marketing	Catalog	Question	45 / 15	ja
arxivqa	Science	Mixed	Question	30 / 499	en
beverages_catalogue_ru	Marketing	Digital Docs	Question	100 / 34	ru
ChartQA	Mixed	Charts	Question	996 / 834	en
CharXiv-en	Science	Charts	Question	999 / 1000	en
docvqa	Mixed	Scans	Question	39 / 499	en
donut_vqa	Medical	Scans / Handwriting	Question	704 / 800	en
docqa_artificial_intelligence	Software / IT	Digital Docs	Question	70 / 962	en
docqa_energy	Energy	Digital Docs	Question	69 / 971	en
docqa_gov_report	Government	Digital Docs	Question	77 / 970	en
docqa_healthcare_industry	Medial	Digital Docs	Question	90 / 961	en
europeana-de-news	Historic	Scans / News Articles	Question	379 / 137	de
europeana-es-news	Historic	Scans / News Articles	Question	474 / 179	es
europeana-fr-news	Historic	Scans / News Articles	Question	237 / 145	fr
europeana-it-scans	Historic	Scans	Question	618 / 265	it
europeana-nl-legal	Legal	Scans	Question	199 / 244	nl
github-readme-retrieval-multilingual†	Software / IT	Markdown Docs	Description	16953 / 16998	ar, bn, de, en, es, fr, hi, id, it, ja, ko, nl pt, ru, th, vi, zh
hindi-gov-vqa	Governmental	Digital Docs	Question	454 / 337	hi
hungarian_doc_qa_hu	Mixed	Digital Docs	Question	54 / 51	hu
infovqa	Mixed	Illustrations	Question	363 / 500	en
jdocqa	News	Digital Docs	Question	744 / 758	ja
jina_2024_yearly_book	Software / IT	Digital Docs	Question	75 / 33	en
medical-prescriptions	Medical	Digital Docs	Question	100 / 100	en
mpmq-a-small	Manuals	Digital Docs	Question	155 / 782	en
MMTab	Mixed	Tables	Fact	987 / 906	en
openai-news	Software / IT	Digital Docs	Question	31 / 30	en
owid_charts_en	Mixed	Charts	Question	132 / 937	en
plotqa	Mixed	Charts	Question	610 / 986	en
ramen_benchmark_jp	Marketing	Catalog	Question	29 / 10	ja
shanghai_master_plan	Governmental	Digital Docs	Question / Key Phrase	57 / 23	zh, en
wikimedia-commons-documents-ml†	Mixed	Mixed	Description	15593 / 15217	ar, bn, de, en, es, fr, hi, hu, id, it, ja, ko, my, nl, pt, ru, th, ur, vi, zh fr
shiftproject	Environmental Documents	Digital Docs	Question	89 / 998	fr
stanford_slide	Education	Slides	Question	14 / 994	en
student-enrollment	Demographics	Charts	Question	1000 / 489	en
tabfquad	Mixed	Tables	Question	126 / 70	fr, en
table-vqa	Science	Tables	Question	992 / 385	en
tatqa	Finance	Digital Docs	Question	121 / 270	en
tqa	Education	Illustrations	Question	981 / 393	en
tweet-stock-synthetic-retrieval†	Finance	Charts	Question	6278 / 10000	ar, de, en, es, fr, hi, hu, ja, ru, zh
wikimedia-commons-maps	Mixed	Maps	Description	443 / 451	en

†For multilingual datasets, the total number of queries and documents is the sum across all language-specific splits.

A.4 JVDR (Visual Document Retrieval) Benchmark Results

Table A12: Overview of JVDR Results

Task	bm25 + OCR	jev3 + OCR	j-clip- v2	colpali- v1.2	dse-qwen2- 2b-mrl-v1	jev4- single	jev4- multi
Average	46.88	48.97	40.96	65.39	68.89	75.47	81.52
medical-prescriptions	38.18	38.12	15.68	66.22	38.86	80.95	97.69
stanford_slide	81.78	95.28	91.48	100.0	100.0	100.0	97.16
donut_vqa	19.39	2.59	1.46	34.12	25.31	78.60	74.08
table-vqa	55.22	63.04	36.34	80.98	85.70	86.57	89.21
ChartQA	28.39	31.47	39.73	54.45	58.38	70.88	71.80
tqa	50.11	24.40	27.80	63.03	65.35	65.44	68.46
openai-news	76.63	87.30	70.05	94.81	93.75	93.97	96.43
europena-de-news	11.26	12.02	11.18	35.20	44.32	48.89	63.76
europena-es-news	51.99	43.82	12.95	45.70	60.66	60.81	80.70
europena-it-scans	39.11	38.77	16.54	58.70	54.28	58.01	73.29
europena-nl-legal	39.38	34.24	11.30	39.13	33.12	42.77	59.82
hindi-gov-vqa	1.83	7.51	5.21	11.43	10.19	15.32	22.49
automobile_catalogue_jp	20.92	50.39	32.54	35.72	66.44	72.22	81.32
beverages_catalogue_ru	11.05	14.09	39.66	68.47	80.32	85.68	87.73
ramen_benchmark_jp	28.02	63.37	41.28	52.03	51.66	90.77	94.65
jdoca_jp_ocr	1.64	7.85	19.94	35.68	67.00	75.63	82.42
hungarian_doc_qa	34.28	57.84	50.44	68.83	55.25	74.64	75.56
arabic_chartqa_ar	9.32	8.63	6.62	26.92	49.35	62.16	66.64
arabic_infographicsvqa_ar	13.26	13.43	50.36	34.76	71.72	85.38	93.21
owid_charts_en	66.19	62.10	57.71	78.17	84.26	92.06	92.29
arxivqa	56.73	54.41	83.41	92.54	93.33	95.44	95.44
docvqa	81.11	50.81	45.29	90.38	86.28	83.06	92.98
shiftproject	62.42	70.25	31.85	75.18	78.54	82.55	91.13
docqa_artificial_intelligence	91.68	82.98	66.52	96.09	97.52	96.43	98.04
docqa_energy	89.97	76.97	65.56	96.03	90.08	88.66	96.28
docqa_gov_report	87.20	82.72	68.84	92.92	94.19	92.03	95.97
docqa_healthcare_industry	86.44	86.88	68.13	93.14	96.14	94.62	97.51
tabfqquad	45.67	80.49	47.04	89.18	92.38	95.57	95.38
mpmq_small	85.54	67.39	59.72	88.88	81.62	80.44	91.28
jina_2024_yearly_book	87.67	85.98	77.12	95.77	93.39	94.29	98.17
wikimedia-commons-maps	5.37	5.06	20.67	27.46	33.06	40.23	53.45
plotqa	61.13	51.44	24.05	70.58	75.99	77.48	78.75
MMTab	74.82	74.06	44.54	84.66	86.04	86.08	90.03
CharXiv-en	46.85	41.47	56.28	79.64	83.86	83.00	87.66
student-enrollment	1.05	1.30	0.70	3.95	4.09	8.04	11.55
tatqa	75.62	49.88	44.23	82.57	80.97	80.14	92.76
shanghai_master_plan	12.69	92.67	75.28	88.87	92.56	95.53	97.41
europena-fr-news	24.55	23.69	16.43	30.33	38.23	36.66	50.16
infovqa	73.61	75.09	63.38	87.53	92.64	92.16	96.69

Models: bm25+OCR: BM25 with EasyOCR, **jev3**

+ OCR: **jina-embeddings-v3** with EasyOCR, colpali-v1.2: **ColPALI-v1.2**, dse-qwen2- 2b-mrl-v1: **DSE-QWen2-2b-MRL-V1**, jev4-single: **jina-embeddings-v4** single-vector, jev4-multi: **jina-embeddings-v4** multi-vector

Table A13: Retrieval performance on ViDoRe (nDCG@5%).

Model	Avg	AQA	DVQA	InfoVQA	Shift	AI	Energy	Gov	Health	TabFQ	TQA
OCR + jina-embeddings-v3	26.02	26.31	12.62	32.79	14.18	22.84	27.47	31.16	45.78	44.54	2.53
jina-clip-v2	53.61	68.33	27.62	60.60	34.12	66.55	64.69	67.47	68.38	46.89	31.43
voyage-multimodal-3	84.20	84.90	55.60	85.40	78.70	94.50	89.50	96.00	95.10	92.80	69.90
colpali-v1.2	83.90	78.00	57.20	82.80	79.10	98.10	95.20	94.80	96.70	89.70	68.10
dse-qwen2-2b-mrl-v1	85.80	85.60	57.10	88.10	82.00	97.50	92.90	96.00	96.40	93.10	69.40
OCR + bm25	65.50	31.60	36.80	62.90	64.30	92.80	85.90	83.90	87.20	46.50	62.70
siglip-so400m-patch14-384	51.40	43.20	30.30	64.10	18.70	62.50	65.70	66.10	79.10	58.10	26.20
jina-embeddings-v4 (single)	84.11	83.57	50.54	87.85	84.07	97.16	91.66	91.48	94.92	94.48	65.35
jina-embeddings-v4 (multi)	90.17	88.95	59.98	93.57	92.35	99.26	96.76	96.95	98.39	95.13	80.34

Tasks: Avg: Mean nDCG@5% over all tasks, AQA: ArxivQA, Shift: Shift Project, DVQA: DocVQA, InfoVQA: InfographicVQA, AI: Artificial Intelligence, Gov: Government Reports, Health: Healthcare Industry, TabFQ: TabFQuad, TQA: TAT-DQA

Table A14: Retrieval performance on ViDoRe V2 (nDCG@5%).

Model	Avg	Bio	ESG-En	ESG-Multi	Econ
colpali-v1.2	50.7	54.1	54.3	50.7	43.7
jina-embeddings-v4 (single)	50.4	57.0	52.6	39.5	52.6
jina-embeddings-v4 (multi)	58.2	60.9	65.1	51.8	55.1

Tasks: Avg: Mean nDCG@5% over all tasks, Bio: MIT Biomedical Multilingual, ESG-En: ESG Restaurant Human English, ESG-Multi: ESG Restaurant Synthetic Multilingual, Econ: Economics Macro Multilingual.

Table A15: Wikimedia Commons Retrieval Benchmark Results

Language	bm25 + OCR	jev3 + OCR	j-clip- v2	colpali- v1.2	dse- qwen2- 2b-mrl- v1	jev4- single	jev4- multi
Average	21.99	37.43	48.63	33.60	58.67	66.04	75.63
Arabic (ar)	19.62	38.40	45.85	28.40	63.06	71.41	81.81
Bengali (bn)	22.93	44.55	49.37	26.63	52.89	66.98	76.41
German (de)	12.74	39.58	52.87	40.36	62.99	70.21	80.86
English (en)	36.45	45.24	56.58	64.98	70.23	73.55	81.66
Spanish (es)	12.75	46.10	54.85	41.34	66.43	71.68	80.82
French (fr)	15.59	36.06	35.73	43.93	41.32	53.58	59.42
Hindi (hi)	16.73	36.94	48.42	18.02	50.94	62.64	71.77
Hungarian (hu)	25.38	33.88	44.42	12.67	52.35	65.86	76.00
Indonesian (id)	28.79	39.48	50.85	40.46	62.03	66.02	73.72
Italian (it)	19.63	37.98	49.77	34.76	60.05	63.96	73.68
Japanese (jp)	21.41	30.43	44.03	28.83	63.71	66.50	77.13
Korean (ko)	34.98	35.24	47.61	29.82	68.37	71.45	81.77
Burmese (my)	22.84	29.45	54.36	10.28	37.61	56.58	65.01
Dutch (nl)	14.90	39.89	50.40	52.29	65.09	68.58	78.94
Portuguese (pt)	23.32	45.85	54.28	51.30	67.53	69.04	78.85
Russian (ru)	16.82	38.95	49.34	31.88	64.44	68.86	80.70
Thai (th)	30.00	29.64	46.25	39.13	56.41	61.68	71.02
Urdu (ur)	13.64	32.73	36.52	9.45	38.76	49.76	62.17
Vietnamese (vi)	32.40	39.80	54.59	43.72	64.62	73.30	80.24
Chinese (zh)	18.82	28.41	46.45	23.82	64.51	69.23	80.58

Table A16: GitHub Readme Retrieval Benchmark Results

Language	bm25 + OCR	jev3 + OCR	j-clip- v2	colpali- v1.2	dse- qwen2- 2b-mrl- v1	jev4- single	jev4- multi
Average	50.11	65.14	39.06	72.91	72.24	85.57	85.69
Arabic (ar)	27.49	27.98	31.02	55.19	55.95	75.02	75.26
Bengali (bn)	1.29	28.27	26.96	49.25	47.30	65.70	66.08
German (de)	60.11	84.58	45.46	84.15	80.62	91.09	91.35
English (en)	87.43	91.67	48.69	91.10	90.69	96.94	97.34
Spanish (es)	78.57	83.31	43.35	84.02	78.70	89.60	90.19
French (fr)	77.55	83.54	42.42	83.73	79.11	90.25	90.45
Hindi (hi)	2.72	48.08	28.55	51.22	46.49	69.31	70.98
Indonesian (id)	78.05	82.46	38.59	79.67	74.57	88.42	88.62
Italian (it)	78.83	86.54	44.26	85.31	80.81	91.76	91.41
Japanese (jp)	14.46	63.20	42.02	69.02	75.42	89.74	90.80
Korean (ko)	40.01	35.23	37.87	64.16	68.83	87.04	86.89
Dutch (nl)	76.52	86.36	43.25	84.10	82.85	92.83	91.37
Portuguese (pt)	80.33	84.46	43.88	85.00	80.09	91.43	91.47
Russian (ru)	39.78	50.86	37.04	78.16	78.92	89.51	88.61
Thai (th)	1.47	36.67	37.62	65.29	65.45	77.61	76.67
Vietnamese (vi)	66.70	79.67	37.14	70.05	68.20	86.90	86.94
Chinese (zh)	40.52	54.53	35.89	60.05	74.05	81.44	82.26

Table A17: Tweet Stock Retrieval Benchmark Results

Language	bm25 + OCR	jev3 + OCR	j-clip- v2	colpali- v1.2	dse- qwen2- 2b-mrl- v1	jev4- single	jev4- multi
Average	22.30	42.77	55.36	76.36	62.76	78.10	85.34
Arabic (ar)	0.38	1.67	49.36	77.31	52.73	66.15	77.66
German (de)	48.27	66.86	52.49	73.53	57.35	79.38	85.63
English (en)	51.38	63.66	48.35	77.13	63.47	77.92	85.36
Spanish (es)	54.28	63.44	53.44	79.02	62.57	78.68	84.62
French (fr)	51.69	64.76	54.94	76.91	62.17	78.65	85.27
Hindi (hi)	0.08	0.08	88.55	93.39	97.00	97.46	96.50
Hungarian (hu)	15.55	62.31	52.30	71.06	58.17	80.09	85.01
Japanese (jp)	0.40	47.80	54.74	70.00	57.76	77.04	85.67
Russian (ru)	0.47	3.07	47.08	70.72	57.43	76.33	83.11
Chinese (zh)	0.45	54.04	52.30	74.54	58.94	69.33	84.55

Table A18: AirBnB Retrieval Benchmark Results

Language	bm25 + OCR	jev3 + OCR	j-clip- v2	colpali- v1.2	dse- qwen2- 2b-mrl- v1	jev4- single	jev4- multi
Average	7.20	1.13	2.13	10.42	11.10	8.18	37.51
Arabic (ar)	1.10	0.40	0.47	3.06	3.64	2.20	6.20
German (de)	4.03	0.71	5.54	20.17	15.09	9.27	41.94
English (en)	48.39	1.70	4.83	23.26	12.94	13.33	64.17
Spanish (es)	6.25	0.18	2.10	18.06	8.61	9.11	39.84
French (fr)	3.86	2.00	2.05	10.86	11.87	8.70	30.55
Hindi (hi)	0.16	0.86	0.82	3.19	4.93	4.05	17.44
Hungarian (hu)	5.58	0.69	3.01	7.34	11.10	6.69	27.30
Japanese (jp)	0.36	1.53	0.54	3.44	14.91	7.63	45.65
Russian (ru)	1.67	1.39	0.88	13.16	13.61	8.66	40.80
Chinese (zh)	0.58	1.84	1.04	1.62	14.28	12.14	61.19

A.5 Data Preparation Prompts

You are an assistant specialized in Multimodal RAG tasks.

The task is the following: given an image from a pdf page, you will have to generate questions that can be asked by a user to retrieve information from a large documentary corpus.

The question should be relevant to the page, and should not be too specific or too general. The question should be about the subject of the page, and the answer needs to be found in the page.

Remember that the question is asked by a user to get some information from a large documentary corpus that contains multimodal data. Generate a question that could be asked by a user without knowing the existence and the content of the corpus.

Generate as well the answer to the question, which should be found in the page. And the format of the answer should be a list of words answering the question.

Generate at most THREE pairs of questions and answers per page in a dictionary with the following format, answer ONLY this dictionary NOTHING ELSE:

```
{
  "questions": [
    {
      "question": "XXXXXX",
      "answer": ["YYYYYY"]
    },
    {
      "question": "XXXXXX",
      "answer": ["YYYYYY"]
    },
    {
      "question": "XXXXXX",
      "answer": ["YYYYYY"]
    }
  ]
}
```

where XXXXXX is the question and ['YYYYYY'] is the corresponding list of answers that could be as long as needed.

Note: If there are no questions to ask about the page, return an empty list. Focus on making relevant questions concerning the page.

Here is the page:

```
<file source="{ (path + '/' if path else '') + image }"/>
```

We use this prompt to generate questions for document images that do not have related text values that can be used to construct text-document pairs. This prompt follows the same formulation as the one introduced in [Faysse et al. \(2025\)](#)

Figure 3: Prompt for generating questions for visually-rich documents

Your task is to categorize each search query into one of the following two classes: VALID or INVALID .

Criteria for VALID queries:

1. VALID queries should not be vague or ambiguous, they must provide enough context for search outside a specific set of documents.
2. VALID queries should not depend on specific documents, charts, tables, but can mention known entities (like individuals, institutions, etc.).

Queries that do not meet the given criteria should be classified as INVALID.

Format for response:

Query: "..."

Class: VALID/INVALID

Explanation: "..."

Examples for reference:

Query: "How are concerns logged and tracked throughout the process?"

Class: INVALID

Explanation: This query does not contain enough information, it is not clear what "process" is being referenced.

Query: "For a married couple filing jointly, what is the withholding amount according to the Tax Withholding table?"

Class: INVALID

Explanation: This query depends on a specific "Tax Withholding" table.

Query: "What is the role of Gnther Oberhofer at Conrad Electronic?"

Class: VALID

Explanation: This query provides enough context by asking about a specific person at a known company.

Query: "Under what circumstances might the store send emails to customers?"

Class: INVALID

Explanation: This query is too vague because it does not specify which store is being referred to.

Query: "What is the premise of the story in Star Divide Ascension Series Book 2?"

CLASS: VALID

Explanation: This query provides enough context for a search by specifying the title of a particular book within a series.

Query: "What action will be taken regarding the trading of BROKEN HILL PROSPECTING LIMITED's securities?"

Class: INVALID

Explanation: The query lacks context such as timeframe, specific events, or responsible entities, making it vague.

Query: "What is the purpose of Tallan's Accessible Web Portal?"

Class: VALID

Explanation: This query inquires the purpose of a well known portal.

Query: "What are some examples of how pupils at Doncaster School for the Deaf are involved in enrichment opportunities?"

Class: VALID

Explanation: This query provides enough context for a search as it specifies a particular school (Doncaster School for the Deaf).

Using the guidelines and format provided above, categorize the following query: "{ query }".

We use this prompt to filter out underspecified or document-dependent questions. It ensures that only contextually self-contained queries—those not assuming prior knowledge of a specific document—are retained. This filtering is necessary in datasets with synthetic questions, where question–document relevance is annotated based on the generation source only.

Figure 4: Prompt for filtering questions

RoBiologyDataChoiceQA: A Romanian Dataset for improving Biology understanding of Large Language Models

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Abstract

In recent years, large language models (LLMs) have demonstrated significant potential across various natural language processing (NLP) tasks. However, their performance in domain-specific applications and non-English languages remains less explored. This study introduces a novel Romanian-language dataset¹ for multiple-choice biology questions, carefully curated to assess LLM comprehension and reasoning capabilities in scientific contexts. Containing approximately 14,000 questions, the dataset provides a comprehensive resource for evaluating and improving LLM performance in biology.

We benchmark several popular LLMs, analyzing their accuracy, reasoning patterns, and ability to understand domain-specific terminology and linguistic nuances. Additionally, we perform comprehensive experiments to evaluate the impact of prompt engineering, fine-tuning, and other optimization techniques on model performance. Our findings highlight both the strengths and limitations of current LLMs in handling specialized knowledge tasks in low-resource languages, offering valuable insights for future research and development.

1 Introduction

Large language models (LLMs) have achieved impressive results across a wide range of natural language processing (NLP) tasks. However, their performance often degrades in specialized domains and non-English languages, making Romania's rich tradition in biology an ideal context for evaluating LLMs' scientific reasoning in a relatively low-resource setting.

To rigorously examine and ultimately improve LLM competence on such domain-specific tasks, we created a Romanian-language dataset of multiple-choice biology questions. The dataset was

developed to assess and enhance LLM performance on authentic Romanian biology tests. It enables the evaluation of model accuracy in a realistic multiple-choice setting and can also be used to fine-tune LLMs on domain-specific Romanian biology terminology.

Our dataset comprises questions from two prestigious national sources: the Romanian Biology Olympiad and medical school admission examinations. The Olympiad is the country's largest biology competition, targeting middle- and high-school students, while medical entrance exams rigorously assess pre-university candidates on foundational biological knowledge. Together, these sources provide a comprehensive and challenging collection of questions, covering a broad range of biological topics, difficulty levels, and linguistic complexity.

This study goes beyond simple benchmarking. We conduct extensive experiments to explore how various factors such as prompt engineering strategies, model origin, and domain-specific fine-tuning influence model performance. Our statistical analyses provide insights into how well LLMs grasp Romanian biological concepts, reveal common failure patterns, and highlight differences across model types.

Our contributions are threefold: (1) we introduce a carefully curated Romanian-language biology dataset suitable for benchmarking and domain adaptation; (2) we assess the capabilities of leading LLMs in scientific reasoning within a low-resource language setting, building on previous work that shows persistent challenges in this area (Huang and Chang, 2023); and (3) we present an in-depth analysis of performance variation across experimental conditions, offering insights that can inform future model development and deployment in specialized domains.

We aim to encourage research on LLMs for non-English and domain-specific tasks, advancing NLP for educational and scientific contexts.

¹RoBiology Dataset - <https://huggingface.co/datasets/RoLLMHub/RoBiologyDataChoiceQA>

2 Related work

Biomedical question-answering (QA) datasets have played a crucial role in advancing domain-specific language models. PubMedQA (Jin et al., 2019) introduced a large-scale English-language biomedical QA dataset with 1,000 expert-annotated, 61,200 unlabeled, and 211,300 artificially generated *yes/no/maybe* questions. While valuable for scientific text comprehension, it does not include multiple-choice questions, which require more complex reasoning over structured information.

A more relevant effort is MedQA (Jin et al., 2021), an open-domain multiple-choice QA dataset collected from professional medical board exams. MedQA covers three languages — English (12,723 questions), simplified Chinese (34,251 questions), and traditional Chinese (14,123 questions) — and requires models to select the correct answer from multiple options rather than extracting answers directly from text. Similarly, MedMCQA (Pal et al., 2022) is an English-language multiple-choice QA dataset designed for medical entrance exams, containing over 194,000 questions. Unlike MedQA, which focuses on board exam questions, MedMCQA emphasizes a wide range of medical knowledge, testing over ten different reasoning abilities.

Efforts to develop language models specialized for Romanian biology are quite limited. One notable contribution is RoQLlama, a lightweight Romanian-adapted language model designed to enhance NLP performance in Romanian-language applications (Dima et al., 2024). RoQLlama was evaluated using the RoMedQA dataset (Crăciun, 2023), a specialized collection of Romanian medical school examination questions.

Our work surpasses this effort by introducing a carefully curated and extended Romanian-language biology dataset extracted from multiple sources, going beyond single-choice questions. We also fine-tune promising models and perform multiple benchmarks. Fine-tuning on our dataset significantly improves LLM performance, making it a valuable resource for enhancing language models in biology. By focusing on this domain, our dataset diversifies the range of available domain-specific resources for Romanian, complementing previous contributions in the medical field and aiming for deeper reasoning.

Guidance on creating and documenting high-quality NLP datasets is essential for ensuring the

utility of research outcomes. The dataset documentation framework proposed by Gebru et al., 2018 provided foundational insights for structuring the description and documentation of our dataset.

The use of LLMs in biology has shown significant potential for transforming research in the life sciences. Bhattacharya et al., 2023 explored the evolution of LLMs from textual comprehension tools to multimodal systems capable of analyzing complex biological data and contributing to advances in molecular biology and medicine. Their findings highlight the importance of LLMs in handling scientific reasoning and specialized terminology, which is central to our work.

3 Dataset Composition

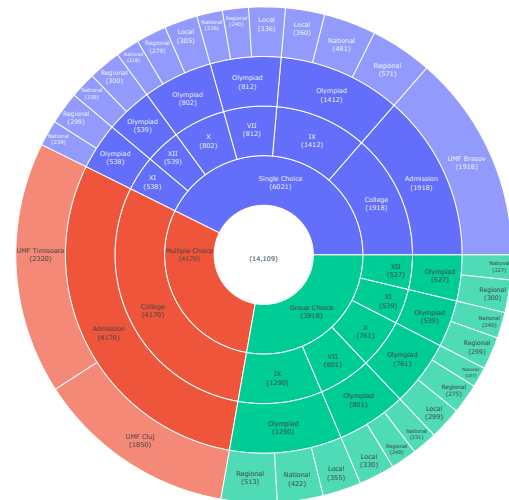


Figure 1: The data distribution based on question type and collection sources details.

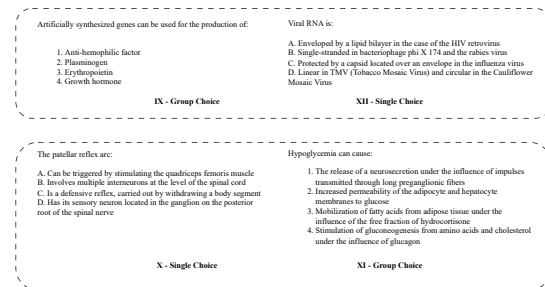


Figure 2: Examples of questions extracted and translated from the dataset

3.1 Olympiads

The *Romanian National Biology Olympiad* is a multiple-choice-based competition structured in multiple stages, covering all high school grades and occasionally including middle school. A typical Olympiad exam consists of three primary question categories:

- **Single-choice questions** – Typically, 30 questions with a single correct answer.
- **Group-choice questions** – Another 30 questions, where each answer can be one of five predefined lettered combinations (further details in A).
- **Complex single-choice questions** – A set of 10 advanced problems requiring analytical problem-solving to determine the correct answer.

There are exceptions to this standard format, particularly in older exams or localized stages, where the structure may differ, featuring only single-choice questions or a varying number of items.

Olympiad data is collected exclusively from **PDF documents** available online, typically hosted on news websites, archived school portals, or dedicated Olympiad platforms such as olimpiade.ro.

As shown in Figure 4, we extract only **single-choice** and **group-choice** questions from multiple grades, covering various competition stages and years (Figure 3). Given that the source documents are predominantly text-based PDFs (with occasional Word files, which we manually convert into PDFs), **PyMuPDF4LLM** (Artifex, 2024) is used to extract content in Markdown format. The extracted text is subsequently parsed into question instances using **regular expressions**.

A major challenge in this process is **word fragmentation** due to inconsistencies in document formatting. To address this, we employ **Gemini 1.5 Flash** and **Gemma2 9B Instruct** for grammar correction, followed by manual validation. Despite instructions to preserve original meaning, models often altered the semantics, particularly by correcting intentionally wrong answer options. This suggests that LLMs exhibit a tendency to favor logically correct statements, indicating that they have either encountered similar data during training or have developed an implicit understanding of correctness through their learned representations.

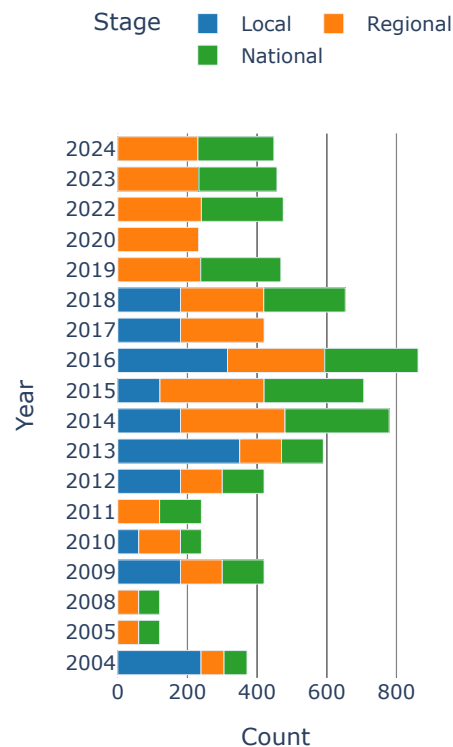


Figure 3: How many questions were collected from each year and of which type.

3.2 College Admission

Several Romanian universities use **multiple-choice-based admission exams**, with each university providing a dedicated question book (Matusz et al., 2020; Costache et al., 2020; Opincariu et al., 2018). These books, authored by university professors, serve as the **primary study resource** for candidates, as the actual exam questions are guaranteed to be similar to them. Our dataset includes approximately **6,000 questions** collected from the admission preparation books of three universities (Figure 4).

Unlike the Olympiad materials, these documents are **scanned books in image-based PDFs**, necessitating Optical Character Recognition (OCR). The lack of Romanian-specialized OCR tools presents a challenge. While **docTR** (Liao et al., 2023), a library known for strong English OCR performance, was tested, it proved inadequate for Romanian text. The most viable alternative was **Tesseract OCR**, optimized with **OpenCV-based noise removal preprocessing** (Kotwal et al., 2021). However, this approach introduced challenges:

- **Inconsistent noise removal** – Some techniques improved OCR accuracy for one page while degrading performance on others.
- **Language constraints** – The texts, although in Romanian, contain **Greek letters** used for specialized terminology (e.g., α , β , γ). While Tesseract supports multiple languages, enabling both Romanian and Greek led to **higher misinterpretation rates** rather than improved detection of Greek symbols.

To mitigate these issues, we explored **AI-based OCR solutions**, relying on context-aware processing for improved accuracy. The **Gemini Flash 1.5** model provided better results in recognizing text within scanned images. However, occasional hallucinations—such as **unintended duplication of questions**—necessitated **manual verification** to ensure proper extraction.

3.3 Deduplication

When identical questions with the same answer options appear across different tests or problem sets, we assign them a shared `dupe_id`, a unique UUID identifying a group of duplicates. Each group contains at least two instances. A question is considered a duplicate if both its text and answer options match, regardless of option order, which, as a matter of fact, could impact performance (Pezeshkpour and Hruschka, 2024). To detect slight rephrasings, we compare text embeddings generated with **jina-embeddings-v3** (Sturua et al., 2024).

Rather than removing duplicates, we mark them, as it is unclear which instance should be deleted. Duplication data may also reveal relationships between different subjects. While duplicates remain in the dataset, users can filter them using the `dupe_id` if needed. We ensure that no duplicates exist between the training, validation, and test splits to maintain dataset integrity.

3.4 Data Splits

The dataset is split into 11,347 training, 1,374 validation, and 1,388 test questions. Stratified sampling was applied across grades, difficulty tiers (national, regional, local), and institutional sources to ensure balanced and representative coverage.

Validation and test sets were constructed via a multi-step grade- and stage-based procedure, detailed in Appendix A. University-level questions were selected chapter-wise from multiple Romanian medical schools, as outlined in the Appendix.

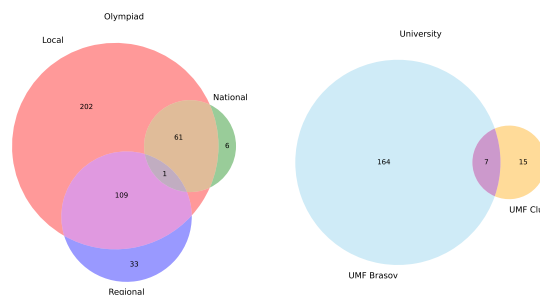


Figure 4: Duplication groups by stage. Overlaps indicate that the same question appears across all the participating stages. There is no duplicate question to be present in both olympiad and university subjects at the same time.

Originally designed with 1,400 questions each, the validation and test sets were slightly reduced following a final round of manual deduplication. Removed duplicates were reassigned to the training set to maintain evaluation integrity.

4 Experiments

We conducted comparisons and benchmarks across several dimensions, including zero-shot vs. few-shot settings, group-choice heuristics, and combined vs. individual predictions. To ensure reproducibility, all experiments were run with temperature set to zero. These experiments were carried out using local hardware, a Google Colab Pro subscription, and various API/runtime services, with a total cost of \$48.73. Although we do not have an exact runtime estimate, the work was completed over 2–3 months of intermittent activity.

4.1 Benchmarking on RoBiologyDataChoiceQA

Acknowledging good benchmarking practices explored by Liang et al., 2023, we evaluate multiple LLMs on the test split of the RoBiologyDataChoiceQA dataset and report their accuracies in Table 1. The selected models include those offering accessible API usage as well as competitive open-source Romanian models. Details regarding the prompts used can be found in the Appendix (B).

Despite the dataset being in Romanian, the Romanian-trained models (*Rogemma2*, *Rollama3-8B-Instruct-Imat*, and *Romistral-7B-Instruct*) did not show a significant advantage over multilingual or primarily English-trained models. Given their explicit training on Romanian (Masala et al., 2024),

we expected them to perform better due to their stronger grasp of Romanian syntax and semantics. However, the observed improvements were marginal, suggesting that language understanding alone is not enough to solve this task. Instead, performance appears to be primarily constrained by the models’ ability to reason about biological concepts and apply domain knowledge rather than by linguistic factors.

Studies (Nguyen et al., 2025; Gao et al., 2024) have shown that running the same models from different providers could yield slightly different accuracies in some contexts. This was not our case, since doing this resulted in nearly identical accuracies, with variations of at most 0.04. Therefore, we do not specify the source for each model. We conduct evaluations both locally and via external providers.

Model	Single Acc.	Group Acc.	Multi Acc.
gemini-2.0-flash	0.733	0.524	0.585
gemini-2.0-flash-exp	0.719	0.537	0.539
qwen-max-2025-01-25	0.699	0.472	0.573
llama-3.1-405B-Instruct-Turbo	0.685	0.426	0.464
gemini-1.5-flash	0.668	0.419	0.406
DeepSeek-V3	0.665	0.453	0.474
llama-3.3-70B-Instruct-Turbo	0.629	0.413	0.378
rogemma2-9b-instruct (Q8)	0.543	0.298	0.198
gemma2-9b-it	0.529	0.346	0.226
llama3-8b-instruct	0.405	0.250	0.093
phi-3.5-mini-instruct (F32)	0.379	0.208	0.080
eurollm-9b-instruct (F16)	0.384	0.220	0.102
rollama3-8b-instruct-imat (FP16)	0.371	0.235	0.102
romistral-7b-instruct (Q8)	0.371	0.252	0.077
mistral-7b-instruct-v0.1 (Q8)	0.221	0.199	0.046
Baseline	0.245	0.200	0.032

Table 1: Accuracies of models benchmarked on zero shot.

Running the models with a few-shot approach did not yield substantial improvements (phenomenon also found in Hendrycks et al., 2021 and Kojima et al., 2023); in fact, some models performed worse, as shown in Figure 5. Notably, certain LLMs exhibited a tendency to overfixate on specific letters after being presented with examples—interestingly, not necessarily the ones included in the prompt. The few-shot examples were provided to the LLMs within the system prompt, as described in Appendix B.

4.2 Benchmarking by source type

We compare model performance on Olympiad data versus university admission data. As shown in Figure 2, models tend to perform better on university-level questions with a single correct answer, suggesting they are more accustomed to medical admission data than to biology Olympiad questions. Alternatively, this may indicate that olympiad ques-

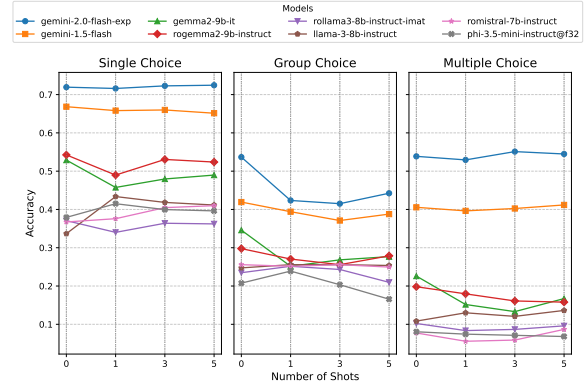


Figure 5: Accuracies of some models over few shot prompting.

Multiple	Single Acc.		Multiple Acc.	
	Olympiad	UMF Braşov	UMF Timişoara	UMF Cluj
gemini-2.0-flash-exp	0.704	0.824	0.615	0.415
qwen-max-2025-01-25	0.679	0.838	0.655	0.439
llama-3.1-405B-Instruct-Turbo	0.665	0.824	0.565	0.301
gemini-1.5-flash	0.658	0.743	0.485	0.276
DeepSeek-V3	0.650	0.770	0.540	0.366
llama-3.3-70B-Instruct-Turbo	0.611	0.757	0.445	0.268
rogemma2-9b-instruct (Q8)	0.531	0.622	0.230	0.146
gemma2-9b-it	0.502	0.716	0.255	0.179
llama3-8b-instruct	0.409	0.378	0.130	0.033
eurollm-9b-instruct (F16)	0.393	0.270	0.110	0.073
phi-3.5-mini-instruct (F32)	0.387	0.324	0.085	0.073
romistral-7b-instruct (Q8)	0.374	0.324	0.085	0.065
rollama3-8b-instruct-imat (FP16)	0.372	0.365	0.120	0.073
mistral-7b-instruct-v0.1 (Q8)	0.210	0.297	0.055	0.033
Baseline	0.250	0.200	0.032	0.032

Table 2: Accuracies of models, separated by source.

tions are potentially more challenging, requiring deeper knowledge and reasoning skills.

In Figure 2, we highlight instances where Olympiad scores surpass university admission scores. Even in these cases, the difference is generally small. However, when university admission scores are higher, the margin tends to be larger.

Comparing the difficulty levels of the three universities, we observe that the UMF Braşov exam appears to be the easiest, as it consists solely of single-answer questions. In contrast, the UMF Timişoara and UMF Cluj exams contain multiple-answer questions, making them more challenging and not directly comparable to UMF Braşov. Additionally, UMF Cluj’s exam seems to be the most difficult, as all models achieve higher scores on UMF Timişoara’s admission questions. This aligns with the common perception that among the three universities analyzed, UMF Cluj has the most difficult admission exam, followed by UMF Timişoara, while UMF Braşov is considered the easiest.

4.3 Finetuning Gemini 1.5 Flash

Google AI Studio allows fine-tuning of the **Gemini 1.5 Flash** model with custom data by providing a CSV file where one column serves as the input and another as the model’s output. Using the training

split of the RoBiologyDataChoiceQA dataset, we set the input as the benchmarking prompt, replacing %question-text% with the formatted question entry. The output corresponds to the correct answer field without additional formatting.

Once training is complete, we evaluate the fine-tuned model on the test split. We train multiple versions with different parameter settings (e.g., number of epochs, batch size) as detailed in Figure 6. Our fine-tuned models achieve new state-of-the-art accuracies, as shown in Table 3.

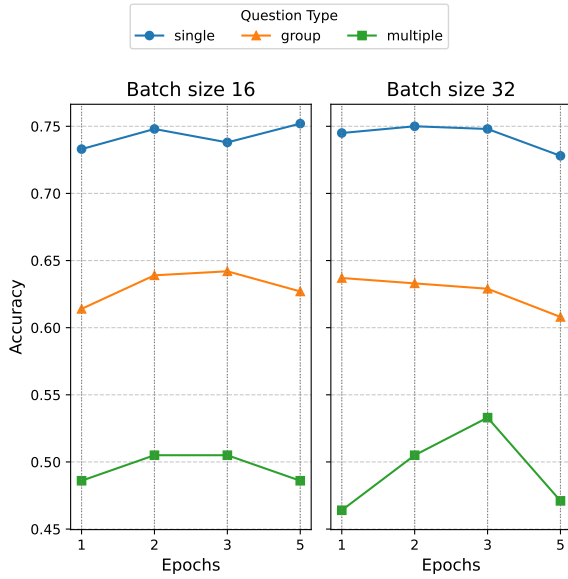


Figure 6: Accuracies of fine-tuned versions of Gemini 1.5 Flash.

Model	Single Accuracy	Group Accuracy	Multiple Accuracy
gemini-2.0-flash	0.733	0.524	0.585
tuned_batch16_epochs5	0.752	0.627	0.486
tuned_batch16_epochs3	0.738	0.642	0.505
tuned_batch16_epochs1	0.733	0.614	0.486
tuned_batch32_epochs5	0.728	0.608	0.471
tuned_batch32_epochs3	0.748	0.629	0.533
tuned_batch32_epochs2	0.750	0.633	0.505
tuned_batch32_epochs1	0.745	0.637	0.464
tuned_batch16_epochs2	0.748	0.639	0.505
tuned_batch64_epochs3	0.733	0.612	0.517
gemini-1.5-flash	0.668	0.419	0.406

Table 3: Accuracies of fine-tuned Gemini 1.5 Flash models

4.4 Finetuning Gemma 2 9B Instruct

After successfully improving Gemini’s performance through fine-tuning, we extend this approach to a smaller model, Gemma 2 9B Instruct, and observe similar accuracy gains, as shown in Figure 7.

For fine-tuning, we employ the LoRA technique (Hu et al., 2021) via the Unsloth framework

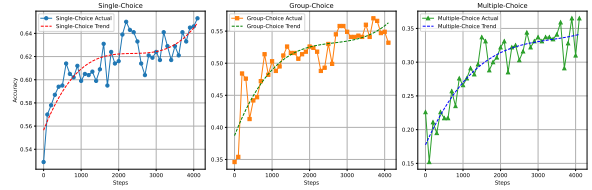


Figure 7: Performance of Gemma 2 9B Instruct on the test split over fine-tuning training steps.

(Daniel Han and Unsloth Team, 2023), training the model for approximately four epochs, with 1,000 steps per epoch. Accuracy is evaluated at intervals of 100 steps. While we halted training at four epochs, the observed trend suggests that further improvements may still be possible, particularly for single-choice and group-choice questions.

	Single Acc.	Group Acc.	Multiple Acc.
gemma2-9b-it	0.529	0.346	0.226
finetune step 3700	0.641	0.570	0.291
finetune step 3900	0.645	0.547	0.365
finetune step 4100	0.653	0.532	0.365
max increase	0.124	0.186	0.139

Table 4: Best accuracies of the model during fine-tuning.

Table 4 reports the highest accuracies obtained during fine-tuning. Compared to the initial model, Gemma 2 9B Instruct achieves improvements of over 12 percentage points. The fine-tuned model attains performance comparable to larger models, significantly narrowing the gap with Gemini 1.5 Flash on single-choice and multiple-choice questions (falling behind by only 1.5 and 4.1 percentage points, respectively). For group-choice questions, it outperforms all models from the initial benchmark, surpassing the previous state-of-the-art by 3.3 percentage points.

4.5 Treating group choice questions as multiple choice

Inspired by Balepur et al., 2024, we hypothesized that LLMs might struggle to correctly apply the grouping rules, particularly in cases where the multiple-choice accuracy was higher. To test this, we reformulated the questions into a multiple-choice format, ran them as if they were multiple-choice questions, and then manually mapped the groupings to their respective answers.

For cases where the model produces invalid combinations that cannot be mapped to a valid answer, we select the first letter (essentially randomizing the answer). This results in a new accuracy, which sometimes exceeds the original.

To further improve this accuracy, we implemented heuristics instead of relying on the random approach for invalid groups. For example, the combination (1, 2) is mapped to (1, 2, 3); (1) or (3) is mapped to (1, 3); (2, 3, 4) is mapped to (1, 2, 3, 4), and so on. For most models, the use of heuristics yields better results than the random selection, as shown in Table 5.

Model	Group	Group As Multiple	With Heuristics
gemini-2.0-flash-exp	0.537	0.449	0.499
DeepSeek-V3	0.453	0.388	0.423
llama-3.1-405B-Instruct-Turbo	0.426	0.453	0.484
gemini-1.5-flash	0.419	0.447	0.480
gemma2-9b-it	0.346	0.300	0.314
rogemma2-9b-instruct (Q8)	0.298	0.258	0.275
llama3-8b-8192	0.252	0.235	0.245
rollama3-8b-instruct-imat (FP16)	0.235	0.241	0.256
phi-3.5-mini-instruct (F32)	0.208	0.231	0.247

Table 5: The accuracies obtained on group choice questions with all strategies. Highlighting signifies a better score with the group-as-multiple approach compared to the initial strategy.

4.6 Accuracy by Grade

We also compare the accuracies obtained on questions, grouped by the corresponding grade level.

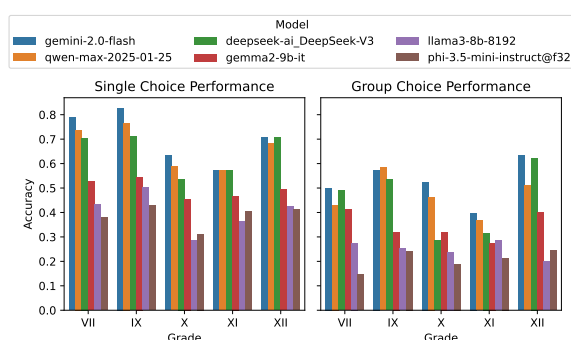


Figure 8: Accuracies of models, grouped by competition grade

As shown in Figure 8, models achieve the lowest scores on grades X and XI, while performing better on grades IX and XII. Performance on grade VII falls between these extremes.

Examining the curricula for these grade levels, we observe a correlation between subject focus and model accuracy. Grades IX and XII emphasize molecular biology and interactions between biological systems, while grades X and XI focus on the physiology and functions of biological systems (see examples in Figure 2). Grade VII provides a broad introduction, covering aspects of all these topics while also including basic principles of hygiene and health.

These results suggest that models perform better on topics related to molecular biology and genetics compared to those centered on the physiology of biological systems.

4.7 Accuracy by Stage

We compare the accuracies obtained on questions from the test split, grouped by the competition stage in which they were presented (local, regional, or national), and report the results in Figure 9.

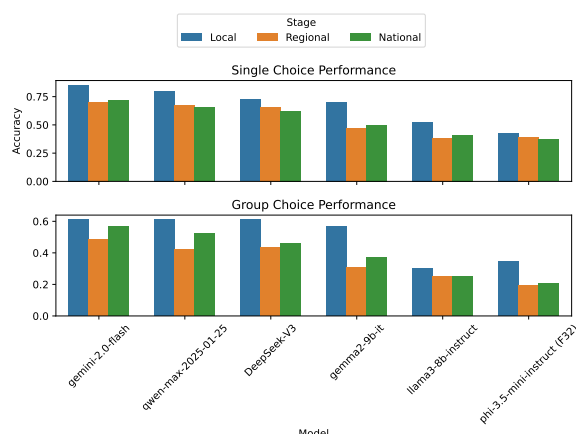


Figure 9: Accuracies of models on different competition stages.

For both single-answer and group-choice questions, models achieve the highest scores on the local stage, confirming that it is indeed the easiest of the three. For single-choice questions, the accuracy remains similar between the regional and national stages, suggesting comparable difficulty levels. However, for group-choice questions, models unexpectedly perform better on the national stage than on the regional stage, despite the expectation that the national stage should be more challenging.

4.8 Model Ensemble

Building on the LLM-Synergy framework proposed by Yang et al. (2023), who used Majority Weighted Voting to aggregate outputs from multiple LLMs for biomedical QA, we implemented a simplified ensemble learning strategy to enhance model performance on our dataset. Specifically, we created three groups of models with comparable individual accuracies: (1) top-performing models, (2) mid-range models, and (3) models fine-tuned on Romanian. Each group included three models, allowing us to use unweighted Majority Voting, as weighting would not affect the outcome. All

experiments were conducted under zero-shot settings and computed separately for single, group, and multiple-choice questions.

Table 6, 7, and 8 present the results of these ensemble experiments.

Although not by a significant difference, the Majority Voting surpassed the individual performances on group-choice questions in all of the chosen model subsets.

Model	Single	Group	Multiple
gemini-2.0-flash	0.733	0.524	0.585
qwen-max-2025-01-25	0.699	0.472	0.573
llama-3.1-405B-Instruct-Turbo	0.685	0.426	0.464
All of the above combined	0.719	0.534	0.560

Table 6: The accuracy of Majority Voting compared to the individual accuracies.

Model	Single	Group	Multiple
DeepSeek-V3	0.665	0.453	0.474
gemini-1.5-flash	0.668	0.419	0.406
llama-3.1-405B-Instruct-Turbo	0.685	0.426	0.464
All of the above combined	0.707	0.457	0.439

Table 7: The accuracy of Majority Voting compared to the individual accuracies.

Model	Single	Group	Multiple
eurolm-9b-instruct (F16)	0.384	0.220	0.102
rollama3-8b-instruct-imat (FP16)	0.371	0.235	0.102
romistral-7b-instruct (Q8)	0.371	0.252	0.077
All of the above combined	0.372	0.266	0.102

Table 8: The accuracy of Majority Voting compared to the individual accuracies.

4.9 Error Analysis

To explore common failure patterns in LLMs, we analyzed 75 questions that were incorrectly answered by all benchmarked models (24 single-choice, 8 group-choice, 43 multiple-choice).

We presented these questions to a medical student and observed that when asked to respond quickly, their responses often resembled those of the models. However, when given more time, the student changed several responses. This indicates a potential need for models to also ponder their responses, which we did not sufficiently investigate (using techniques like multi-turn prompting or thinking tokens).

Beyond this, we observed that models often rely on superficial associative reasoning. For instance, when prompted with “Hiperglicemia poate determina o:” (“Hyperglycemia can determine a:”), mod-

els alternated between “hyposecretion of insulin” and “hypersecretion of glucagon,” whereas the correct answer was “hyposecretion of glucocorticoids.” We hypothesize this results from a bias toward more frequently co-occurring hormone-glucose relations in public corpora, and a lack of exposure to nuanced clinical cases.

Models also struggle with traps involving lexical similarity or subtle qualifiers. All failed a question by confusing “bronhii” (bronchi) with “bronhiol” (bronchioles). In another, most selected “gravitational pull for veins located below the heart level” as promoting venous return, an incorrect answer due to the phrasing “below” instead of “above”. These patterns suggest a lack of deeper contextual reasoning.

5 Conclusion

This study introduced RoBiologyDataChoiceQA, a novel Romanian-language dataset designed to evaluate biology comprehension in large language models (LLMs). Sourced from the Romanian Biology Olympiad and medical school entrance exams, it provides a diverse and challenging benchmark for assessing domain-specific reasoning in a low-resource language.

Our benchmarking experiments revealed significant variations in model performance, highlighting both strengths and limitations of LLMs in specialized tasks. While some models performed well on structured, single-answer university questions, their ability to handle grouped-choice and reasoning tasks remained inconsistent. Fine-tuning Gemini 1.5 Flash and Gemma 2 9B Instruct improved accuracy in certain cases, demonstrating that targeted adaptation can be effective.

Beyond model evaluation, our study offers insights into the impact of prompt engineering, fine-tuning strategies, and dataset characteristics on LLM performance. These findings contribute to the broader effort of advancing NLP applications in non-English languages and scientific domains.

Future research should focus on expanding the dataset with fine-grained subdomain annotations, improving OCR processing, experimenting with other fine-tuning strategies and model architectures, and addressing dataset biases by comparing performance across question sources. Enhancing answer verification through expert validation will also be essential for benchmark reliability.

6 Limitations

While our study provides valuable insights into LLM performance on Romanian-language biology questions, several limitations should be considered when interpreting the results.

- **Limited computational resources** – Most experiments were conducted using a single NVIDIA RTX 3070 GPU (8 GB VRAM) paired with 32 GB of system RAM, along with external API and runtime providers. This constrained our ability to perform large-scale experimentation, including multiple training runs, broader hyperparameter sweeps, and evaluation of larger models.
- **Lack of fine-grained tagging** – The dataset does not include detailed annotations distinguishing specific biological subdomains (e.g., genetics, physiology, ecology). This limits the ability to analyze model performance at a more granular level and identify knowledge gaps in specialized areas.
- **Potential inaccuracies in answer keys** – Although we rely on authoritative sources, occasional ambiguities or errors in the provided answer keys may affect benchmarking accuracy. While we performed additional verification, some uncertainties remain.
- **Challenges with OCR-extracted data** – The dataset includes content extracted from scanned PDFs, particularly for university admission exams. Despite preprocessing and manual validation, some errors introduced by OCR remain, potentially affecting model training and evaluation.
- **Limited scope of fine-tuning experiments** While we observed improvements when fine-tuning Gemini 1.5 Flash and Gemma 2 9B Instruct, additional experiments with different architectures and training strategies could yield further insights. Exploring other Romanian-adapted models could provide a broader perspective.
- **Domain-specific biases in LLMs** – Our results suggest that models perform better on university admission questions than on Olympiad questions, likely due to differences in training data exposure. Investigating

whether this bias stems from pretraining corpora, difficulty of questions, or inherent reasoning limitations could further refine model evaluation.

- **Language vs. Domain Effects:** We do not perform a cross-lingual evaluation (e.g., testing models on an English version of the dataset or on other Romanian-language datasets) to isolate the impact of language from domain complexity. As such, we cannot fully disentangle whether observed model weaknesses stem primarily from Romanian language handling or from the specialized nature of biology. We leave this analysis to future work.
- **Potential Data Leakage:** We do not explicitly verify whether the dataset’s questions appear in the training data of the evaluated language models, particularly open-weight models. Due to the lack of transparency around training corpora and the impracticality of exhaustively checking large-scale pretraining data, this remains a potential source of data leakage. While API-based models’ training data are even less accessible, we acknowledge that possible overlap could bias performance results. We consider this an important caveat and encourage future work to investigate this aspect more thoroughly.

7 Ethical Statement

To promote transparency and responsible use, we release the dataset under the *Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0)* license. This license allows for non-commercial use, sharing, and adaptation with proper attribution.

No personally identifiable or sensitive information is included in the dataset. We encourage ethical research practices and responsible AI development when using our dataset. However, a potential risk is that it could inadvertently encourage the use of LLMs in biology exams for cheating, rather than for legitimate educational or research purposes. We urge users to adopt responsible policies to prevent misuse in academic settings.

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A Datasheet

A.1 Motivation for Dataset Creation

Why was the dataset created?

The dataset was developed to assess and enhance the performance of large language models (LLMs) on domain-specific tasks, specifically Romanian biology tests. It offers choice-based questions to evaluate LLM accuracy and can also be used for fine-tuning LLMs to understand specialized Romanian biology terminology.

What (other) tasks could the dataset be used for?

One potential application of this dataset is its use as training data for models designed to generate multiple-choice questions. Additionally, the dataset could be utilized for automatically assessing question difficulty.

A.2 Dataset Composition

What are the instances?

The instances consist of (single, group, or multiple) choice questions sourced from Romanian biology olympiads and college admission exam books. Each question is paired with its correct answer(s), extracted from the corresponding answer keys. Additional identifying information is also appended to each instance, as detailed in the following paragraphs.

Are relationships between instances made explicit in the data?

Yes, relationships between instances are explicitly marked. Using question identification metadata, instances can be grouped by attributes such as source, year, grade, and stage. When identical questions with identical answer options appear across different tests or problem sets, they are assigned a shared *dupe_id*.

Duplicates are retained rather than removed for several reasons:

- To analyze patterns of data repetition (e.g., identifying sources of inspiration between tests).
- To avoid arbitrarily deciding which instance to delete, leaving duplicate removal to the user’s discretion.

All known duplicates are included exclusively in the training split.

How many instances of each type are there?

The dataset contains a total of 14,109 extracted questions:

- Single choice: 6,021
- Group choice: 3,918
- Multiple choice: 4,170

Of these, 8,021 questions are sourced from biology olympiads, while 6,088 come from college admission books. The tests span multiple years (2004–2024), although they are not uniformly distributed.

What data does each instance consist of?

We will explain each field:

- **question_number** = an integer stored as string; for olympiads it takes values from 1 to 80. Most tests tend to have at most 60, but the very old ones (2004) do not quite respect the format. As for college admissions, those take values from 1 to 800 (not uniformly, there are tests/chapters with random number of questions, no general rule).

- **question** = the question text

- **type** - can be one of the following:

- *single-choice*: indicating the question has exactly one correct answer.
- *group-choice*: indicating that the answer is a single letter, which corresponds to a combination of options being true together:

A - if ONLY the options numbered by 1, 2 and 3 are correct

B - if ONLY the options numbered by 1 and 3 are correct

C - if ONLY the options numbered by 2 and 4 are correct

D - if ONLY the option numbered by 4 is correct

E - if ALL of the numbered options are correct

The group choice is the only type that has options identified by numbers, while the others have them identified by letters.

- *multiple-choice*: indicating that the answer is represented by any alphabetically ordered combination of the given options. Even though it is multiple, the answer CAN STILL be a single letter)

- **options** = a list of texts (usually statements or list of items) that in combination with the question text can be considered true or false. Olympiad tests have 4 options, while college admission tests have 5.

- **grade** = where the test/problem set was extracted from; it takes 6 values: *facultate* (college), *XII*, *XI*, *X*, *IX* (highschool), *VII* (middle school).

- **stage** = for college it is fixed on *admitere* (admission). For olympiad it represents the chain

of theoretical importance and difficulty: *locala* -> *judeteană* -> *natională* (local -> regional -> national).

- **year** = the year (as a string) in which the problem set/test was used in a competition

- **right_answer** = a letter for single-choice and group-choice (check the explanations above) and multiple (non-repeating) letters concatenated in a string with no other characters, in alphabetical order for multiple-choice.

- **source** = *olimpiada* (Olympiad of Biology in Romania) or, in the case of college, the university it was taken from (currently 3 possible values: *UMF Cluj*, *UMF Braşov*, *UMF Timişoara*)

- **id_in_source** = a string that has the purpose of further recognising the question within the problem set it was given, in case of ambiguity. Ensures uniqueness when combined with the other fields recommended for identifying the questions. Keep in mind that it contains spaces.

- **dupe_id** = a UUID that uniquely identifies a group of duplicated questions. The group may contain 2 or more instances. The instance is considered a duplicate if and only if both the question and options are the same (not necessarily in the same order for options). Two texts are considered the same if they are identical/use synonyms for common words/are obviously rephrased versions of each other. If a text adds extra words but besides that it is identical with another text, it is *not* marked as a duplicate.

For uniquely identifying a question/instance we recommend the following combination of fields:

$$\left\{ \begin{array}{l} \text{item['year'],} \\ \text{item['source'],} \\ \text{item['id_in_source'],} \\ \text{item['grade'],} \\ \text{item['stage'],} \\ \text{item['question_number']} \end{array} \right\}$$

Is everything included or does the data rely on external resources?

Everything is included.

Are there recommended data splits or evaluation measures?

The data is currently split into three: train, valid, test. We attempted a uniform distribution of the data, based on both quantity and quality of the data.

Both the *test* and *valid* splits were sampled via the recipe explained below.

First we do a grade-based separation:

- Grade XII: 175 questions
 - 75 national level
 - 100 state level
- Grade XI: 175 questions
 - 75 national level
 - 100 state level
- Grade X: 200 questions
 - 55 national level
 - 125 state level
 - 20 local level
- Grade IX: 250 questions
 - 115 national level
 - 115 state level
 - 20 local level
- Grade VII: 200 questions
 - 85 national level
 - 85 state level
 - 30 local level
- University Level (*Facultate*): 400 questions (detailed division below)
 1. *UMF Timișoara*: 200 questions
 - 11 chapters total, 18 questions per chapter, except for the *Nervous System*, which has 20 questions due to higher coverage.
 2. *UMF Brașov*: 75 questions
 - Derived from 15 questions from each synthesis test.
 3. *UMF Cluj*: 125 questions
 - *Physiology* (for medical assistant students): 8 questions (1 question per chapter for 5 chapters, plus 3 random questions)
 - *Anatomy* (for medical assistant students): 8 questions (same structure as *Physiology*)
 - *Physiology* (for medical students): 55 questions (4 questions from each of the first 13 chapters, plus 3 questions from Chapter 14)
 - *Anatomy* (for medical students): 54 questions

(similar to *Physiology*, but only 2 questions from Chapter 14)

Grade-Stage Yearly Distribution

The tables 9, 10, 11 present the yearly distribution of how many questions to select for each grade, per stage: “-” means no data was available for that year, while “X” means nothing was selected.

Note: While each split originally contained 1,400 questions (summing everything mentioned above), the validation and test splits have fewer questions than expected. Although duplicates were identified prior to splitting, an additional round of manual duplicate verification was conducted specifically for the validation and test sets. Newly identified duplicates were moved to the training split, reducing the size of the validation and test splits.

A.3 Data Collection Process

How was the data collected?

Olympiad data: Sourced from public online archives, primarily from *olimpiade.ro* (<https://www.olimpiade.ro/>). Additional data was retrieved through separate online searches when needed.

College admission books: Obtained from the internet. The collected data consists of PDFs, with some containing parsable text and others consisting of images that required additional processing.

Who was involved in the data collection process?

The PDF data was collected by our team, with guidance from medical students who provided valuable insights on where to locate the relevant materials.

Over what time-frame was the data collected?

It took roughly one month to collect the data.

How was the data associated with each instance acquired?

	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
VII	-	-	-	-	-	5	5	7	8	8	12	15	15	-	-	-	-	-	-	-	-
IX	2	2	-	-	4	4	-	5	5	5	8	8	8	-	10	12	-	-	12	15	15
X	-	-	-	-	-	-	-	-	-	-	3	3	4	-	5	7	-	-	8	10	15
XI	-	-	-	-	-	-	-	-	-	-	5	5	7	-	8	8	-	-	12	15	15
XII	-	-	-	-	-	-	-	-	-	-	5	5	7	-	8	8	-	-	12	15	15

Table 9: Number of questions to select in test/validation data for each grade in every year from the **national** stage of the olympiad.

	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
VII	-	-	-	-	-	5	5	7	8	12	13	15	-	-	-	-	-	-	-	-	-
IX	1	1	-	-	1	2	2	3	3	3	4	4	6	8	10	12	12	-	13	15	15
X	-	-	-	-	-	-	-	-	-	-	5	5	6	8	10	12	14	-	20	20	25
XI	-	-	-	-	-	-	-	-	-	-	4	4	6	8	8	12	14	-	14	15	15
XII	-	-	-	-	-	-	-	-	-	-	4	4	6	8	8	12	14	-	14	15	15

Table 10: Number of questions to select in test/validation data for each grade in every year from the **regional** stage of the olympiad.

The data was initially collected as PDF files. To standardize the format, a Word-to-PDF converter was sometimes used. The PDFs either contained parsable text or had text embedded in images. While the quality of some images was questionable, most of the information was successfully recognized.

For PDFs with parsable text, Python libraries were used for data extraction, with occasional manual verification and refactoring. For PDFs containing images, Gemini 1.5 Flash was employed to extract the data. Random sampling was performed to verify the accuracy of the extracted data.

Does the dataset contain all possible instances?

No. Some olympiads, although we know for sure existed, were not found on the internet. Additionally, there is more data collected in PDF format that has not yet been parsed into actual instances.

If the dataset is a sample, then what is the population?

The population includes additional college admissions and olympiads from Romania that can be found and parsed. It can also contain closely related national contests that feature choice-based questions, which could be included.

Is there information missing from the dataset and why?

Questions that included images/figures were removed as this is not a multi-modal dataset (at the moment).

Are there any known errors, sources of noise, or redundancies in the data?

There are several potential sources of error and redundancy in the data:

- *Parsing issues:* Questions with options represented as tables might have been parsed incorrectly. Some parsing errors may result in typos (e.g., words broken into two segments) or missing words at the end of an option. Many of these errors have been manually corrected, especially in the test split, which should be free of such issues.
- *Image noise:* The images for college admissions can present noise, but Gemini 1.5 Flash processed them relatively well. Some hallucinations may still exist, although we manually searched for them.
- *Duplicates:* Some questions and options are duplicated across different problem sets or even within the same source. We have marked the obvious duplicates, but repetition of questions and answer options could still occur.
- *Answer errors:* Some answers might be wrong due to parsing errors or LLM hallucinations. Although we have manually checked every parsed answer, human error is still a possibility. Additionally, there could be mistakes in the original answer sheets, where wrong answers may have been transcribed. Despite thorough checks (as the collected data is from national contests with official sources), it is

	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
VII	X	-	-	-	-	X	X	-	X	X	X	X	X	15	15	-	-	-	-	-	-
IX	X	-	-	-	-	X	-	-	X	X	X	X	X	15	15	-	-	-	-	-	-
X	X	-	-	-	-	X	-	-	X	X	X	-	X	10	10	-	-	-	-	-	-
XI	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
XII	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Table 11: Number of questions to select in test/validation data for each grade in every year from the **local** stage of the olympiad.

possible that a few incorrect answers might have slipped through.

- *Image dependent questions*: We have tried to filter out any question that was dependent on a figure, as we do not intend for the dataset at the moment to be multi-modal, but some questions might have slipped through. This is possible only for the olympiad questions.

A.4 Data Pre-processing

What pre-processing/cleaning was done?

After extraction, several pre-processing and cleaning steps were applied to standardize and structure the data:

1. Extracted the question number from the question text and placed it in a separate field.
2. Standardized option identifiers to uppercase letters.
3. Ensured all options followed the structure: "[identifier]. [text]", where [identifier] is either a letter (A–D, or A–E for five-option lists) or a number (1–4 for group-choice questions).
4. Replaced multiple spaces with a single space.
5. Replaced newline characters with spaces.
6. Standardized quotes by replacing Romanian quotation marks with English ones.
7. Normalized diacritics to proper Romanian characters (e.g., ș, ț, â, ă).
8. Manually corrected grammar issues and typos.
9. Removed trailing characters such as commas, dots, spaces, and semicolons from option texts.
10. Made Gemini 1.5 Flash act as a grammar correcting tool to help us further find typos. Manually checked the output of it as the LLM has a tendency to replace words besides the typos. (Also used Gemma-2-9B when Gemini 1.5 Flash was unavailable).

Was the “raw” data saved in addition to the preprocessed/cleaned data?

The PDF files are saved privately.

Is the pre-processing software available?

No.

Does this dataset collection/processing procedure achieve the motivation for creating the dataset stated in the first section of this datasheet?

This dataset successfully provides specialized (Romanian) biology terms that can be used for training or knowledge evaluation.

B Prompts

User Prompts Used for Benchmarking

Single Choice

%question-text%

You received a biology question in Romanian with multiple options. The biology question is collected from either national high school olympiads or admission exams for medical universities. Only one answer is correct.

You will output only the letter of the right answer. Do not give any explanations.

The letter of the right answer is:

Group Choice

%question-text%

You received a biology question in Romanian with multiple numbered options. The question is from national high school olympiads or medical university admission exams.

To answer:

1. Identify correct options.
2. If only option 4 is correct, the answer must be D.
3. If only options 1,3 are correct, the answer must be B.
4. If only options 2,4 are correct, the answer must be C.
5. If only options 1,2,3 are correct, the answer must be A.
6. If all options are correct, the answer must be E.

Do not give any explanations.

The right answer is:

Multiple Choice

%question-text%

You received a biology question in Romanian with multiple options. The question is from national high school olympiads or medical university admission exams. One or multiple answers are correct.

You will output the letter(s) of all the correct answers. Do not give any explanations.

The letters of the right answers, as compact as possible, are:

System Prompts Used for Benchmarking

We include only five-shot prompts; one- and three-shot follow the same format with fewer questions. The displayed prompts use translated questions, but LLMs receive the original Romanian versions.

Single Choice - Five Shot

Here are some examples of biology questions in Romanian with multiple options and the correct format for answering them:

Question: The prokaryotic cell:

- A. characterizes viruses, bacteria, and blue-green algae
- B. contains peptidoglycan in the composition of the cell membrane
- C. does not have a cell wall
- D. the nuclear material is a circular double-stranded DNA molecule

Answer: D

— # Question: The mesosomes of prokaryotes:

- A. have a role in respiration
- B. are made up of rRNA and proteins
- C. are invaginations of the plasma membrane in the form of lamellae
- D. have a role in photosynthesis

Answer: A

— # Question: The sciatic nerve:

- A. is a cranial nerve
- B. contains only motor fibers
- C. contains both sensory and motor fibers
- D. originates in the medulla oblongata

Answer: C

— # Question: Contain hydrolytic enzymes with a role in intracellular digestion:

- A. ribosomes
- B. lysosomes
- C. centrosome
- D. centrioles

Answer: B

— # Question: Photosynthetic plastids are:

- A. oleoplasts
- B. leucoplasts
- C. rhodoplasts
- D. amyloplast

Answer: C

Group Choice - Five Shot

Here are some examples of biology questions in Romanian with multiple numbered options and the correct format for answering them:

Question: Organic substances with a structural role include:

- 1. lipids
- 2. carbohydrates
- 3. proteins
- 4. nucleic acids

Explanation: 1,3 are correct; 2,4 are not

Answer: B

— # Question: The fundamental substance is present in the structure of:

- 1. mitochondria
- 2. chloroplasts
- 3. the nucleus
- 4. vacuoles

Explanation: 1,2,3 are correct; 4 is not

Answer: A

— # Question: The nucleolus:

- 1. is surrounded by its own membrane
- 2. is the densest part of the nucleus
- 3. is the site of mRNA synthesis
- 4. its volume depends on the physiological state of the cell

Explanation: 2,4 are correct; 1,3 are not

Answer: C

— # Question: The granum of chloroplasts:

- 1. is found freely in the stroma
- 2. contains DNA, RNA, proteins, and metals
- 3. is surrounded by a double porous membrane
- 4. contains photosynthetic pigments

Explanation: 4 is correct; 1,2,3 are not

Answer: D

— # Question: The interphase:

- 1. represents the time interval between two successive cell divisions
- 2. is characterized by DNA, RNA, and protein synthesis
- 3. is the most metabolically active stage
- 4. precedes the division phase of the cell cycle

Explanation: 1,2,3,4 are correct

Answer: E

Multiple Choice - Five Shot

Here are some examples of biology questions in Romanian with multiple options and the correct format for answering them:

Question: The heart:

- A. has the mitral valve between the right atrium and right ventricle
- B. is equipped with trabeculae in the atria
- C. is a parenchymatous organ due to its strong ventricular musculature
- D. is equipped with 2 valves
- E. contains the His bundle, which plays a role in automatism with a discharge frequency of 25 impulses/min

Answer: E

— # Question: The right atrium is characterized by:

- A. containing the sinoatrial node
- B. having trabeculae inside

- C. receiving the inferior venae cavae
 - D. having a systole duration of 0.1s
 - E. being the site where pulmonary veins open
- # Answer: ACD

Question: The following associations are correct:

- A. chordae tendineae - atrioventricular valves
- B. sinoatrial node - interatrial septum
- C. cardiac cycle - 0.8s at a heart rate of 100 beats/min
- D. venous pressure at the level of the right atrium is 10 mmHg
- E. tricuspid valve - right atrioventricular orifice

Answer: AE

Question: Arteries that originate directly from the subclavian artery include:

- A. external carotid
- B. vertebral
- C. brachial
- D. internal thoracic
- E. anterior intercostal

Answer: BD

Question: The pulmonary veins:

- A. are two in number
- B. open into the left atrium, which contains the sinoatrial node
- C. are part of the small circulation, which begins in the right ventricle
- D. bring oxygenated blood to the heart from the alveolar-capillary membrane, which has an average thickness of 0.6 microns
- E. like the venae cavae, bring venous blood into the atria

Answer: CD

Mind the (Language) Gap: Towards Probing Numerical and Cross-Lingual Limits of LVLMs

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<https://huggingface.co/datasets/DIALab/MMCricBench>

Abstract

We introduce MMCRICBENCH-3K, a benchmark for Visual Question Answering (VQA) on cricket scorecards, designed to evaluate large vision-language models (LVLMs) on complex numerical and cross-lingual reasoning over semi-structured tabular images. MMCRICBENCH-3K comprises 1,463 synthetically generated scorecard images from ODI, T20, and Test formats, accompanied by 1,500 English QA pairs. It includes two subsets: MMCRICBENCH-E-1.5K, featuring English scorecards, and MMCRICBENCH-H-1.5K, containing visually similar Hindi scorecards, with all questions and answers kept in English to enable controlled cross-script evaluation. The task demands reasoning over structured numerical data, multi-image context, and implicit domain knowledge. Empirical results show that even state-of-the-art LVLMs, such as GPT-4o and Qwen2.5VL, struggle on the English subset despite it being their primary training language and exhibit a further drop in performance on the Hindi subset. This reveals key limitations in structure-aware visual text understanding, numerical reasoning, and cross-lingual generalization. The dataset is publicly available via Hugging Face at <https://huggingface.co/datasets/DIALab/MMCricBench>, to promote LVLM research in this direction.

1 Introduction

Text-centric visual question answering (VQA) has seen considerable progress with benchmarks such as TextVQA (Singh et al., 2019b), ST-VQA (Xia et al., 2023), DocVQA (Mathew et al., 2021), VisualMRC (Tanaka et al., 2021), and OCR-Bench (Liu et al., 2024c), which evaluate models on tasks requiring OCR-based understanding and textual reasoning. More recently, tabular VQA datasets like TableVQA-Bench (Kim

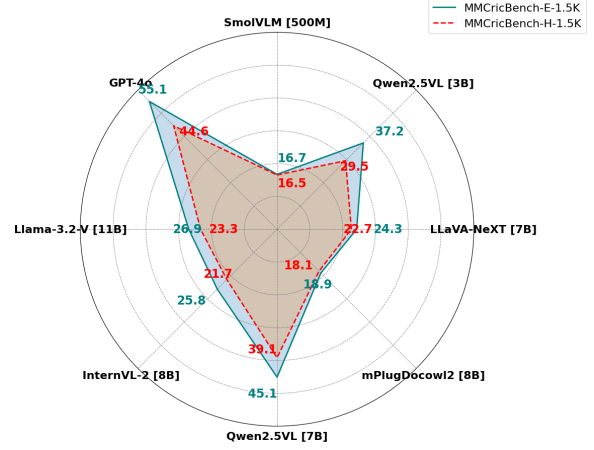


Figure 1: LVLm performance on MMCRICBENCH-E-1.5K (English) and MMCRICBENCH-H-1.5K (Hindi) cricket scorecards. While accuracy on English scorecards peaks at 55.1%, performance on visually similar Hindi scorecards remains consistently lower, highlighting a persistent gap in cross-lingual structure-aware numerical reasoning over images.

et al., 2024), TabComp (Gautam et al., 2025), and ComTQA (Zhao et al., 2024) have introduced structure-aware challenges focusing on numerical reasoning and table comprehension. However, as summarized in Table 1, these benchmarks often fall short in one or more dimensions: they are primarily monolingual (mostly English), lack multi-image contextual reasoning, and offer limited evaluation of fine-grained domain-specific numerical reasoning.

Cricket scorecard images, on the other hand, represent a compelling testbed for evaluating such capabilities. These semi-structured layouts combine tabular numeric data (runs, overs, wickets) with implicit contextual information (e.g., Which bowler has bowled the most wides in the match? Q3 in Figure 2), sometimes spanning across multiple images. In this work, we introduce MMCRICBENCH-3K, a novel benchmark for visual question answering on cricket score-

*Equal contribution.

England (Batting 1st Innings)						
Batsman Name	Bowler/Catcher	Runs	Balls	4s	6s	Strike Rate
Tom Banton	lbw b Santner	31	20	4	1	155.0
Jonny Bairstow	c Mitchell b Santner	8	9	1	0	88.89
David Malan	not out	103	51	9	6	201.96
Eoin Morgan	c Mitchell b Southee	91	41	7	Q3	221.95
Sam Billings	not out	0	1	0	0	0.0
Extras (lb 3, b 0, w 3, nb 2)		8				
Total		Q2 241				

New Zealand (Bowling 1st Innings)						
Bowler Name	Over	Maiden	Runs	Wicket	Economy	0s 4s 6s WD NB
Trent Boult	4.0	0	35	0	8.75	11 4 2 0 0
Tim Southee	4.0	0	47	1	11.75	5 6 1 0 0
Mitchell Santner	4.0	0	32	2	8.0	10 1 2 2 1
Blair Tuckner	4.0	0	50	0	12.5	5 6 2 0 1
Ish Sodhi	3.0	0	49	0	16.33	1 3 4 0 0
Daryl Mitchell	1.0	0	25	0	25.0	1 1 3 1 0

England (Batting 2nd Innings)						
Batsman Name	Bowler/Catcher	Runs	Balls	4s	6s	Strike Rate
Martin Gupthill	c Malan b TK Curran	27	14	1	3	192.86
Colin Munro	c Brown b Parkinson	30	21	3	0	142.86
Tim Seifert	c TK Curran b Jordan	3	4	0	0	75.0
Colin de Grandhomme	c Banton b Parkinson	7	3	0	1	233.33
Ross Taylor	c Banton b Brown	14	10	0	1	140.0
Daryl Mitchell	c Jordan b Parkinson	2	5	0	0	40.0
Mitchell Santner	c Billings b SM Curran	10	8	1	0	125.0
Tim Southee	lbw b Parkinson	39	15	2	4	260.0
Ish Sodhi	run out (Jordan)	9	7	0	1	128.57
Trent Boult	b Jordan	8	8	1	0	100.0
Blair Tuckner	not out	5	6	0	0	83.33
Extras (lb 3, b 0, w 8, nb 0)		11				
Total		165				

New Zealand (Bowling 2nd Innings)						
Bowler Name	Over	Maiden	Runs	Wicket	Economy	0s 4s 6s WD NB
Sam Curran	4.0	0	36	1	9.0	8 2 1 2 0
Tom Curran	3.0	0	26	1	8.66	3 2 1 0 0
Chris Jordan	2.5	0	24	2	8.47	7 1 2 1 0
Matt Parkinson	4.0	0	47	4	11.75	9 2 5 0 0
Pat Brown	3.0	0	29	1	9.66	4 1 1 5 0

Q1 : What is Colin Munro's strike rate?

A1 : 142.86 ✓

Q2 :How many batsmen have been dismissed for a duck?

A2 : 1 ✗

Q3 : How many batsmen had a strike rate greater than 70 in the first innings?

A3 : 4 ✓

Q1 : What is Colin Munro's strike rate?

A1 : 142.86 ✓

Q2 : How many batsmen have been dismissed for a duck?

A2 : 1 ✗

Q3 : How many batsmen had a strike rate greater than 70 in the first innings?

A3 : 3 ✗

Figure 2: Examples of LVLMS (dis)parity between MMCricBENCH-E-1.5K and MMCricBENCH-H-1.5K. Example predictions by Qwen2.5VL-7B on English (left) and Hindi (right) scorecards. Q1 is a simple retrieval question, correctly answered in both cases. Q2 requires structure-aware, domain-specific reasoning, leading to failure in both. Q3 reveals a cross-lingual gap answered correctly on the English scorecard but incorrectly on the Hindi one, despite identical content.

cards, designed to evaluate the *structure-aware*, *mathematical*, *multi-image*, and *cross-lingual* reasoning capabilities of large vision-language models (LVLMS). MMCricBENCH-3K comprises 1,463 synthetically generated scorecard images (822 single-image and 641 multi-image examples), along with 1,500 English QA pairs. It includes two subsets: MMCricBENCH-E-1.5K (English scorecards) and MMCricBENCH-H-1.5K (Hindi scorecards), with all questions and answers provided in English to enable controlled evaluation across script variations.

Large Vision-Language Models (LVLMS) (LLaVA-1.5 (Liu et al., 2024b), MiniGPT4 (Chen et al., 2023), mPLUG-Owl (Ye et al., 2024), Qwen-VL (Wang et al., 2024), and InternVL2 (Chen et al., 2024)) have become the de facto approaches for visual question answering tasks, including

text-aware visual tasks (Penamakuri and Mishra, 2024a). Recent LVLMS such as Qwen2.5VL (Bai et al., 2025), mPLUG-DocOwl2 (Hu et al., 2024), InternVL2 (Chen et al., 2024), and TextMonkey (Liu et al., 2024d) have further advanced the bar on text-aware tasks, including VQA, by incorporating text-aware objectives into their pretraining or instruction-tuning stages. While studies exist to show strong performance of these models on English benchmarks, similar studies to understand their robustness across low-resource languages like Hindi¹ remains unexplored in the literature.

To this end, we leverage our MMCricBENCH-H-1.5K benchmark to understand and evaluate cross-lingual mathematical reasoning abilities of

¹Hindi as a textual language is not a low-resource language, however, when we look at visual text space, Hindi is a low-resource language.

LVLMS. Our experiments reveal a consistent performance drop when these LVLMS are evaluated on MMCRICBENCH-H-1.5K (As illustrated in Figure 1), highlighting significant shortcomings in structure-aware, cross-lingual, and intensive numerical reasoning. Although advanced paradigms like Chain-of-Thought (CoT) prompting improve performance over naive variant, they still fall short compared to their performance on English scorecards.

In summary, our contributions are three-fold: (i) We introduce MMCRICBENCH-3K, a novel structure-aware text-centric VQA benchmark to cover for the shortcomings of existing OCR and table-based VQA benchmarks by incorporating cross-lingual, multi-image, structure-aware, and numerically rich reasoning tasks grounded in the domain of cricket analytics. (ii) We comprehensively benchmark a range of leading LVLMS (open and closed-source) across different model sizes and show that they struggle on this benchmark, revealing key limitations in structure-aware visual understanding, numerical reasoning, and cross-lingual robustness. (iii) We conduct extensive ablations incorporating specialized components such as Optical Character Recognition (OCR), Table Structure Recognition (TSR), and advanced prompting strategies including Chain-of-Thought (CoT) reasoning. While these methods improve performance, they still fall short compared to the model’s strong results on conventional text-centric benchmarks, highlighting the unique difficulty of our task.

2 MMCRICBENCH-3K Dataset

We introduce MMCRICBENCH-3K, a novel dataset designed to study a visual question answering (VQA) task on cricket scorecard images. Cricket scorecard images represent unstructured yet complex tabular images. VQA on such scorecards requires structural understanding, numerical data extraction, and implicit contextual reasoning across image(s). To the best of our knowledge, our work is the first principled work on studying VQA over cricket scorecard images. Specifically, we present two sub-benchmarks under MMCRICBENCH-3K: MMCRICBENCH-E-1.5K (with English scorecards) and MMCRICBENCH-H-1.5K (with Hindi scorecards), with English question-answer annotations. This dataset is aimed at benchmarking

the capabilities of Large Vision-Language Models (LVLMS) in performing cross-lingual deep mathematical reasoning over semi-structured content.

MMCRICBENCH-3K consists of cricket scorecards sourced from various international game formats: ODI, T20, Test Match, and popular regional leagues: the Big Bash League (BBL, Australia) and the Indian Premier League (IPL, India). We provide carefully curated QA annotations to evaluate the numerical comprehension and deep mathematical reasoning abilities of LVLMS. Next, we explain the dataset curation pipeline.

Data Collection and Annotation: We begin to collect data for our benchmark by identifying publicly available datasets and repositories that contain cricket scorecard information. The initial dataset was obtained from Kaggle², which provides detailed cricket match statistics in CSV format. This dataset includes essential match statistics such as runs, wickets, and strike rates across different cricket formats (international game formats and regional leagues). Note that the data curated from the above-mentioned source does not contain scorecard images.

Scorecard Image Generation: We employed the open-source library Weasy Print³ to convert CSV records into visually coherent scorecard tables. The generation process was inspired by design templates from various publicly accessible sports websites, ensuring diversity in fonts, styles, and table structures. We generated two distinct types of scorecard visualizations to support different VQA scenarios: (i) single-image scorecards for limited-overs formats (ODI, T20, and league matches) containing both innings in one comprehensive image, and (ii) multi-image scorecards for Test matches, where each image contains one inning, resulting in n images per match where n is the number of innings in the match. This dual approach allows us to evaluate both standard single-image VQA capabilities and more complex multi-image reasoning where models must synthesize information across multiple visual inputs. The multi-image format particularly challenges models to maintain contextual awareness and perform cross-referential numerical reasoning across separate visual sources. Each scorecard image contains semi-structured tabular information such as player names, runs, balls faced, boundaries, and

²<https://www.kaggle.com/datasets/raghuvansht/cricket-scorecard-and-commentary-dataset>

³<https://weasyprint.org/>

Category	Category Name	Example Question
C1	Direct Retrieval & Simple Inference	Which bowler has bowled the most wides in the match? Who got out for a duck in the first innings? Did any bowler take a 4-fer in the match? Has [Batsman X] taken more wickets than [Batsman Y]? Which bowler has conceded the most extras? Who has hit the maximum sixes? Does [Batsman X] hit more sixes than [Batsman Y]? How many extras were bowled in the first innings?
C2	Basic Arithmetic Reasoning & Conditional Logic	What is [Batsman X] strike rate? Did [Batsman X] score better in the first innings or the second innings? Which batsman scored a century in the match? Which bowler took a 4-fer in the match? Has [Batsman X] hit more boundaries than [Batsman X]? Which batsman was dismissed for a golden duck in the match?
C3	Multi-step Reasoning & Quantitative Analysis	Which batsman had the highest strike rate (minimum 10 balls faced)? Which batsman had the highest boundary percentage? Which bowler had the better economy rate in the first innings? Which innings had the higher run rate? Which batsman had a strike rate greater than 70 in the first innings? Has the same fielder caught any batsman twice? Has any batsman been dismissed twice by the same bowler?

Table 2: Category and example questions. A full table containing statistics for each one of the single-image and multi-image questions is provided in the Appendix (Table A.4).

using: $\text{Strike Rate} = \frac{\text{Runs}}{\text{Balls}} \times 100$. The model must correctly localize relevant cells, extract values, and apply the correct reasoning. **(iii) Multi-step Reasoning & Quantitative Analysis - C3:** This task involves combining information across multiple players or sections in the scorecard. For instance, to answer: “*Who has the highest boundary percentage?*”, the model needs to compute $\frac{(4s \times 4 + 6s \times 6)}{\text{Total Runs}} \times 100$ for each player and select the maximum. This requires layout-aware text extraction, numerical computation, and multi-row comparison across the image.

Few question templates across the three categories are shown in Table 2. Detailed questions and statistics under all three categories are shown in Appendix A.4.

Answer Extraction via SQL: To ensure accuracy and consistency in answer generation, we used SQL queries to derive answers directly from the structured CSV data. This approach minimized manual errors and ensured the traceability of answers back to the original data. The SQL queries were formulated based on the question type and corresponding data structure. For instance:

- To retrieve highest boundary percentage:

```
SELECT Batsman_Name FROM batting
WHERE Innings = 1 AND Balls > 0
ORDER BY ((([4s]*4 + [6s]*6) * 100.0 / Runs)) DESC LIMIT 1;
```

- To retrieve better economy rate in innings 1:

```
SELECT Bowler_Name, ROUND((SUM(Runs)
* 1.0 / SUM(Over)), 2) AS Economy_Rate
FROM bowling WHERE Innings = 1 GROUP
BY Bowler_Name ORDER BY Economy_Rate
ASC LIMIT 1;
```

SQL queries for every question template in MMCRCIBENCH-3K are shown in Table 12 in the Appendix. Further, the question-answer pairs are subjected to manual verification for possible factual and mathematical errors.

Further, we categorized answers into four categories, namely, (i) Binary (Yes/No), (ii) Numerical, (iii) Categorical (1/2/3/4 for innings-based questions), and (iv) Open-ended (Person names). Detailed statistics of MMCRCIBENCH-3K for are shown in the Figure 6 (a). Further, a selection of a few QA samples for each of the answer categories is shown in Table 9 in the Appendix.

3 Experiments

Baselines. We chose the VLMs from three selection criteria: (a) **VLMs with no OCR-aware tasks** during their pretraining or instruction tuning stages: LLaVA-Next (Liu et al., 2024a), and (b) **VLMs based on the size of their parameters:** (i) *Small VLMs (SVLMs)* with parameters less than 5B: SmolVLM-500M (Marafioti et al., 2025), Qwen2.5VL-2B (Wang et al., 2024), (ii) *Large*

Model [#params]	MMCriBench-E-1.5K				MMCriBench-H-1.5K				$\Sigma \uparrow$	$\Delta \downarrow$	
	C1	C2	C3	Avg.	C1	C2	C3	Avg.			
Open-source											
Small VLM ($\leq 3B$ params)											
SmolVLM [500M]	19.5	21.6	15.9	19.2	20.4	12.9	24.3	19.0	19.1	0.2	
Qwen2.5VL [3B]	38.7	40.1	41.7	40.2	39.8	24.5	35.5	33.3	36.8	6.9	
Large VLM (params $>3B$ and $<10B$)											
LLaVA-NeXT [7B]	40.2	10.8	33.9	28.3	35.7	10.8	33.3	26.6	27.4	1.7	
mPlugDocowl2 [8B]	33.9	13.9	14.2	20.7	33.6	13.7	12.3	19.9	20.3	0.8	
Qwen2.5VL [7B]	64.6	52.1	30.6	49.1	62.7	39.8	25.2	42.6	45.8	6.5	
InternVL-2 [8B]	33.6	26.3	28.2	29.4	28.5	16.4	25.2	23.4	26.4	6.0	
X-Large VLM ($>10B$)											
Llama-3.2-V [11B]	26.7	35.3	19.8	27.3	25.2	26.9	22.2	24.8	26.0	2.5	
Closed-source											
GPT-4o	56.0	65.1	50.6	57.3	54.6	49.7	30.9	45.1	50.5	12.2	

Table 3: Results on single-image questions split of MMCRIBENCH-3K.

Method [#params]	MMCrIBench-E-1.5K				MMCrIBench-H-1.5K				$\Sigma \uparrow$	$\Delta \downarrow$
	C1	C2	C3	Avg.	C1	C2	C3	Avg.		
LLMs+OCR										
Llama-3.2 [3B]	32.1	31.4	22.8	28.8	24.1	7.4	18.3	16.6	22.7	12.2
Qwen2.5 [3B]	36.6	31.4	16.5	28.2	34.2	13.1	13.5	20.3	24.2	7.9
VLMs Chain-of-Thought										
Qwen2.5VL [7B]	69.1	55.7	36.0	53.6	65.2	40.7	31.5	45.8	49.7	7.8

Table 4: Results on single-image of our ablation: LLMs+OCR vs VLMs on MMCRIBENCH-3K.

VLMs (LVLMs) with parameters between 5B-14B: InternVL2-8B (Chen et al., 2024), Qwen2.5VL-7B (Bai et al., 2025), mPLUG-DocOwl2 (Hu et al., 2024), (c) *X-Large VLMs* with parameters greater than 14B: Llama-3.2-V-11B (Grattafiori et al., 2024) and (iii) **closed-source VLMs**: GPT-4o (OpenAI, 2024).

3.1 Result and Discussion

Performance of Open-Source Models Across Scales: Tables 3 and 5 present results for single-image and multi-image setups, revealing a consistent trend: model scale has a notable impact on performance across all question categories. Larger models generally outperform their smaller counterparts, with more pronounced gains on complex reasoning categories such as C2 (arithmetic) and C3 (multi-hop reasoning). For instance, Qwen2.5VL-7B (Bai et al., 2025) significantly outperforms its smaller 3B variant across all settings, with an average performance gap of 8.5 points. While this scaling advantage is particularly evident in higher-complexity tasks, the gains are less pronounced on simpler C1 (retrieval-based) questions, as expected.

Closed-Source vs Open-Source Models: Closed-

source models, notably GPT-4o, consistently outperform open-source models across both the English (MMCRIBENCH-E-1.5K) and Hindi (MMCRIBENCH-H-1.5K) subsets. On single-image questions, GPT-4o achieves the highest average accuracy of 57.3% on English and 45.1% on Hindi, while in the multi-image setting, it scores 50.6% on English and 43.6% on Hindi. This reflects a clear cross-lingual drop of 12.2 and 7.0 points in the single- and multi-image settings, respectively. Although GPT-4o is not immune to the challenges posed by script variation, it still outperforms the closest open-source model Qwen2.5VL-7B by an average margin of 8.2 points across all tasks and subsets. These results highlight the robustness gap that remains between open and closed-source models, particularly in structured, cross-lingual VQA settings.

Comparison of cross-lingual capabilities: Models consistently exhibit a significant performance drop when transitioning from English to Hindi scorecards, particularly in categories requiring arithmetic reasoning (C2) and multi-step reasoning (C3). This decline highlights the limitations of cross-lingual generalization that scaling alone fails to address. For instance, GPT-4o, the strongest

Model [#params]	MMCriBench-E-1.5K				MMCriBench-H-1.5K				$\Sigma \uparrow$	$\Delta \downarrow$
	C1	C2	C3	Avg.	C1	C2	C3	Avg.		
Open-source										
<i>Small VLM ($\leq 3B$ params)</i>										
SmolVLM [500M]	14.4	10.8	10.2	11.8	20.0	6.0	9.0	11.6	11.7	0.2
Qwen2.5VL [3B]	34.1	35.3	24.1	31.2	27.5	19.8	18.7	22.0	26.6	9.2
<i>Large VLM (params $>3B$ and $<10B$)</i>										
LLaVA-NeXT [7B]	27.5	6.6	14.4	16.2	24.5	5.4	14.5	14.8	15.5	1.4
mPlugDocowl2 [8B]	24.7	7.5	13.2	15.2	23.3	7.1	12.6	14.4	14.8	0.8
Qwen2.5VL [7B]	41.9	41.9	27.1	37.0	37.7	33.5	25.3	32.2	34.6	4.8
InternVL-2 [8B]	29.3	5.4	21.1	18.6	28.1	4.8	21.7	18.2	18.4	0.4
<i>X-Large VLM ($>10B$)</i>										
Llama-3.2-V [11B]	34.7	14.3	29.5	26.2	29.3	11.3	20.4	20.4	23.3	5.8
Closed-source										
GPT-4o	50.3	61.1	40.4	50.6	39.5	53.8	37.3	43.6	47.1	7.0

Table 5: Results on multi-image questions split of MMCRICBENCH-3K.

Method [#params]	MMCrBench-E-1.5K				MMCrBench-H-1.5K				$\Sigma \uparrow$	$\Delta \downarrow$
	C1	C2	C3	Avg.	C1	C2	C3	Avg.		
LLMs+OCR										
Llama-3.2 [3B]	24.5	17.9	25.9	22.8	18.5	1.8	14.4	11.6	17.2	11.2
Qwen2.5 [3B]	30.5	24.5	27.7	27.6	23.3	10.7	22.8	19.0	23.3	8.6
VLMs Chain-of-Thought										
Qwen2.5VL [7B]	40.7	40.7	22.9	34.8	36.5	29.9	23.5	30.0	32.4	4.8

Table 6: Results on multi-image of our ablation: LLMs+OCR vs VLMs on MMCRICBENCH-3K.

overall performer shows a substantial drop of 12.2 points (single-image) and 7.0 points (multi-image) on average when evaluated on Hindi scorecards. Similarly, Qwen2.5VL-7B experiences a 6.5 to 6.9 point decrease across both subsets. These degradations indicate that even state-of-the-art models with strong English capabilities are not robust to script variation in visually embedded text. Our findings suggest that effective VQA on cricket scorecards requires a combination of table structure understanding, OCR, and visual text grounding capabilities that current models struggle to achieve in non-Latin scripts and low-resource visual text languages like Hindi.

3.1.1 Ablations

LLMs + OCR: To isolate the role of visual perception in scorecard-based VQA, we evaluate a baseline that combines OCR with text-only large language models (LLMs). Specifically, we extract text from scorecard images using the Tesseract OCR engine (Smith, 2007) and feed the output into two LLMs: LLaMA-3.2-3B (Dubey et al., 2024) and Qwen2.5-3B (Yang et al., 2024). This setting evaluates whether textual cues alone are sufficient to reason over cricket scorecards. As shown in Tables 4 and 6, both models perform sig-

nificantly worse than vision-language models. On average across MMCRICBENCH-3K, LLaMA-3.2-3B exhibits a performance drop of 4.7%, while Qwen2.5-3B shows a much larger drop of 16.5% compared to their vision counterparts. These results highlight the limitations of OCR+LLM pipelines: despite having access to textual input, these models struggle to capture structural cues such as column alignment and row grouping that are essential for tabular reasoning. The English-Hindi gap remains wide, showing that OCR-based pipelines struggle in cross-lingual, visually complex settings.

CoT Prompting vs. Regular Prompting: Applying Chain-of-Thought (CoT) prompting to Qwen2.5VL-7B improves overall performance in the single-image setting, with accuracy increasing from 45.8% to 49.7%. This gain is especially notable in reasoning-heavy categories such as arithmetic (C2) and multi-step (C3), indicating that CoT helps the model decompose complex queries into interpretable steps. However, in the multi-image setting, overall performance drops slightly from 34.6% to 32.4%, suggesting that CoT may not transfer well when reasoning must span multiple visual contexts. While CoT improves reason-

ing behaviour, the cross-lingual gap still remains.

4 Comparison with Related Work

LVLMS for VQA over text images: Recent advancements of large vision-language models (LVLMS) have transformed visual question-answering (VQA) tasks into gaining impressive zero-shot performance across diverse scenarios (OpenAI, 2024; Yang et al., 2024; Chen et al., 2024; Liu et al., 2024a) including text-centric VQA. On these lines, DocPedia (Feng et al., 2024) processes high-resolution inputs without increasing token sequence length. mPLUG-DocOwl (Ye et al., 2024), Qwen2-VL (Wang et al., 2024), and TextMonkey (Liu et al., 2024d) further leverage publicly available document VQA datasets to boost text performance. Extensions of the LLaVA (Liu et al., 2024b) framework such as LLaVAR (Zhang et al., 2023), InternVL (Chen et al., 2024), KaLMA (Penamakuri and Mishra, 2024b) and UniDoc (Feng et al., 2023) have broadened LLM capabilities in visual text by leveraging both textual content and visual content, thereby setting a new benchmark for text-centric VQA including their knowledge-aware counterparts (e.g. TextKVQA (Singh et al., 2019a)). Despite these significant strides, LVLMS fall short in complex tasks like MMCRCIBENCH-3K as discussed in Section 3.

Text-centric VQA: The existing text VQA datasets TextVQA (Singh et al., 2019b), ST-VQA (Biten et al., 2019), DocVQA (Mathew et al., 2021), and VisualMRC (Tanaka et al., 2021) solely focus on the English language. While EST-VQA (Wang et al., 2020) and MTVQA (Tang et al., 2024) are multilingual, they do not cover low-resource visual languages e.g. Hindi. Further, existing datasets either primarily focus on single-image QA or lack questions that require structure-aware mathematical reasoning (summarized in Table 1). We aim to address this gap.

Models and Datasets for Table VQA: While benchmark datasets like TableVQA-Bench (Kim et al., 2024), TabComp (Gautam et al., 2025), and ComTQA (Zhao et al., 2024) exist for VQA over table images, they are all English-focused with answers directly in the images. However, table image datasets to evaluate the cross-lingual mathematical reasoning capabilities of LVLMS remain underexplored.

Multi-image VQA: Several benchmarks (Talmor

et al., 2021; Mathew et al., 2021; Bansal et al., 2020; Chang et al., 2022; Penamakuri et al., 2023; Wu et al., 2025) explore reasoning across multiple image. However, these tasks largely overlook structure-aware tabular understanding, numerical reasoning, and cross-lingual robustness, which are central to our setting. In contrast, we include a dedicated multi-image subset within MMCRCIBENCH-3K, where answering a question requires aggregating statistics across multiple images representing different innings of a match, thereby combining tabular, numerical, and cross-lingual reasoning.

Table Reasoning Ability of LLMs: LLMs and multimodal LLMs (MLLMs) are evaluated in (Deng et al., 2024) using tables presented as either text or images, finding that text-based representations yield better results, while image-based table reasoning remains weak for current models. To enhance reasoning, (Lu et al., 2024) introduced TART, a tool-augmented framework that enables step-by-step table question answering by integrating LLMs with symbolic tools. Similarly, (Nahid and Rafiei, 2024) proposed TabSQLify, which improves efficiency by decomposing large tables into smaller, relevant segments using text-to-SQL conversion. Furthermore, (Zhao et al., 2022) proposed ReasTAP, a pretraining strategy using synthetic table reasoning examples to inject structured reasoning ability into LLMs. Despite these advances, most research focuses on structured tables in English. A critical gap remains in (i) table reasoning in low-resource languages (such as Hindi in our dataset), particularly visually complex, domain-specific formats like cricket scorecards, (ii) evaluating multi-step reasoning and conditional logic in understanding the tabular content. Our work addresses this need by introducing MMCRCIBENCH-H-1.5K, a benchmark designed to push the limits of visual-text reasoning in Hindi.

5 Conclusion

We presented MMCRCIBENCH-3K, a novel benchmark for VQA on cricket scorecards that addresses critical gaps in existing datasets by incorporating cross-lingual understanding, multi-image reasoning, and domain-specific numerical analysis. Our evaluation across MMCRCIBENCH-E-1.5K (English) and MMCRCIBENCH-H-1.5K (Hindi) scorecards reveals a significant perfor-

mance disparity among state-of-the-art LVLMS. While these models show reasonable proficiency with English scorecards, they struggle substantially with Hindi variants despite identical information content. Even advanced prompting strategies like CoT fail to bridge this performance gap. These findings highlight a critical weakness in cross-lingual visual reasoning capabilities, highlighting the need for more robust models that can effectively process structured numerical data across language boundaries. As AI applications expand globally, addressing these limitations becomes increasingly crucial. MMCRIKBENCH-3K provides researchers with a challenging testbed for advancing LVLMS capabilities beyond English-centric contexts, particularly in domains requiring precise analysis of semi-structured information.

6 Limitations

Despite the strengths of MMCRIKBENCH-3K in evaluating structure-aware and cross-lingual visual question answering, several limitations persist. First, the dataset’s linguistic scope is limited to English and Hindi, leaving out other regional scripts and languages prevalent in cricket contexts. Second, the use of synthetically generated scorecards, while visually coherent, may not fully capture the complexity and noise present in real-world documents.

Ethical Considerations

Our benchmark, MMCRIKBENCH-3K, is synthetically generated using publicly available cricket statistics, with no private or sensitive personal information involved. All scorecard data is derived from open datasets (e.g., Kaggle) and only includes publicly known player names and match events. We translate content using automated tools (e.g., Google Translate), and manually verify for correctness to minimize cultural or linguistic bias.

While our dataset uses Hindi as a representative low-resource script for cross-lingual evaluation, we acknowledge the limitations of focusing only on English-Hindi and encourage future extensions to other regional languages and scripts. Additionally, though we simulate realistic scorecards, real-world images may include noise, varied layouts, or OCR artifacts that are not fully captured in our synthetic setup. Our work aims to support fair and inclusive evaluation of vision-language models in global contexts. No human annotators were

subjected to sensitive or harmful content during data creation, and no demographic or identity information is used or inferred in this study.

Acknowledgments

Abhirama is deeply grateful to his PhD advisor, Dr. Anand Mishra, for his unwavering guidance and mentorship throughout his PhD journey, which has profoundly shaped his research outlook and provided the foundation that enabled this work. Abhirama is supported by the Prime Ministers Research Fellowship (PMRF), Ministry of Education, Government of India.

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A Appendix

A.1 Implementation Details

We conduct all of our experiments on the baseline VLMs in a zero-shot setting, with their default setting provided in their respective implementations. When prompted with these methods, we faced two challenges: (i) verbose answers and (ii) digits written in text, e.g. Fifth in place of 5. To overcome these challenges and generate precise and concise answers, we added a brief instruction to the prompt: ‘Answer precisely in 1-2 words, answer in digits when required’ before the main question. We conducted all our experiments on a cloud machine with 3 A6000 Nvidia GPUs (48 GB each) rented from online cloud GPU provider TensorDock ([TensorDock Inc., 2024](#)).

A.2 Cricket Specific Terms and Their Calculations

In cricket, performance metrics help quantify a player’s efficiency in both batting and bowling. Two key metrics are the Strike Rate and the Economy Rate. The following explanations and formulas provide a detailed understanding of these terms.

A.2.1 Strike Rate

The Strike Rate is primarily used to measure a batsman’s scoring efficiency. It represents the average number of runs scored per 100 balls faced, indicating how quickly a batsman can accumulate runs.

Calculation: The basic formula for Strike Rate is:

$$\text{Strike Rate (SR)} = \frac{\text{Total Runs Scored}}{\text{Total Balls Faced}} \times 100$$

Example: For instance, if a batsman scores 50 runs from 40 balls, the Strike Rate is calculated as:

$$\text{SR} = \frac{50}{40} \times 100 = 125$$

Country
Afghanistan
Australia
Bangladesh
England
India
Ireland
New Zealand
Pakistan
South Africa
Sri Lanka
West Indies
Zimbabwe
Netherlands

Table 7: Distribution of Scorecards Across 13 Countries.

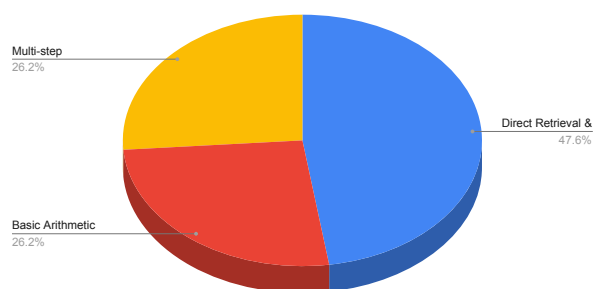


Figure 5: Category Distribution for Batting and Bowling Questions.

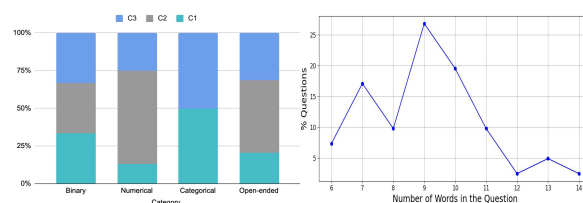


Figure 6: MMCRICBENCH-3K questions and answers analysis: (a) Answer distribution over various question categories, (b) Distribution of the number of words across questions.

providing a comprehensive representation of crick-
eting data across different regions and formats.
The country list is in table 7.

A.4 Remaining set of questions and their category

Table A.4 containing the remaining set of ques-
tions and their categories.

A.5 SQL Query for extracting answers

Table 12 contains questions and SQL queries used
for getting answers.

Category	Ingredient	Specification
Setup	Page setup & font	20 px margins; white background; Arial, sans-serif font.
	Table layout	Full-width tables; collapsed borders; centered; 20 px vertical margins.
	Cell padding	1 px padding on all header and data cells.
Styling	Header row styling	Custom background color; black text; 14 px font; left-aligned.
	Data cell styling	14 px font; centered text.
	Column widths	First column left-aligned (min-width 120 px); others centered (min-width 60 px).
	Team-name banner	Bold 12 px text on customizable background; 5 px padding and vertical margins.
	Section separation	1 px bottom border + extra spacing between innings.
Color variants	Special rows	Bold white rows for Extras and Total.
	Variant 1	Banner #DA8EE7; header #CCCCFF.
	Variant 2	Banner #E8CCFF; header #CCE7FF.
	Variant 3	Banner #D0CCFF; header #E8CCFF.
	Variant 4	Banner #CCFFE7; header #CCFFCC.

Table 8: Template ingredients for scorecard image generation.

Model		MMCRICBENCH-E-1.5K								MMCRICBENCH-H-1.5K							
		Single				Multi				Single				Multi			
		Cat.	i	ii	iii	iv	i	ii	iii	iv	i	ii	iii	iv	i	ii	iii
GPT4o	C1	84.1	30.6	50.0	45.0	79.6	28.33	16.6	50.0	81.3	15.9	50.0	30.4	71.1	15.0	41.6	27.7
	C2	67.9	94.4	NA	50.2	60.0	75.00	NA	56.90	55.5	75.0	NA	27.1	33.3	80.56	NA	48.2
	C3	57.6	65.8	44.7	35.7	69.23	17.14	NA	31.6	35.7	33.3	36.8	16.3	67.3	25.7	NA	22.78
Qwen2.5VL [7B]	C1	87.3	68.1	0.0	25.6	72.8	21.6	33.3	27.7	85.8	69.9	0.0	18.2	76.2	20.0	16.6	11.1
	C2	55.5	69.5	NA	42.5	46.6	69.4	NA	33.3	32.7	72.8	0.0	19.1	46.6	63.8	NA	22.4
	C3	58.9	10.7	5.2	30.1	59.6	2.8	Na	16.4	51.5	10.7	13.1	18.1	67.3	2.8	NA	7.5

Table 9: Answer-type-wise accuracy (%) of GPT-4o and Qwen2.5VL [7B] on MMCRICBENCH-E-1.5K and MMCRICBENCH-H-1.5K across single-image and multi-image settings. The table highlights the models’ performance breakdown by question category (C1-C3) and answer type: (i) Binary, (ii) Numerical, (iii) Categorical, and (iv) Open-ended.

Country	India	Australia	Pakistan
League Teams	Mumbai Indians	Sydney Thunder	Islamabad United
	Kolkata Knight Riders	Adelaide Strikers	Lahore Qalandars
	Kings XI Punjab	Melbourne Renegades	Karachi Kings
	Royal Challengers Bangalore	Sydney Sixers	Peshawar Zalmi
	Gujarat Lions	Perth Scorchers	Multan Sultans
	Delhi Daredevils	Hobart Hurricanes	Quetta Gladiators
	Sunrisers Hyderabad	Brisbane Heat	
	Rising Pune Supergiants	Melbourne Stars	
	Chennai Super Kings		
	Rajasthan Royals		
	Delhi Capitals		

Table 10: List of franchise Cricket teams by Country and League included in the dataset.

Cat.	Category Name	Example Question	#sQ's	#mQ's	#Total	%
C1	Direct Retrieval & Simple Inference	Which bowler has bowled the most no-balls in the match?	9	5	14	0.93
		Who got out for a duck in the second innings?	16	12	28	1.87
		Did any batsman score a century in the match?	25	11	36	2.4
		Which bowler has bowled the maximum maidens?	4	15	19	1.27
		Did any bowler take a 3-fer in the match?	24	9	33	2.2
		Did any bowler take a 5-fer in the match?	18	7	25	1.67
		Did any bowler take a 6-fer in the match?	23	8	31	2.07
		How many wides were bowled by Team 1?	27	13	40	2.67
		How many no balls were bowled by Team 1?	24	9	33	2.2
		How many leg byes did Team 1 concede?	23	6	29	1.93
		How many byes did Team 1 concede?	49	24	73	4.87
		How many extras are bowled in match?	35	11	46	3.07
		Which bowler has bowled the most wides in the match?	22	8	30	2
		Who got out for a duck in the first innings?	6	5	11	0.73
		Did any bowler take a 4-fer in the match?	15	7	22	1.47
		Has [Batsman X] taken more wickets than [Batsman Y]?	30	19	49	3.27
		Which bowler has conceded the most extras?	57	16	73	4.87
		Who has hit the maximum sixes?	24	8	32	2.13
		Does [Batsmax X] hit more sixes than [Batsman Y]?	16	15	31	2.07
		How many extras were bowled in the first innings?	46	18	64	4.27
C2	Basic Arithmetic Reasoning & Conditional Logic	How many batsmen have scored a century?	19	6	25	1.67
		How many batsmen have been dismissed for a duck?	20	16	36	2.4
		Which bowler took a 3-fer in the match?	27	21	48	3.2
		Which bowler took a 5-fer in the match?	-	9	9	0.6
		Which bowler took a 6-fer in the match?	-	2	2	0.13
		What is [Batsman X] strike rate?	46	18	64	4.27
		Did [Batsman X] score better in the first innings or the second innings?	-	7	7	0.47
		Which batsman scored a century in the match?	11	15	26	1.73
		Which bowler took a 4-fer in the match?	6	11	17	1.13
		Has [Batsman X] hit more boundaries than [Batsman X]?	13	2	15	1
		Which batsman was dismissed for a golden duck in the match?	24	15	39	2.6
		C3	Multi-step Reasoning & Quantitative Analysis	How many batsmen had a strike rate greater than 70 in the first innings?	21	11
Which innings had the maximum maidens?	4			12	16	1.07
Has any batsman been dismissed for a golden duck in the match?	54			15	69	4.6
Which batsman had the highest strike rate (minimum 10 balls faced)?	37			17	54	3.6
Which batsman had the highest boundary percentage?	35			18	53	3.53
Which bowler had the better economy rate in the first innings?	38			18	56	3.73
Which innings had the higher run rate?	38			15	53	3.53
Which batsman had a strike rate greater than 70 in the first innings?	49			13	62	4.13
Has the same fielder caught any batsman twice?	37			14	51	3.4
		Has any batsman been dismissed twice by the same bowler?	28	19	47	3.13
Total			1000	500	1500	100

Table 11: Statistics of single-image and multi-image questions.

Question	SQL Query
Which bowler has bowled the most wides in the match?	SELECT Bowler_Name, SUM(WD) AS Total_Wides FROM bowling GROUP BY Bowler_Name ORDER BY Total_Wides DESC LIMIT 1;
Who got out for a duck in the first innings?	SELECT Batsman_Name FROM batting WHERE Runs = 0 AND Innings = 1 AND 'Bowler/Catcher' NOT LIKE 'not out%';
Did any bowler take a 4-fer in the match?	SELECT Bowler_Name, Wicket, Innings FROM bowling WHERE Wicket >= 4;
Has Batsman X taken more wickets than Batsman Y?	SELECT CASE WHEN SUM(CASE WHEN Bowler_Name = 'Bowler X' THEN Wicket ELSE 0 END) > SUM(CASE WHEN Bowler_Name = 'Bowler Y' THEN Wicket ELSE 0 END) THEN 'Yes' ELSE 'No' END AS Result FROM bowling WHERE Bowler_Name IN ('Bowler X', 'Bowler Y');
Which bowler has conceded the most extras?	SELECT Bowler_Name, SUM(WD + NB) AS total_extras FROM bowling_data GROUP BY Bowler_Name ORDER BY total_extras DESC LIMIT 1;
Who has hit the maximum sixes?	SELECT Batsman_Name, MAX("6s") AS max_sixes FROM batting_data;
Does Batsman X hit more sixes than Batsman Y?	SELECT Batsman_Name, SUM("6s") AS Total_Sixes FROM batting WHERE Batsman_Name IN ('Batsman X', 'Batsman Y') GROUP BY Batsman_Name;
How many extras were bowled in the first innings?	SELECT SUM(WD + NB) AS Total_Extras FROM bowling WHERE Innings = 1; for leg bye and bye we calculated manually
Which bowler has bowled the most no-balls in the match?	SELECT Bowler_Name, SUM(NB) AS Total_Wides FROM bowling GROUP BY Bowler_Name ORDER BY Total_NB DESC LIMIT 1;
Who got out for a duck in the second innings?	SELECT Batsman_Name FROM batting WHERE Runs = 0 AND Innings = 2 AND 'Bowler/Catcher' NOT LIKE 'not out%';
Did any batsman score a century in the match?	SELECT Batsman_Name, Runs, Innings FROM batting WHERE Runs >= 100;
Which bowler has bowled the maximum maidens?	SELECT Bowler_Name, SUM(Maiden) AS Total_Maidens FROM bowling GROUP BY Bowler_Name HAVING Total_Maidens > 1 ORDER BY Total_Maidens DESC;
Did any bowler take a 3-fer in the match?	SELECT Bowler_Name, Wicket, Innings FROM bowling WHERE Wicket >= 3;
Did any bowler take a 5-fer in the match?	SELECT Bowler_Name, Wicket, Innings FROM bowling WHERE Wicket >= 5;
Did any bowler take a 6-fer in the match?	SELECT Bowler_Name, Wicket, Innings FROM bowling WHERE Wicket >= 6;
How many wides were bowled by Team 1?	SELECT SUM(WD) AS Total_Wides_By_Team1 FROM bowling WHERE Innings IN (1, 3);
How many no balls were bowled by Team 1?	SELECT SUM(NB) AS Total_Wides_By_Team1 FROM bowling WHERE Innings IN (1, 3);
How many leg byes did Team 1 concede?	SELECT SUM(byes) AS Total_Wides_By_Team1 FROM bowling WHERE Innings IN (1, 3);
How many byes did Team 1 concede?	SELECT SUM(legbyes) AS Total_Wides_By_Team1 FROM bowling WHERE Innings IN (1, 3);
How many extras are bowled in match?	SELECT SUM(WD + NB) AS Total_Extras_In_Match FROM bowling;
How many batsmen have scored a century?	SELECT COUNT(*) AS Century_Count FROM batting WHERE Runs >= 100 AND "Bowler/Catcher" NOT LIKE '%not out%';
How many batsmen have been dismissed for a duck?	SELECT CASE WHEN COUNT(*) = 0 THEN 'None' ELSE CAST(COUNT(*) AS TEXT) END AS Duck_Result FROM batting WHERE Runs = 0 AND "Bowler/Catcher" NOT LIKE '%not out%';
Which bowler took a 3-fer in the match?	SELECT Bowler_Name, Wicket, Innings FROM bowling WHERE Wicket >= 3;
Which bowler took a 5-fer in the match?	SELECT Bowler_Name, Wicket, Innings FROM bowling WHERE Wicket >= 5;
Which bowler took a 6-fer in the match?	SELECT Bowler_Name, Wicket, Innings FROM bowling WHERE Wicket >= 6;
What is Batsman X strike rate?	SELECT ROUND((SUM(Runs) * 100.0 / SUM(Balls)), 2) AS Strike_Rate FROM batting WHERE Batsman_Name = 'batsman X' AND Innings = 1;
Did Batsman X score better in the first innings or the second innings?	SELECT CASE WHEN SUM(CASE WHEN Innings = 0 THEN Runs ELSE 0 END) > SUM(CASE WHEN Innings = 2 THEN Runs ELSE 0 END) THEN '1st Innings' WHEN SUM(CASE WHEN Innings = 2 THEN Runs ELSE 0 END) > SUM(CASE WHEN Innings = 0 THEN Runs ELSE 0 END) THEN '2nd Innings' ELSE 'None' END AS Better_Innings FROM batting WHERE Batsman_Name = 'batsman X';
Which batsman scored a century in the match?	SELECT Batsman_Name, Runs, Innings FROM batting WHERE Runs >= 100;
Which bowler took a 4-fer in the match?	SELECT Bowler_Name, Wicket, Innings FROM bowling WHERE Wicket = 4;

Table 12: Question and its SQL query to extract answer from CSV.

Question	SQL Query
Has Batsman X hit more boundaries than Batsman Y?	SELECT CASE WHEN SUM(CASE WHEN Batsman_Name = 'batsman X' THEN '4s' + '6s' ELSE 0 END) > SUM(CASE WHEN Batsman_Name = 'batsman Y' THEN '4s' + '6s' ELSE 0 END) THEN 'Yes' ELSE 'No' END AS Result FROM batting WHERE Batsman_Name IN ('batsman X', 'batsman Y');
Which batsman was dismissed for a golden duck in the match?	SELECT Batsman_Name FROM batting WHERE Runs = 0 AND 'Bowler/Catcher' NOT LIKE 'not out%';
How many batsmen had a strike rate greater than 70 in the first innings?	SELECT COUNT(DISTINCT Batsman_Name) AS Count FROM batting WHERE Innings = 1 AND Strike_Rate > 70;
Which innings had the maximum maidens?	SELECT Innings, SUM(Maiden) AS Total_Maidens FROM bowling GROUP BY Innings HAVING Total_Maidens > 1 ORDER BY Total_Maidens DESC LIMIT 1;
Has any batsman been dismissed for a golden duck in the match?	SELECT Batsman_Name, Innings FROM batting WHERE Runs = 0 AND Balls = 1;
Which batsman had the highest strike rate (minimum 10 balls faced)?	SELECT Batsman_Name FROM batting WHERE Innings = 1 AND Balls >= 10 ORDER BY Strike_Rate DESC LIMIT 1;
Which batsman had the highest boundary percentage?	SELECT Batsman_Name FROM batting WHERE Innings = 1 AND Balls > 0 ORDER BY ((([4s]*4 + [6s]*6) * 100.0 / Runs)) DESC LIMIT 1;
Which bowler had the better economy rate in the first innings?	SELECT Bowler_Name, ROUND((SUM(Runs) * 1.0 / SUM(Over)), 2) AS Economy_Rate FROM bowling WHERE Innings = 1 GROUP BY Bowler_Name ORDER BY Economy_Rate ASC LIMIT 1;
Which innings had the higher run rate?	SELECT Innings FROM batting GROUP BY Innings ORDER BY SUM(Runs)*1.0/COUNT(DISTINCT Batsman_Name) DESC LIMIT 1;
Which batsman had a strike rate greater than 70 in the first innings?	SELECT GROUP_CONCAT(Batsman_Name) AS Aggressive_Batsmen FROM batting WHERE Innings = 1 AND Strike_Rate > 70 AND Balls >= 10 GROUP BY Batsman_Name HAVING Strike_Rate > 70;
Has the same fielder caught any batsman twice?	SELECT TRIM(SUBSTR('Bowler/Catcher', 3, INSTR('Bowler/Catcher', 'b') - 3)) AS Fielder, COUNT(*) AS Catches FROM batting WHERE 'Bowler/Catcher' LIKE 'c %b %' GROUP BY Fielder HAVING Catches > 1;
Has any batsman been dismissed twice by the same bowler?	SELECT Batsman_Name, SUBSTR('Bowler/Catcher', INSTR('Bowler/Catcher', 'b ') + 2) AS Bowler, COUNT(*) AS Dismissals FROM batting WHERE 'Bowler/Catcher' LIKE '%b %' GROUP BY Batsman_Name, Bowler HAVING Dismissals > 1;

Table 13: Question and its SQL query to extract answer from CSV continued.

☕ MUG-Eval: A Proxy Evaluation Framework for Multilingual Generation Capabilities in Any Language

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Abstract

Evaluating text generation capabilities of large language models (LLMs) is challenging, particularly for low-resource languages where methods for direct assessment are scarce. We propose ☕ MUG-Eval, a novel framework that evaluates LLMs’ multilingual generation capabilities by transforming existing benchmarks into conversational tasks and measuring the LLMs’ accuracies on those tasks. We specifically designed these conversational tasks to require effective communication in the target language. Then, we simply use task success rate as a proxy for successful conversation generation. Our approach offers two key advantages: it is independent of language-specific NLP tools or annotated datasets, which are limited for most languages, and it does not rely on LLMs-as-judges, whose evaluation quality degrades outside a few high-resource languages. We evaluate 8 LLMs across 30 languages spanning high, mid, and low-resource categories, and we find that MUG-Eval correlates strongly with established benchmarks ($r > 0.75$) while enabling standardized comparisons across languages and models. Our framework provides a robust and resource-efficient solution for evaluating multilingual generation that can be extended to thousands of languages.

1 Introduction

Large language models (LLMs) have demonstrated remarkable capabilities in many languages, but evaluating their multilingual generation abilities remains a significant challenge, particularly for low-resource languages. These challenges are particularly pronounced for low-resource languages, which often lack robust natural language processing tools, comprehensive reference corpora, or established benchmarks. Consequently, evaluation resources for these low-resource languages predominantly derive from massively multilingual

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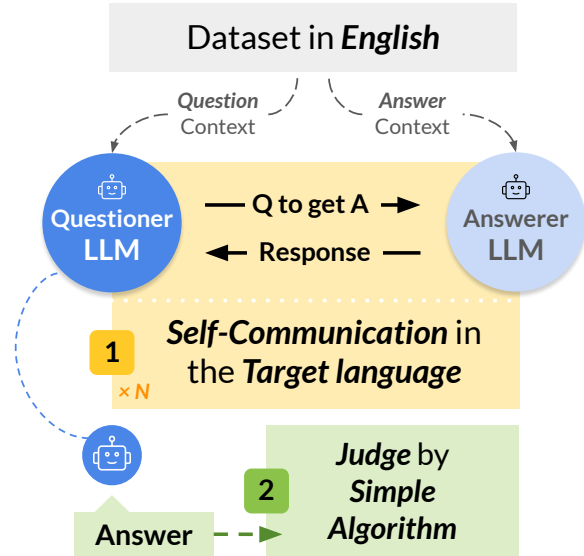


Figure 1: General concept of ☕ MUG-Eval. Two instances of the same LLM engage in self-communication in the target language to complete information-gap tasks. Model outputs are evaluated using algorithmic methods (e.g., string matching or code testing), without requiring language-specific tools or LLMs-as-judges. Task success rate serves as a proxy for measuring the model’s multilingual generation capability.

evaluation benchmarks (Hasan et al., 2021; Goyal et al., 2022; Bandarkar et al., 2024; Adelani et al., 2024, *inter alia*). Extending and evaluating natural language generation tasks presents considerable complexity, especially in the absence of language-specific resources.

Recent approaches (Holtermann et al., 2024; Pombal et al., 2025) have employed LLMs-as-judges, but they face an inherent limitation—the reliability of judgments depends on the evaluator LLM’s performance in the target language. While this limitation may be less pronounced for high-resource languages (Pombal et al., 2025), the applicability of such approaches to low-resource languages remains unclear and has not been rigorously validated. Conventional evaluation approaches for


Feature	Global-MMLU	Belebele	Flores-101	XL-Sum	MultiQ	 MuG-Eval
Evaluates generation (not comprehension)	✗	✗	✓	✓	✓	✓
Metrics comparable across languages	✓	✓	✗	✗	✓	✓
No LLMs-as-Judges required	✓	✓	✓	✓	✗	✓
Native speaker annotation is optional	✗	✗	✗	✗	✓	✓
# of languages supported	42	122	101	47	137	2,102

Table 1: Positioning of MuG-Eval among multilingual evaluation benchmarks. MuG-Eval uniquely combines: (1) evaluation of generation capability (not just comprehension), (2) cross-linguistically comparable metrics, and (3) objective scoring without LLMs-as-judges, and (4) reduced dependency on cross-lingual annotation. Tested on 30 languages, MuG-Eval currently supports 2,102 languages via GlotLID (Kargaran et al., 2023), with the potential to scale further as more advanced language identification tools develop. Benchmarks referenced are MultiQ (Holtermann et al., 2024), Flores-101 (Goyal et al., 2022), XL-Sum (Hasan et al., 2021), Global-MMLU (Singh et al., 2025), and Belebele (Bandarkar et al., 2024).

generation ability often require human-annotated ground truth data, such as BLEU (Papineni et al., 2002) for machine translation or ROUGE (Lin, 2004) for summarization. Overall, there exists a gap in methodologies that offer both reliability and scalability for quantifying LLM generation performance across diverse languages.

In this paper, we propose MuG-Eval, a framework for evaluating the multilingual generation capabilities of LLMs, particularly for languages where direct evaluation proves challenging or infeasible. Our methodology creates information-gap scenarios that require successful communication in the target language to complete tasks, such as providing hidden information to one agent while another must discover it through questioning. We implement three tasks in MuG-Eval by adapting existing benchmarks into conversational and multilingual settings—Easy Twenty Questions (Zhang et al., 2024), MCQ Conversation (Bandarkar et al., 2024), and Code Reconstruction (Muennighoff et al., 2024)—where task completion rates serve as proxies for different aspects of generation ability: reasoning, instruction following, and programming (§3.1). Our approach builds on the insight from Muennighoff et al. (2024): instead of directly assessing LLM-generated text quality, we can indirectly measure how well the LLM comprehends what it has itself generated.

We evaluate 8 LLMs across 30 languages from high-, mid-, and low-resource categories as defined by Singh et al. (2024). Our experiments demonstrate that MuG-Eval has strong discriminative power, enabling precise comparisons both across languages and across models (§4.1). The framework shows high internal consistency among its three tasks and correlates strongly (Pearson’s

$r > 0.75$) with established benchmarks including Belebele (Bandarkar et al., 2024), MultiQ (Holtermann et al., 2024), and Global-MMLU (Singh et al., 2025) (§5.1). Additionally, our analysis of MCQ Conversation reveals that when native-language references are unavailable, English is not always the optimal substitute language, particularly for low-resource languages (§5.2).

Our primary contribution lies in proposing MuG-Eval¹, a novel language-agnostic framework for evaluating multilingual generation in large language models through self-comprehension tasks, without relying on language-specific NLP tools or human annotations. To demonstrate the utility and effectiveness of this framework, we structure the paper as follows. We begin by reviewing the landscape of multilingual generation evaluation, identifying critical gaps in existing methodologies that motivate our approach (§2). We then present the design of MuG-Eval, introducing three conversational tasks that recast generation evaluation as a communication-based task (§3). We evaluate eight large language models in 30 linguistically diverse languages, demonstrating strong correlations with established benchmarks while offering unprecedented scalability (§4). Through detailed analysis, we uncover cross-linguistic performance patterns and validate the effectiveness of MuG-Eval as a robust, language-agnostic evaluation framework (§5), and conclude with directions for future work in multilingual LLM evaluation (§6).

2 Related Work

Reference-based metrics such as BLEU (Papineni et al., 2002), ROUGE (Lin, 2004), and

¹Code and dataset available at <https://github.com/seyoungsong/mugeval>.

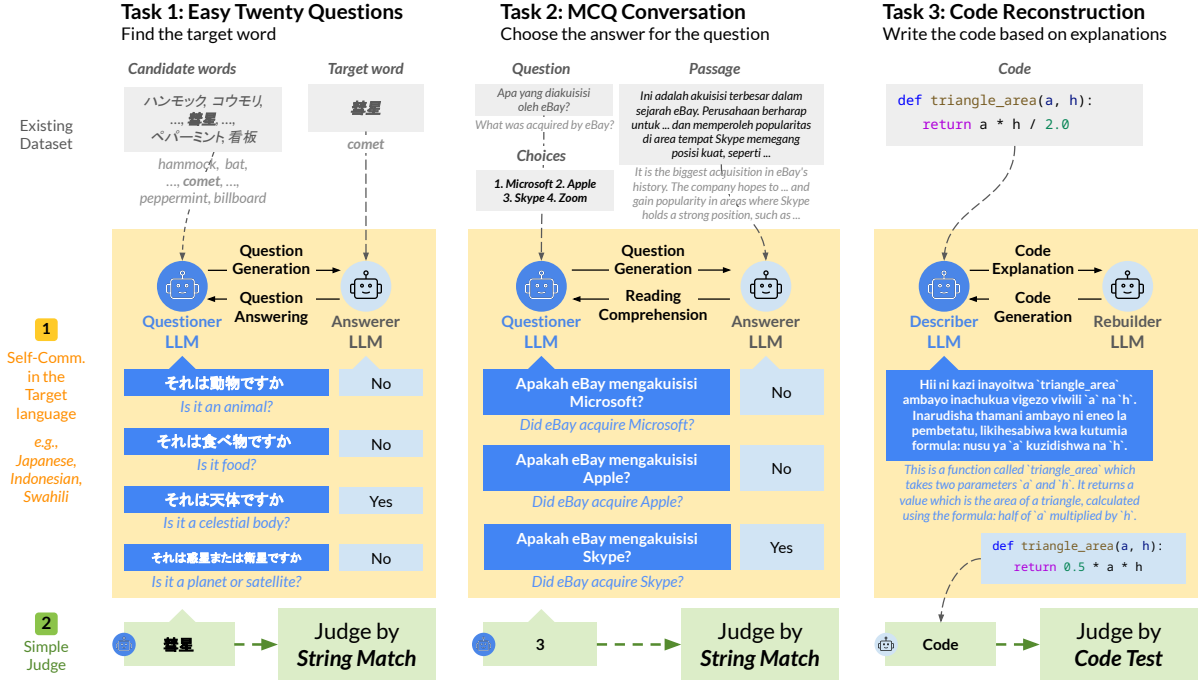


Figure 2: Overview of evaluation tasks. Two instances of the same LLM engage in self-communication in the target language to complete information-gap tasks: (1) Easy Twenty Questions—guessing a hidden word, (2) MCQ Conversation—finding the answer through passage-based dialogue, and (3) Code Reconstruction—explaining and reconstructing code.

chrF (Popović, 2015) assess generation quality by comparing outputs against reference texts, usually requiring human-generated target texts as ground truth. These metrics are widely adopted in benchmarks such as MEGA (Ahuja et al., 2023), GlotEval (Luo et al., 2025), Multi-IF (He et al., 2024), and BenchMAX (Huang et al., 2025). However, such reference-based approaches are limited by their reliance on high-quality parallel data, which is scarce in many languages. Moreover, they struggle in cross-lingual comparisons due to their sensitivity to lexical and syntactic features.

To address these limitations, reference-free methods—particularly those using LLMs as evaluators—gained attention (Dang et al., 2024; Holtermann et al., 2024; Pombal et al., 2025). Nonetheless, Hada et al. (2024b) highlights the instability and reduced reliability of LLM evaluators in low-resource or non-Latin script languages, raising concerns about fairness and generalizability.

An emerging line of work evaluates generation quality through downstream utility, assessing how well generated content supports task completion. Recent benchmarks explore the generation-comprehension link through interactive information-gap tasks that require mutual understanding. These include clarifying ques-

tion generation (Gan et al., 2024), reference games (Gul and Artzi, 2024; Eisenstein et al., 2023), bidirectional code understanding (Muennighoff et al., 2024), and multi-turn interactive benchmarks such as HumanEvalComm (Wu and Fard, 2025), telephone-game simulations (Perez et al., 2025), and 20Q (Zhang et al., 2024).

Drawing inspiration from 20Q (Zhang et al., 2024) and HumanEvalExplain (Muennighoff et al., 2024), our framework builds on tasks that inherently require both comprehension and generation, foregrounding successful communication as the central evaluation criterion. Designed to be language-agnostic, reference-free, and LLM-independent, it offers a more equitable and scalable multilingual evaluation across an unlimited spectrum of languages.

3 MUG-Eval: A Language-Agnostic Evaluation Framework

MUG-Eval consists of three tasks adapted from existing benchmarks (Zhang et al., 2024; Bandarkar et al., 2024; Muennighoff et al., 2024) to evaluate multilingual generation capabilities. The benchmarks for Easy Twenty Questions and Code Reconstruction were originally English-only, while the

source for the MCQ Conversation task is the multilingual Belebele dataset. Each task is structured as a self-communication scenario between two “LLM instances”—separate API calls to the same model, each assigned a distinct conversational role (*e.g.*, Questioner or Answerer) with a unique system prompt and access to different information. The instances communicate turn-by-turn in the target language, with the output from one serving as the input for the next. The model’s capability is measured by the task completion rate, which serves as the primary evaluation metric.

This section provides detailed descriptions of each task and evaluation procedures. Additional details, including prompts and generation parameters, are provided in the Appendix B.2.

3.1 Tasks

Easy Twenty Questions. This task evaluates reasoning and strategic questioning abilities through a word-guessing game. Drawing from the *Things* dataset (Zhang et al., 2024), we translate 140 English words into 30 languages using Google Translate. One model instance (answerer) receives a hidden word from this set, while another (questioner) must identify it from a list of 100 candidates. The questioner poses up to 20 yes/no questions in the target language, to which the answerer responds only with “yes,” “no,” or “maybe” in English. The predefined candidates ensure consistent evaluation across languages, mitigating lexical diversity from affecting task difficulty or scoring mechanisms.

MCQ Conversation. We transform the Belebele benchmark (Bandarkar et al., 2024)—a reading comprehension dataset spanning 122 languages—into a conversational task. From the original dataset of 900 samples, we separate the reading passages from their corresponding questions and answer choices. Similar to the previous task, the answerer instance accesses only the passage, while the questioner sees the question and four answer options. To discover the correct answer, the questioner may ask up to 10 yes/no questions in the target language, receiving “yes,” “no,” or “maybe” responses in English, similar to the previous task. This design tests multi-turn instruction-following capabilities.

Code Reconstruction. This task adapts HumanEvalExplain (Muennighoff et al., 2024) to assess code generation abilities across languages, not

only in English. Using 164 Python function samples with corresponding unit tests, one model instance (describer) generates a natural language explanation of the code in the target language. Another instance (rebuilder) then reconstructs the original function from this description and the function declaration snippet. Success is measured by whether the reconstructed code passes all unit tests.

3.2 Evaluation Metrics

Task completion rate serves as our primary metric, calculated as the ratio of successfully completed tasks. We use exact string matching for word or choice predictions, with responses prompted to appear within double brackets and extracted via regular expressions. We employ GlotLID (Kargaran et al., 2023) to ensure the model’s responses are in the target language. Tasks fail when models: (1) produce a question or description in the wrong language, (2) produce invalid responses, or (3) violate task-specific constraints such as including more than 20 consecutive source code characters in explanations.

4 Experiments

Models. We evaluate eight multilingual large language models to assess their generation capabilities across diverse languages. Our selection includes four open-weight models: Llama 3.3-70B (Llama Team, 2024), Llama 3.1-8B, Qwen2.5-72B (Qwen Team, 2024), and Qwen2.5-7B, alongside four closed-source models: GPT-4o (OpenAI, 2024), GPT-4o-mini, Gemini 2.5 Flash (Google, 2025), and Gemini 2.0 Flash (Google, 2024). All models are accessed via API endpoints, with GPT-4o variants served through Azure OpenAI Services and the remaining models through OpenRouter. Detailed model information is provided in the Appendix B.1.

Languages. We test our framework on 30 languages grouped by resource availability following Singh et al. (2024)’s classification, with 10 languages selected from each resource category. We include high-resource languages Arabic (arb), Chinese (zho), English (eng), French (fra), German (deu), Hindi (hin), Italian (ita), Japanese (jpn), Portuguese (por), and Spanish (spa); mid-resource languages Bengali (ben), Greek (ell), Hebrew (heb), Indonesian (ind), Korean (kor), Lithuanian (lit), Malay (zsm), Romanian (ron), Thai (tha), and Ukrainian (ukr); and low-resource languages Amharic (amh), Hausa (hau), Igbo (ibo),

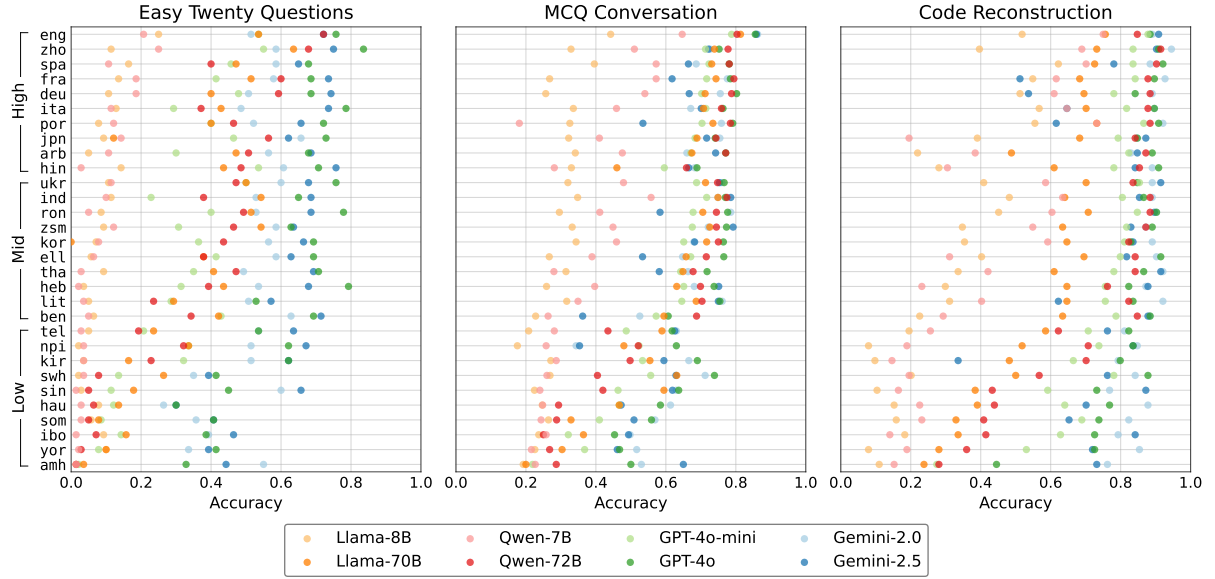


Figure 3: Accuracy of 8 LLMs across three tasks in 30 languages. Languages are grouped by resource level and sorted by average performance within each group. Results show that Code Reconstruction is the easiest task, followed by MCQ Conversation and Easy Twenty Questions. The gap is minor between high and mid-resource languages, but substantial between mid and low. Larger models consistently outperform smaller ones in the same language family, and tasks exhibit distinct ceiling effect.

Model	Easy Twenty Questions					MCQ Conversation					Code Reconstruction				
	All	ENG	High	Mid	Low	All	ENG	High	Mid	Low	All	ENG	High	Mid	Low
GPT-4o	62.21	75.71	72.64	69.21	44.79	70.14	85.56	77.31	74.33	58.78	<u>83.43</u>	88.41	<u>89.02</u>	86.59	74.70
Gemini-2.0-flash	51.93	51.43	56.07	55.57	44.14	<u>66.72</u>	86.22	73.33	69.74	<u>57.08</u>	86.79	<u>89.02</u>	89.21	89.45	81.71
Gemini-2.5-flash	62.26	<u>72.14</u>	<u>70.57</u>	<u>66.36</u>	49.86	62.90	<u>85.89</u>	68.90	65.74	54.07	77.05	90.85	74.63	84.39	72.13
Qwen2.5-72B	35.17	<u>72.14</u>	53.86	40.64	11.00	61.90	<u>80.33</u>	<u>76.61</u>	<u>72.44</u>	36.63	73.68	84.76	87.56	84.15	49.33
GPT-4o-mini	31.95	53.57	44.29	35.93	15.64	59.83	78.78	70.11	65.91	43.48	75.02	87.80	82.50	80.12	62.44
Llama-3.3-70B	33.79	53.57	44.14	40.36	16.86	61.15	81.33	70.04	68.29	45.12	58.03	75.61	68.05	65.61	40.43
Qwen2.5-7B	7.90	20.71	14.50	6.64	2.57	37.33	64.67	46.48	40.33	25.17	40.47	75.00	56.28	46.22	18.90
Llama-3.1-8B	8.45	25.00	12.64	7.71	5.00	28.94	44.22	33.46	30.23	23.13	31.95	51.83	46.10	36.16	13.60

Table 2: Average accuracy (%) of 8 LLMs across three tasks, grouped by language resource categories. The best and the second-best performances within each task and resource category are **bolded** and underlined, respectively. A consistent performance degradation is observed as the language resource level decreases from high (including English) to low.

Kyrgyz (kir), Nepali (npi), Sinhala (sin), Somali (som), Swahili (swh), Telugu (tel), and Yoruba (yor). This selection covers diverse language families and writing systems, including Latin, Cyrillic, and Devanagari scripts, ensuring comprehensive evaluation across typologically distinct languages. Detailed language information is provided in the Appendix A.1.

4.1 Results

Table 2 summarizes overall accuracy, and Figure 3 visualizes trends by language and task. Full results are provided in Appendix C.1.

How difficult is MUG-Eval? Average accuracy scores across tasks vary depending on the model

and the resource level of the language. Code Reconstruction is the easiest task, followed by MCQ Conversation, while Easy Twenty Questions challenges the most. This may be due to the number of interaction turns: multi-turn tasks are more error-prone as mistakes accumulate. This pattern aligns with average turn counts (Table 9): Easy Twenty Questions requires the most turns, MCQ Conversation fewer, and Code Reconstruction only one.

Performance varies across resource levels and models. The performance gap between high- and mid-resource language groups is relatively small compared to the much larger gap observed between mid- and low-resource groups. Additionally, larger models consistently outperform smaller ones

within the same model family. Despite some variation in task-wise rankings, overall trends of task rankings remain stable across models.

Complementary ceiling effects exist across tasks. Code Reconstruction and MCQ Conversation saturate near the upper bound—around 0.9 and 0.8, indicating 90% and 80% accuracy. In contrast, Easy Twenty Questions exhibits saturation toward the lower end, with many scores concentrated near zero—especially in low-resource languages and smaller models. MCQ Conversation shows lower saturation than its original benchmark, Belebele (0.8 vs. 0.95; see Figure 4), likely due to its split-agent design, which can produce ambiguous question generations, leading to unsolvable cases.

These differing saturation patterns enhance the discriminative power of MUG-Eval. Easier tasks are more effective at separating weaker models and low-resource languages, while the harder task better distinguishes stronger models and high-resource languages. Together, they ensure that MUG-Eval maintains discriminative power across the full performance spectrum.

5 Discussion

5.1 Comparative Analysis

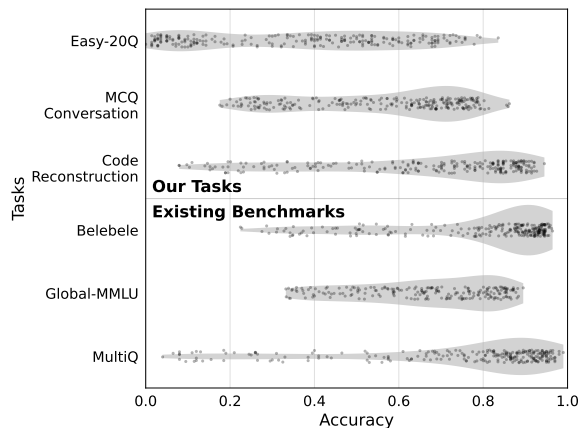


Figure 4: Score distributions across six evaluation tasks, demonstrating varying discriminative powers. Notably, MCQ Conversation, derived from the Belebele task, exhibits greater statistical dispersion, indicating greater ability to distinguish between models than the original Belebele benchmark.

Which tasks best distinguish between models?

Figure 4 presents violin plots of accuracy scores for six tasks, including the three introduced in MUG-Eval. Easy Twenty Questions exhibited a broad

distribution of scores, indicating strong discriminative power and the ability to distinguish models with varying capabilities. In contrast, Code Reconstruction showed a much narrower range, suggesting limited differentiation among a few models. Notably, MUG-Eval’s MCQ Conversation demonstrated substantially greater discriminative power compared to the original Belebele task, highlighting its usefulness in evaluating multilingual understanding with finer granularity. Overall, all three tasks in MUG-Eval show greater discriminative capability than the three existing benchmarks.

How consistent is performance across different tasks?

To validate the internal consistency of our framework, we analyzed performance correlations across our three tasks. While the tasks measure distinct abilities, a moderate positive correlation suggests that they capture a consistent, general signal of a model’s multilingual capabilities. Figure 5 compares these performance correlations across six tasks, including the three introduced in MUG-Eval. Pearson correlation coefficients are all above 0.75, indicating strong consistency between task accuracy. Spearman’s rank correlation coefficients exceed 0.75 in all cases, suggesting positive correlations in rank ordering. The reason why the correlations are not perfect is likely due to the distinct capabilities each task targets. Easy Twenty Questions primarily evaluates the reasoning aspect of generation, MCQ Conversation focuses on instruction following, Code Reconstruction assesses coding under information asymmetry. These differences account for the variation observed across tasks despite overall similarity.

Validation against established benchmarks.

Figure 5 also compares performance correlations across six tasks, including the three introduced in MUG-Eval. While neither Pearson’s nor Spearman’s coefficients indicate perfect alignment between the three tasks in MUG-Eval and existing benchmarks, the figure demonstrates a high degree of correlation. This suggests that MUG-Eval produces reliable results in terms of both accuracy and ranking, despite its low cost due to the absence of human-annotated datasets. The detailed visualization result on Pearson’s r is provided in Appendix C.2.

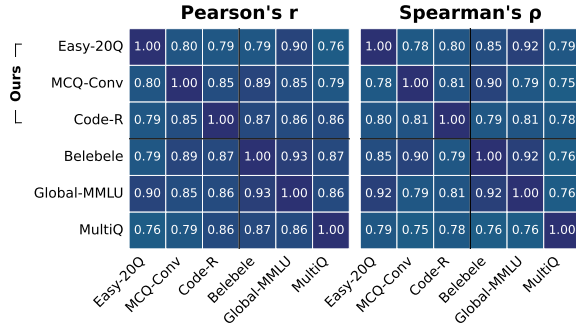


Figure 5: Correlation analysis between MUG-Eval tasks and existing multilingual benchmarks. Heatmaps show Pearson’s r (left) and Spearman’s ρ (right) correlation coefficients between three MUG-Eval tasks and three established benchmarks. All correlations exceed 0.75, demonstrating strong consistency between MUG-Eval and existing evaluation methods, validating its effectiveness as a multilingual evaluation framework.

5.2 Language Resource Flexibility: A Substitution Analysis

The original MCQ Conversation task assumes that the answerer receives a passage written in the target language. This raises a practical question: if such a passage is unavailable, can an English passage be used instead without significantly affecting performance? Would using passages from other high-resource languages yield a better substitute?

To investigate this, three experimental settings were compared: (1) using the original target language passage, (2) using an English passage, and (3) using five separate versions of each passage, each written in one of the high-resource languages—English, Chinese, Arabic, Japanese, or Hindi. Two models, GPT-4o and GPT-4o-mini, were evaluated,¹ with the GPT-4o result presented in Figure 6. The result on the other model (GPT-4o-mini) is provided in the Appendix C.3.

On average, performance based on the five high-resource language passages more closely approximated that of the target-language baseline than when using English alone. This indicates that incorporating diverse high-resource languages may provide a better alternative when native-language passages are unavailable.

To further validate the applicability of MCQ Conversation, we conducted an evaluation to assess whether replacing native-language passages with those in five high-resource languages main-

¹This resource-intensive analysis was limited to the GPT models available via Azure OpenAI Service to stay within our computational budget.

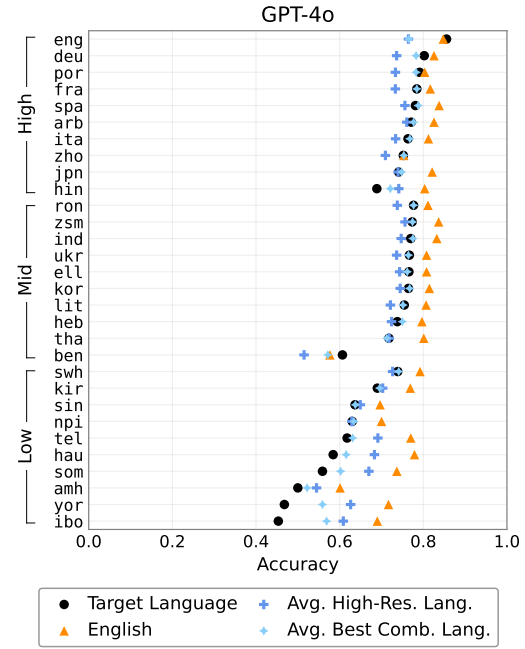


Figure 6: MCQ Conversation accuracy comparison across 30 languages for GPT-4o using passages in: (1) the target language, (2) English, and (3) five fixed high-resource languages (averaged), and (4) an optimized subset of up to five high-resource languages most similar to the target language. Results demonstrate that high-resource language substitution more closely approximates native language performance than using English alone, especially for low-resource languages.

tains consistent performance patterns across languages. The correlation between results using original target-language passages and those using the high-resource substitutes was 0.60 for Pearson (based on raw scores) and 0.71 for Spearman (based on rank-order consistency). Given that MUG-Eval is ultimately designed for cross-lingual comparisons, the higher Spearman correlation suggests that relative language rankings are preserved without native-language input.

To deepen the analysis, we identified the high-resource language combination that best approximates the native passage for each target language. MCQ Conversation was executed across all target languages using the five high-resource passages across two models: GPT-4o and GPT-4o-mini.

For each case, the L2 distance between the performance with the substituted passage and that on the original native-language passage was calculated. The combination of high-resource language that minimizes this distance is reported in Table 7 and plotted in Figure 6. Results show that for high- and mid-resource languages, the best-performing

combination typically includes English. However, for low-resource languages, combinations excluding English usually performed better. This indicates that English is not always the optimal substitute, especially for low-resource languages. The details about the best combinations on each language is provided in Appendix C.4.

5.3 Qualitative Error Analysis: GPT-4o in English and Korean

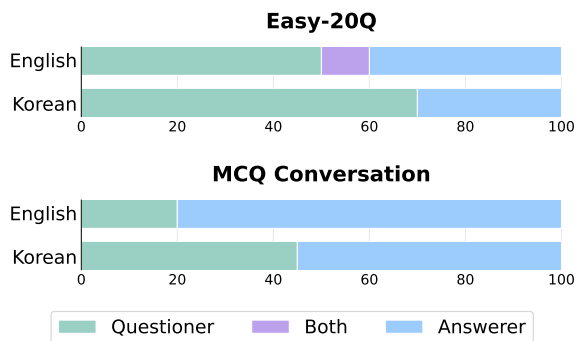


Figure 7: Attribution of errors by conversational role. Bars show the percentage of failures caused by Questioner (green), Answerer (blue), or Both roles (purple).

Setup. To validate that task completion rates reflect genuine language capabilities, we conducted a fine-grained error analysis on GPT-4o outputs in English and Korean. We chose GPT-4o as a representative high-performing model and selected English and Korean to leverage the authors’ proficiency for reliable annotation. The authors manually annotated 160 GPT-4o conversation logs, sampling 20 success and failure cases each for Easy Twenty Questions and MCQ Conversation in English and Korean. Initial classification was performed using Gemini-2.5-flash, then manually corrected by two authors proficient in both languages.

Findings. Figure 7 reveals systematic task-specific error patterns that validate our framework design. The Code Reconstruction task is excluded from this role-based error analysis, as attributing failure to either the ‘describer’ or ‘rebuilder’ is inherently ambiguous. Easy Twenty Questions failed primarily due to questioner errors, reflecting strategic question generation challenges, while MCQ Conversation showed predominantly answerer errors, indicating passage comprehension difficulties. These patterns remained consistent across languages, confirming that failures stem from genuine communicative challenges rather than external

factors. Success cases showed minimal errors in both roles, while rare successful cases with conversational errors reflected expected random chance. The LLM-based initial annotation achieved 78.8% accuracy (62.5% for failure cases, 95.0% for success cases).

Representative Error Case. In the MCQ Conversation task, Questioner errors often stemmed from failures to faithfully incorporate all relevant information from the original query when generating questions. Key semantic or lexical elements were frequently omitted, resulting in questions that lacked sufficient grounding in the passage—ultimately leading to unanswerable or misleading queries. In contrast, Answerer errors primarily reflected incorrect inference from the passage. Detailed examples of representative error cases are provided in Appendix C.5.

In the Easy Twenty Questions task, Questioner errors were typically caused by ineffective information-seeking strategies, such as asking insufficiently discriminative questions within the 20-turn limit or making premature guesses despite the presence of multiple plausible candidates. Most Answerer errors in this task were due to hallucinated responses, where the model generated logically incorrect “yes”/“no”/“maybe” answers.

5.4 Generation Statistics

While running the experiments, we collected detailed generation statistics, averaged over models and language groups. Specifically, we measured (1) token count, (2) sequence length, (3) language fidelity, (4) instruction-following of the Answerer, and (5) interaction length. A full description of these statistics is provided in Appendix D. We summarize key findings below:

- **Token Count and Sequence Length:** Output length varied by language resource level, with English being the shortest and low-resource languages generally producing the longest outputs.
- **Language Fidelity:** Although slightly lower in low-resource languages, fidelity scores remained similarly high across all groups.
- **Answerer Instruction-Following and Interaction Length:** These metrics were largely consistent across language resource groups

and models. On average, Easy Twenty Questions involved 14.3 turns, and MCQ Conversation 4.0.

6 Conclusion

A fundamental limitation in multilingual evaluation is the reliance on ground-truth references or LLM-based judgments, which are often unreliable or infeasible for low-resource languages. To address this, we introduce 🍷 **MUG-Eval**, a language-agnostic evaluation framework based on three conversational task completion between LLMs that assess both generation and comprehension.

We evaluate 8 LLMs across 30 languages using MUG-Eval. Our framework demonstrates strong internal consistency and aligns well with established multilingual benchmarks, while remaining reference-free and cost-effective. Our results highlight a few implications. First, MUG-Eval enables fine-grained performance comparisons even in low-resource settings due to its task diversity and saturation characteristics. Second, we find that substituting native-language passages with English often degrades performance—especially for low-resource languages—underscoring the need for evaluation methods that go beyond English-centric assumptions.

Limitations

MUG-Eval measures whether communication succeeds, but not how well it succeeds—a model generating minimal functional text scores identically to one producing sophisticated, nuanced output, as long as both complete the task. This limitation poses challenges for applications requiring natural, culturally appropriate, or stylistically rich text generation. Furthermore, comparing linguistic quality across languages remains fundamentally difficult because notions of richness and quality vary significantly across linguistic and cultural contexts, making it challenging to establish universal cross-linguistic metrics. This focus on communicative effectiveness over stylistic quality is an intentional design choice, ensuring our framework remains scalable and objective in low-resource settings where fluency evaluation is often infeasible. While this trade-off enables our language-agnostic evaluation approach, it remains a limitation for comprehensively assessing generation quality.

While MUG-Eval’s reliability is supported by its strong correlations with existing benchmarks,

comprehensive human evaluation has not yet been conducted. Our qualitative error analysis of 160 conversation logs (§5.3) provided initial validation of failure patterns and confirmed that task failures stem from genuine communicative challenges rather than external factors. However, broader human validation across all 30 languages would provide deeper insights into the framework’s fairness across different languages and enable more detailed qualitative analysis of model performance patterns. Given the conversational nature of MUG-Eval’s tasks, human evaluation could reveal which specific conversational aspects challenge different models, particularly since performance varies significantly depending on conversational roles.

Despite MUG-Eval’s language-agnostic design, certain implementation aspects remain English-centric. The difficulty of accurately translating prompts into all target languages, especially low-resource ones, necessitated using English for instructional prompts in the conversational scenarios. Additionally, the Code Reconstruction task employs Latin script for code, with variable and function names following English naming conventions. These factors may introduce systematic biases against non-Latin script languages and low-resource language contexts, potentially affecting the framework’s cross-linguistic validity.

Ethical Considerations

Our human evaluation study was conducted with approval from the Institutional Review Board (IRB), ensuring all procedures adhered to established ethical research standards. All participants recruited for the annotation task were compensated for their time at a rate of 30,000 KRW (approximately 21.76 USD as of September 2025), a rate that meets or exceeds fair compensation guidelines for our region.

Acknowledgments

This work was supported by Institute of Information & communications Technology Planning & Evaluation (IITP) grant funded by the Korea government (MSIT) (No. RS-2024-00509258 and No. RS-2024-00469482, Global AI Frontier Lab).

This research project has benefitted from the Microsoft Accelerate Foundation Models Research (AFMR) grant program through which leading foundation models hosted by Microsoft Azure along with access to Azure credits were provided

to conduct the research.

We acknowledge using ChatGPT¹ and Claude² for writing and coding assistance, and Perplexity³ and OpenScholar (Asai et al., 2024) for literature search.

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Appendix

A Data Preparation

A.1 Languages

Throughout this paper, we evaluated LLMs across 30 languages: 10 high-resource, 10 mid-resource, and 10 low-resource languages. The resource classification follows the categorization defined by Singh et al. (2024).

ISO Code	Language	Script	Resources
arb_Arab	Arabic	Arabic	High
deu_Latn	German	Latin	High
eng_Latn	English	Latin	High
fra_Latn	French	Latin	High
hin_Deva	Hindi	Devanagari	High
ita_Latn	Italian	Latin	High
jpn_Jpan	Japanese	Japanese	High
por_Latn	Portuguese	Latin	High
spa_Latn	Spanish	Latin	High
zho_Hans	Chinese	Simplified Han	High
ben_Beng	Bengali	Bengali	Mid
ell_Grek	Greek	Greek	Mid
heb_Hebr	Hebrew	Hebrew	Mid
ind_Latn	Indonesian	Latin	Mid
kor_Hang	Korean	Hangul	Mid
lit_Latn	Lithuanian	Latin	Mid
ron_Latn	Romanian	Latin	Mid
tha_Thai	Thai	Thai	Mid
ukr_Cyrl	Ukrainian	Cyrillic	Mid
zsm_Latn	Malay	Latin	Mid
amh_Ethi	Amharic	Ethiopic	Low
hau_Latn	Hausa	Latin	Low
ibo_Latn	Igbo	Latin	Low
kir_Cyrl	Kyrgyz	Cyrillic	Low
npi_Deva	Nepali	Devanagari	Low
sin_Sinh	Sinhala	Sinhala	Low
som_Latn	Somali	Latin	Low
swl_Latn	Swahili	Latin	Low
tel_Telu	Telugu	Telugu	Low
yor_Latn	Yoruba	Latin	Low

Table 3: All 30 languages used in this paper with each language’s corresponding ISO codes, scripts, and resource classifications defined by Singh et al. (2024)

A.2 Datasets

Easy Twenty Questions. We began with 200 English words from the dev and test sets of the *Things*¹ dataset (Zhang et al., 2024). We translated these words into all 30 target languages using Google Translate². To ensure consistency and quality, we

¹<https://github.com/apple/ml-entity-deduction-arena>
²<https://translate.google.com>

applied several filtering steps: we removed words where Latin characters persisted in non-Latin script languages, eliminated duplicates within each language, and filtered out remaining loan words to ensure semantic consistency across all languages. This filtering process yielded a final set of 140 words that maintained equivalence across all 30 languages. For each target word in each language, we randomly sampled 99 additional words from the same language to create a candidate pool of 100 words. The composition of these candidate pools and their ordering were kept consistent across all languages to ensure fair comparison. Table 4 provides example target words used in the Easy Twenty Questions task.

Other tasks and benchmarks. We utilized datasets available on Hugging Face for Belebele³, HumanEvalExplain⁴, Global-MMLU⁵, and MultiQ⁶. Our experiments included the same 30 languages for Belebele and MultiQ that we used in our framework, while Global-MMLU experiments covered 29 languages (excluding Thai). For Global-MMLU, we specifically used only the Culturally-Agnostic (CA) subset to ensure fair cross-lingual comparability across all evaluated languages.

B Experimental Setup

B.1 Models

We conduct our evaluation by selecting recent LLMs, accessing with APIs. This information is summarized in Table 5.

B.2 Generations

The tasks used in our evaluation were configured with different generation parameters, such as temperature, token limits, and thresholds for fidelity scoring. Details for each task are provided in Table 6.

Generation settings. We modified several benchmark settings to ensure fair multilingual comparison. Key adjustments included explicitly prompting models to use the target language, rather than assuming responses would match the question language. For Code Reconstruction, we removed code description length limits since consistent length

³<https://hf.co/datasets/facebook/belebele>

⁴<https://hf.co/datasets/bigcode/humanevalpack>

⁵<https://hf.co/datasets/CohereLabs/>

Global-MMLU

⁶<https://hf.co/datasets/caro-holt/MultiQ>

ISO Code	Translated Words		
	Foam	Mango	Ice
amh_Ethi	አረፋ	ማንጎ	በረዶ
arb_Arab	رغوة	مانجو	ثلج
ben_Beng	ফোম	আম্র	বরফ
deu_Latn	Schaum	Mango	Eis
ell_Grek	Αφρός	Μάνγκο	Πάγος
eng_Latn	Foam	Mango	Ice
fra_Latn	Mousse	Mangue	Glace
hau_Latn	Kumfa	Mango	kankara
heb_Hebr	קצף	מנגו	קרח
hin_Deva	फोम	मैंगो	बर्फ
ibo_Latn	ufufu	Mango	ice
ind_Latn	Busa	Mangga	Es
ita_Latn	Schiuma	Mango	Ghiaccio
jpn_Jpan	泡	マンゴー	氷
kir_Cyrl	көбүк	Маңго	Мүз
kor_Hang	거품	망고	얼음
lit_Latn	Putos	Mangas	Ledas
npi_Deva	फोम	आँप	बरफ
por_Latn	Espuma	Manga	Gelo
ron_Latn	Spumă	Mango	Gheață
sin_Sinh	පිට්ට	අඹ	අයිස්
som_Latn	xumbo	Cambaha	baraf
spa_Latn	Espuma	Mango	Hielo
swh_Latn	Povu	Embe	barafu
tel_Telu	నురుగు	మామిడి	ఐస్
tha_Thai	โฟม	มะม่วง	น้ำแข็ง
ukr_Cyrl	Піна	Манго	Лід
yor_Latn	Foomu	Mango	Yinyin
zho_Hans	泡沫	芒果	冰
zsm_Latn	Buih	Mangga	Ais

Table 4: Example target words used in the Easy Twenty Questions task. Words were sourced from the *Things* dataset and translated into 30 languages via Google Translate.

constraints across different scripts isn’t feasible. We use 5-shot prompting for Global-MMLU and zero-shot for Belebele.

Prompts. We provide prompts used for the three main tasks introduced in Section 3.1, as well as for established benchmarks which are Belebele (Bansdarkar et al., 2024), MultiQ (Holtermann et al.,

2024), and Global-MMLU (Singh et al., 2025) (for section §5.1). Each table outlines the role-specific prompts that we provided to two separate model instances. For Easy Twenty Questions and MCQ Conversation, the instances act as a *questioner* and an *answerer*; for Code Reconstruction, they act as a *describer* and a *rebuilder*. The prompt for Easy Twenty Questions is provided in Table 11, MCQ Conversation is in Table 12, and Code Reconstruction is in Table 13. The prompts for the preexisting three tasks are provided in Table 14.

Cost Analysis. The total cost to replicate our main results (Table 2) was approximately 608 USD, calculated using API pricing from OpenRouter and Azure OpenAI Service. The costs were distributed across the tasks as follows: Easy Twenty Questions (252 USD), MCQ Conversation (338 USD), and Code Reconstruction (18 USD). Notably, the evaluation of GPT-4o, our most expensive model, accounted for the majority of this expenditure at 449 USD.

C Detailed Experiment Results and Analysis

This section presents a comprehensive breakdown of our experimental results, including task-specific performance and its cross-lingual comparisons across multiple models. We also provide visualizations of task-wise correlations and additional evaluation results not included in the main paper.

C.1 Results on all languages on all models

Table 17, 18 present the evaluation results for all eight models across 30 languages and three tasks. For each model, we report task-wise accuracy scores across all languages, along with their corresponding Z-scores.

To account for varying task difficulties and enable a unified language ranking per model, we compute Z-scores that aggregate performance across the three tasks. Each task’s scores are standardized independently, using the global mean and standard deviation computed over all models and languages for that task. This ensures that task-specific differences in difficulty are normalized appropriately. We then compute the average Z-score across the three tasks per language, allowing for relative performance comparisons across languages within each model.

A Z-score above 0 indicates that the model’s accuracy on that language is above the global aver-

Model	Model Identifier	API Provider
GPT-4o	gpt-4o-2024-08-06	Azure OpenAI Service
GPT-4o-mini	gpt-4o-mini-2024-07-18	
Gemini-2.5-flash	gemini-2.5-flash-preview-04-17	OpenRouter
Gemini-2.0-flash	gemini-2.0-flash-001	
Qwen2.5-72B	Qwen/Qwen2.5-72B-Instruct	
Qwen2.5-7B	Qwen/Qwen2.5-7B-Instruct	
Llama-3.3-70B	meta-llama/Llama-3.3-70B-Instruct	
Llama-3.1-8B	meta-llama/Llama-3.1-8B-Instruct	

Table 5: Model identifiers and API providers used in experiments

Name	Temperature	Max Tokens	Fidelity Threshold
Easy Twenty Questions	0.7	Questioner: 1024 Answerer: 128	Language: 0.7 Answer: 0.9
MCQ conversation	0.7	Questioner: 2048 Answerer: 256	Language: 0.9 Answer: 0.9
Code Reconstruction	Describer: 0.7 Rebuilder: 0.2	2048	Language: 0.9
Global MMLU	0.0	32	N/A
Belebele	0.7	2048	N/A
MultiQ	0.0	Model: 256 Judge: 32	Language: 0.9

Table 6: Task-specific generation settings used in the evaluation

age, while a negative score suggests below-average performance. These aggregated Z-scores provide a normalized basis for ranking languages within each model and allow for interpretable comparisons.

C.2 Visualizations of task-wise correlations

We present a set of 6×6 scatter plots in Figure 10, visualizing pairwise correlations between the six tasks. Each plot compares the accuracy scores of two tasks across all 30 languages for 8 models, resulting in one point per language per model.

Each point in a scatter plot represents the performance of a particular language on two different tasks, with the x - and y -axes indicating the accuracy scores for each task. These visualizations help identify trends and clusters, revealing how performance on one task relates to another across languages.

These scatter plots serve as a visual counterpart to the Pearson correlation coefficients (r) reported in Figure 5, offering an intuitive understanding of inter-task relationships observed in our experiments.

C.3 Additional plot about language resource flexibility on MCQ Conversation

Following up on the analysis in Section 5.2, we conducted the same experiment with GPT-4o-mini under identical settings.

Figure 8 presents the MCQ Conversation accuracy across 30 languages when passages are provided in four different conditions: (1) the target language, (2) English, (3) a fixed set of five high-resource languages (averaged), and (4) a selection of up to five high-resource languages that are most similar to the target language. The overall trend is consistent with that of GPT-4o (Figure 6).

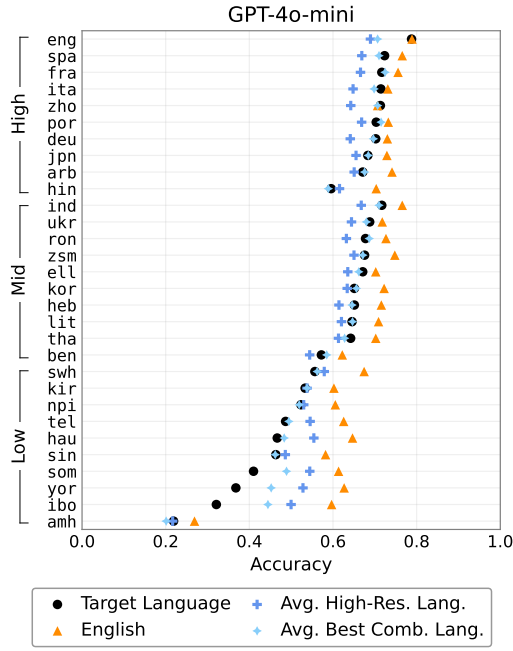


Figure 8: MCQ Conversation accuracy comparison across 30 languages for GPT-4o-mini, using passages in: (1) the target language, (2) English, (3) a fixed set of five high-resource languages (averaged), and (4) a selection of up to five high-resource languages most similar to the target language, with scores averaged.

C.4 Additional analysis about language resource flexibility on MCQ Conversation

To complement the substitution analysis in Section 5.2, Table 7 lists, for each of the 30 target languages, the subset of high-resource languages (selected from English, Chinese, Japanese, Hindi, and Arabic) that most closely approximates the original target-language passage in terms of MCQ Conversation accuracy.

The optimal subset for each target language was determined by selecting the combination (up to five languages) that minimizes the L2 distance from the original accuracy, as described in Section 5.2. When the target language itself was one of the five high-resource languages, it was excluded from its own substitution set. These exclusions are marked with **X** in the corresponding table entries.

ISO Code	Language	Resources	ENG	ZHO	ARB	JPN	HIN
spa_Latn	Spanish	High	✓	✓	✓		
arb_Arab	Arabic	High	✓	✓	X	✓	
deu_Latn	German	High	✓	✓			
fra_Latn	French	High	✓	✓			
ita_Latn	Italian	High	✓	✓			
por_Latn	Portuguese	High	✓	✓			
zho_Hans	Chinese	High	✓	X			
eng_Latn	English	High	X	✓			
jpn_Jpan	Japanese	High		✓		X	
hin_Deva	Hindi	High				✓	X
zsm_Latn	Malay	Mid	✓	✓	✓	✓	
lit_Latn	Lithuanian	Mid	✓	✓	✓		
kor_Hang	Korean	Mid	✓		✓	✓	
ben_Beng	Bengali	Mid	✓	✓			
ron_Latn	Romanian	Mid	✓	✓			
ukr_Cyrl	Ukrainian	Mid	✓		✓		
ell_Grek	Greek	Mid	✓			✓	
heb_Hebr	Hebrew	Mid	✓			✓	
ind_Latn	Indonesian	Mid	✓			✓	
tha_Thai	Thai	Mid	✓				✓
sin_Sinh	Sinhala	Low		✓	✓	✓	✓
npi_Deva	Nepali	Low	✓		✓	✓	✓
kir_Cyrl	Kyrgyz	Low		✓	✓	✓	
amh_Ethi	Amharic	Low			✓	✓	
swh_Latn	Swahili	Low			✓		
hau_Latn	Hausa	Low					✓
ibo_Latn	Igbo	Low					✓
som_Latn	Somali	Low					✓
tel_Telu	Telugu	Low					✓
yor_Latn	Yoruba	Low					✓

Table 7: Optimal subsets of high-resource languages (selected from English, Chinese, Japanese, Hindi, and Arabic) for approximating the native-language passage performance in the MCQ Conversation task. For each target language, the listed subset scores the lowest L2 distance from the original accuracy. If the target language is one of the five high-resource options, it is excluded from its own substitution set, denoted with **X**.

C.5 Human analysis case on MCQ Conversation Errors

As described in Section 5.3, we conducted a qualitative error analysis for both the Easy Twenty Questions and MCQ Conversation tasks. Specifically, we examined which conversational agent—the Questioner or the Answerer—was primarily responsible for task failure in each case. Tables 15 and 16 provide illustrative examples of typical errors for each role, along with our analysis of the underlying issues.

C.6 Correlation with Human Evaluation on MultiQ

To further validate MUG-Eval’s effectiveness as a proxy for human evaluation, we conducted a human analysis for MultiQ dataset on 14 languages and 8 models.

C.6.1 Setup

To empirically validate MUG-Eval’s automated scores against human judgments, we conduct a human evaluation study. Because the conversational logs from our framework are highly structured, we use the more open-ended MultiQ benchmark (Holtermann et al., 2024) to test whether MUG-Eval scores generalize as a reliable proxy for general-purpose text quality. This study evaluates outputs from the eight LLMs for a set of 15 questions sampled from the original 200 in the MultiQ benchmark. The evaluation spans 14 languages selected to cover high-resource (Arabic, Chinese, English, French, Hindi), mid-resource (Bengali, Indonesian, Korean, Malay, Thai), and low-resource (Amharic, Kyrgyz, Sinhala, Swahili) categories.

We recruit 12 annotators—primarily university students in South Korea—each a native speaker of their assigned language(s). Ten annotators cover a single language, while two bilingual annotators are responsible for two languages each (French/Arabic and Chinese/Malay). The same 15 questions are selected for all languages. To ensure the evaluation is both manageable and effective at differentiating model performance, we prioritize the most challenging questions based on a preliminary LLM-as-judge scoring using Gemini-2.5-flash. Before the main task, annotators are calibrated using a standardized set of English examples scored by the authors to ensure consistent judgment. Each participant evaluates the full set of generated responses for their language(s) in a two-hour session. Following a rubric adapted from Hada et al. (2024a), responses are scored on a 5-point Likert scale across three criteria: Linguistic Acceptability (fluency and naturalness), Output Content Quality (coherence and clarity), and Task Quality (how well the response addresses the question).

C.6.2 Result

For each question–answer set across 14 languages and 8 models, we first computed annotation scores for three metrics—Linguistic Acceptability, Output Content Quality, and Task Quality—and then averaged them to obtain a Total Average score per sample. These final annotation scores were subsequently averaged across samples for each language–model pair, yielding 112 aggregated scores (14 languages \times 8 models). We then examined the correlation between these human evaluation scores (based on the three criteria) and task-specific scores from MUG-Eval as well as three existing multilin-

gual benchmarks, all provided per language and model. Correlation statistics are reported in Figure 9.

The results show moderate to strong correlations between human judgments and MUG-Eval scores across tasks and metrics. This demonstrates that although MUG-Eval was originally designed for structured, information-gap tasks, its task completion–based scores generalize well to open-ended question answering in MultiQ. The strongest correlation was with Task Quality and the weakest with Linguistic Acceptability, reflecting MUG-Eval’s focus on accurate information transfer rather than fluency. These findings suggest that MUG-Eval scores align well with human evaluation, though the three metrics are not fully independent.

		Pearson’s r				Spearman’s ρ			
Ours	Global-MMLU	0.60	0.51	0.54	0.62	0.51	0.45	0.44	0.55
	Code-R	0.59	0.49	0.58	0.57	0.54	0.46	0.54	0.51
	MCQ Conv	0.56	0.46	0.56	0.53	0.53	0.44	0.54	0.49
	Belebele	0.58	0.51	0.56	0.55	0.59	0.52	0.57	0.54
	Multi Q	0.62	0.55	0.59	0.59	0.54	0.49	0.53	0.49
	Easy-20Q	0.49	0.43	0.45	0.47	0.49	0.45	0.44	0.47
		Total Average	Linguistic Acceptability	Output Content Quality	Task Quality	Total Average	Linguistic Acceptability	Output Content Quality	Task Quality

Figure 9: Correlation analysis between human annotation on MultiQ data and six tasks consisting of MUG-Eval and existing multilingual benchmarks. Heatmaps show Pearson’s r (left) and Spearman’s ρ (right) correlation coefficients between human annotation and six tasks. All correlations exceed 0.4, demonstrating medium to strong consistency between human annotation with other six tasks, validating MUG-Eval’s effectiveness as a multilingual evaluation framework.

C.7 Extending MUG-Eval to Summarization

To demonstrate the extensibility of the MUG-Eval framework beyond our initial three tasks, we implement a new summarization task based on the same “information-gap” paradigm underlying MUG-Eval’s design.

C.7.1 Methodology

We employed the same 8 models and 30 languages from MUG-Eval. The summarization evaluation was conducted as follows:

Summarization-Length Limit Normalization:

Using the FLORES+ (Goyal et al., 2022) dataset, which primarily contains human-translated texts, we sampled 100 English sentences and retrieved their translations in 30 target languages. For each pair, we computed the ratio of character lengths by dividing the length of the translated sentence in a target language by the length of the corresponding English sentence, using Python’s `len()` function. These ratios were then applied for length control in multilingual summarization.

Dataset: We sampled 100 articles from the QAGS (Wang et al., 2020) dataset, each originally in English. For each article, we generated 5 English question–answer pairs using GPT-4o-mini, with answers reflecting key factual entities.

Evaluation Process: For each model, language, and article, we followed this process:

1. A Summarizer LLM (target model) produced a summary of the article in the target language. Its language was verified using GlotLID, and the length was constrained to $(\text{Original English article length}) \times 0.5 \times (\text{language length ratio})$.
2. An Answerer LLM (target model) received only the target-language summary and the English questions, and generated answers in English.
3. The generated answers were compared to the gold answers using an LLM-as-Judge (GPT-4o-mini). Since both gold and generated answers were in English, this evaluation setup avoids translation-related bias.

C.7.2 Results

The average accuracy of the Answerer LLM across all models and languages is reported in Table 10, and its correlation score with six tasks consisting of MUG-Eval and existing multilingual benchmarks is reported in Table 8. This experiment shows that MUG-Eval can be readily extended to summarization while preserving its information-gap design, enabling scalable evaluation without references or human judgments. The results further exhibit moderate-to-strong correlations with the original MUG-Eval tasks, indicating that the framework captures a generalizable signal of multilingual generation quality.

D Generation Statistics

As stated in Section 5.4, we report detailed generation statistics in Table 9, averaged over models

and language groups. Specifically, we measured the following:

- **Token Count and Sequence Length:** The number of tokens (# Token) and total character count (# Char) are computed from outputs generated in the target language by the questioner or the describer. The number of tokens were computed using the tokenizer associated with each model used in the experiments.
- **Language Fidelity:** Fidelity is measured as the percentage of questioner or describer outputs identified by GlotLID as matching the target language.
- **Instruction-Following of the Answerer:** Answerer Instruction-Following (A I-F) is defined for Easy Twenty Questions and MCQ Conversation as the proportion of answerer responses that strictly follow the output format (“yes,” “no,” and “maybe”).
- **Interaction Length:** The number of question turns per interaction (# Turn) is reported for Easy Twenty Questions and MCQ Conversation, both of which are multi-turn tasks.

	Pearson	Spearman
Easy Twenty Questions	0.65	0.63
MCQ Conversation	0.65	0.61
Code Reconstruction	0.79	0.74
Global MMLU	0.68	0.68
Belebele	0.66	0.65
MultiQ	0.62	0.65

Table 8: Correlation score of summarization task with six tasks consisting of MUG-Eval and existing multilingual benchmarks. Overall correlation scores show high correlation, suggesting that the extension of MUG-Eval to other domains is plausible.

		Easy Twenty Questions					MCQ Conversation					Code Reconstruction		
		# Token	# Char.	Fidelity	A I-F	# Turn	# Token	# Char.	Fidelity	A I-F	# Turn	# Token	# Char.	Fidelity
Language	All	29.95	52.12	95.00	99.57	14.33	49.07	103.85	98.32	99.50	3.99	181.04	374.30	97.72
	ENG	11.19	45.28	96.52	100.00	14.32	23.22	111.43	99.88	99.95	4.05	93.50	412.86	99.63
	High	16.19	44.47	95.78	99.30	14.25	30.24	94.63	97.76	99.37	3.98	113.36	341.29	97.91
	Mid	18.88	41.97	95.59	99.53	14.32	38.16	92.54	98.93	99.72	3.95	147.26	344.32	98.64
	Low	54.77	69.87	93.61	99.88	14.42	78.70	124.31	98.28	99.40	4.04	282.50	437.31	96.61
Model	GPT-4o	14.80	38.52	97.16	100.00	13.96	27.10	71.54	99.80	100.00	4.02	123.68	345.46	99.91
	Gemini-2.0-flash	9.81	22.60	94.49	99.99	15.59	44.15	110.25	99.06	100.00	4.21	124.75	332.00	99.85
	Gemini-2.5-flash	9.70	24.23	95.28	99.90	14.02	55.10	178.68	91.88	99.88	3.95	117.67	296.46	96.48
	Qwen2.5-72B	57.47	78.58	96.48	100.00	14.24	61.42	98.82	99.85	100.00	3.94	288.51	494.24	99.46
	GPT-4o-mini	14.28	34.67	97.64	100.00	16.00	47.45	81.39	99.85	100.00	4.08	124.70	351.47	99.98
	Llama-3.3-70B	38.33	82.68	91.52	99.93	11.07	46.92	82.72	99.86	98.85	4.00	139.93	256.66	99.83
	Qwen2.5-7B	61.22	81.07	93.78	99.83	16.50	77.60	128.97	97.16	99.92	3.30	256.50	443.95	92.84
	Llama-3.1-8B	33.83	54.97	93.62	96.89	13.25	87.03	138.48	99.12	97.34	4.40	272.59	474.21	93.39

Table 9: Average token count (# Token), character-level sequence length (# Character), GlotLID-based language fidelity (Fidelity), instruction-following rate of the answerer (A I-F), and average number of question turns (# Turn) are computed per task, model, and language group.

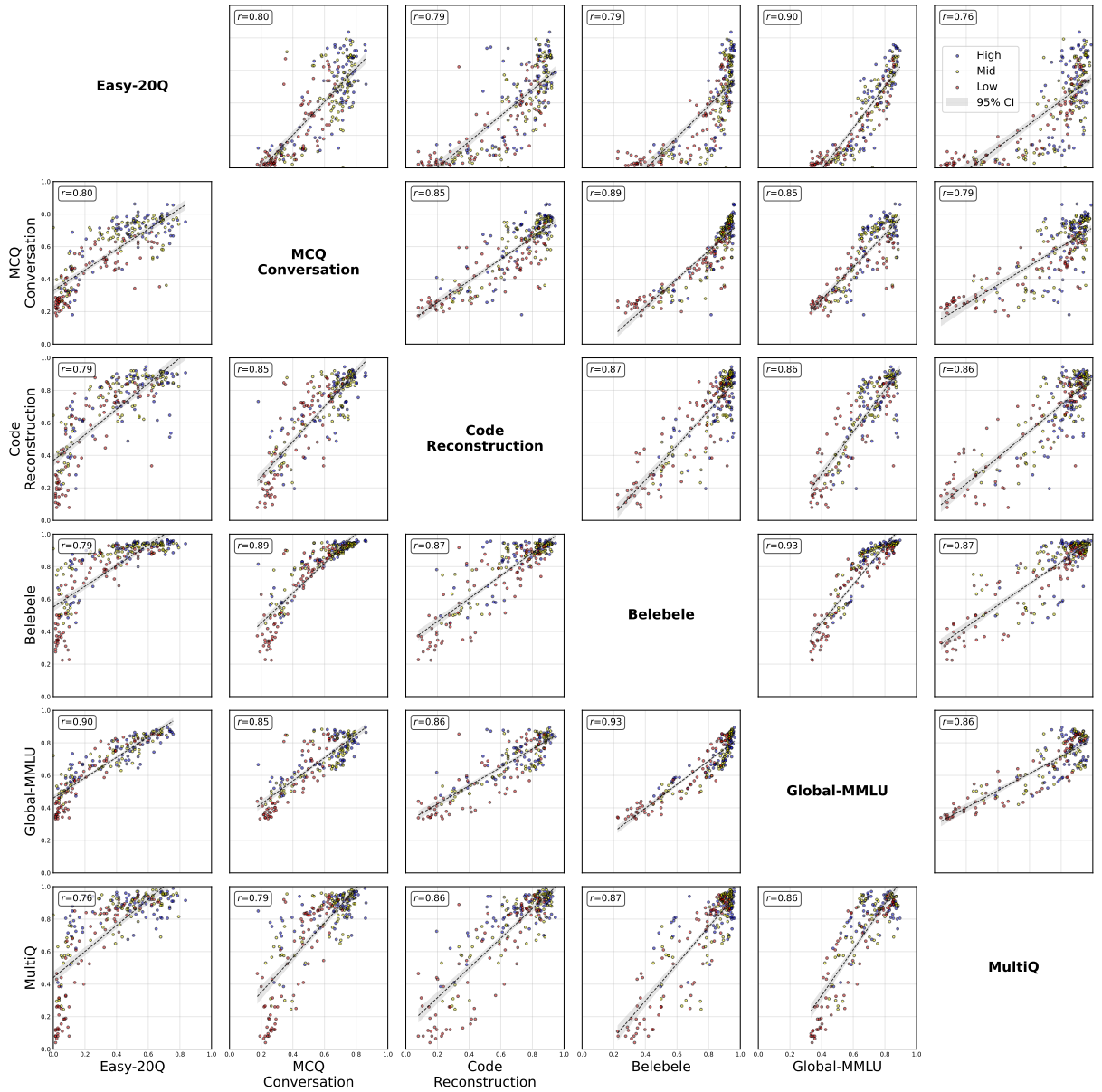


Figure 10: Correlation matrix showing relationships between MUG-Eval tasks and existing multilingual benchmarks. Each cell displays Pearson’s correlation coefficient (r) with 95% confidence intervals, with points colored by language resource level.

	gpt-4o	gpt-4o-mini	gemini-2.5- flash	gemini-2.0- flash	qwen-2.5- 72b	qwen-2.5-7b	llama-3.3- 70b	llama-3.1-8b
Spanish	0.76	0.77	0.78	0.79	0.81	0.62	0.52	0.4
Arabic	0.57	0.56	0.54	<u>0.53</u>	0.57	0.3	<u>0.25</u>	0.07
German	0.76	0.78	0.8	0.75	0.81	0.55	0.49	0.39
French	0.76	0.76	0.79	0.76	0.8	0.6	0.46	0.46
Italian	0.76	0.75	0.8	0.78	0.8	0.6	0.45	0.34
Portuguese	0.79	0.77	0.78	0.74	0.82	0.57	0.5	0.39
Chinese	0.56	0.56	0.6	0.63	0.75	0.56	0.36	0.18
English	0.79	0.76	0.83	0.74	0.8	0.64	0.52	0.42
Japanese	0.58	0.52	0.6	0.65	0.71	0.47	0.37	0.11
Hindi	0.6	0.64	0.63	0.58	0.61	0.45	0.4	0.27
Malay	0.73	0.78	0.79	0.75	0.69	0.29	0.44	0.25
Lithuanian	0.71	0.71	0.71	0.67	0.71	0.47	0.42	0.33
Korean	0.6	0.52	0.6	0.68	0.62	0.37	0.38	0.13
Bengali	0.69	0.68	0.68	0.72	0.72	0.42	0.45	0.3
Romanian	0.76	0.78	0.78	0.76	0.8	0.54	0.5	0.39
Ukrainian	0.69	0.73	0.75	0.71	0.73	0.45	0.44	0.26
Greek	0.73	0.69	0.78	0.73	0.72	0.44	0.47	<u>0.06</u>
Hebrew	0.67	0.63	0.68	0.67	0.51	0.26	0.43	0.22
Indonesian	0.77	0.77	0.78	0.73	0.85	0.6	0.5	0.38
Thai	0.73	0.65	0.72	0.74	0.73	0.49	0.42	0.08
Sinhala	0.52	0.47	0.69	0.64	0.5	0.28	0.36	0.11
Nepali	0.68	0.65	0.74	0.74	0.64	0.44	0.42	0.1
Kyrgyz	0.65	0.65	0.7	0.72	0.61	0.4	0.34	0.11
Amharic	<u>0.35</u>	<u>0.35</u>	<u>0.53</u>	0.58	<u>0.42</u>	<u>0.21</u>	0.31	0.18
Swahili	<u>0.75</u>	<u>0.75</u>	<u>0.79</u>	0.75	<u>0.65</u>	<u>0.41</u>	0.42	0.33
Hausa	0.74	0.77	0.77	0.72	0.66	0.4	0.45	0.3
Igbo	0.71	0.78	0.8	0.73	0.64	0.42	0.45	0.26
Somali	0.73	0.7	0.74	0.74	0.63	0.36	0.46	0.28
Telugu	0.65	0.61	0.7	0.69	0.57	0.33	0.41	0.33
Yoruba	0.67	0.71	0.78	0.71	0.63	0.44	0.5	0.26

Table 10: Results of the summarization task: average accuracy of the Answerer LLM across 8 models and 30 languages, demonstrating the extensibility of MuG-Eval framework

Role	Type	Prompt
Questioner	Initial Instruction	<p>You will be solving an entity deduction game by asking questions about a hidden item in {lang_full}. Your goal is to identify exactly one correct entity from a list of 100 items through strategic questioning, using as few questions as possible. You can ask yes/no/maybe questions in {lang_full}, one at a time. Each question must be concise and answerable only with "Yes," "No," or "Maybe." Do not ask for hints or the answer directly.</p> <p>Among the list, exactly one is correct. You have a maximum of 20 questions before making your final choice, but fewer questions are better. When you have determined the correct entity, provide your final answer using double brackets: [[entity]]. The entity must be exactly as it appears in the Entity List (do not translate to another language).</p> <p>< Entity List > {entity_list}</p> <p>< Language > {lang_full}</p> <p>Begin with your first question.</p>
Answerer	Instruction	<p>"Answer the following question about the hidden entity: {entity}. Respond only with ""Yes," ""No," or ""Maybe"" (including the period) without providing explanations or additional words. Do not use ""Maybe"" if the answer can be definitively ""Yes"" or ""No."" Your responses must be in English. Never mention the entity in your response. If the query contains two or more questions asked simultaneously, consider it invalid and respond with ""Maybe.""</p> <p>< Entity > {entity}</p> <p>< Language > {lang_full}</p> <p>< Question > {question}</p> <p>< Options ></p> <p>- Yes. - No. - Maybe.</p>
Questioner	Final Instruction After 20 Turns	<p>You have now used all available questions. Based on the responses you've received, provide your final guess of the entity. Even if you cannot determine the entity with confidence, provide your best guess based on the information gathered. Indicate your answer in double brackets: [[entity]]. The entity must be exactly as it appears in the Entity List (do not translate to another language).</p>

Table 11: Prompt design for the Easy Twenty Questions task. The questioner and answerer are separately prompted with role-specific instructions to simulate a Twenty Questions game. The prompts include task rules, language constraints, response formatting requirements, and structured input fields (e.g., {entity_list}, {lang_full}, {question})

Role	Type	Prompt
Questioner	Initial	<p>You will be solving a multiple-choice question by asking questions about a hidden passage. I am serving as an intermediary between you and a person who has this passage. You can ask me questions about the passage content, and I will relay these to the person. They will respond with only “yes,” “no,” or “maybe,” which I will then share with you.</p> <p>Your questions must be in {lang_full} and you can only ask one question at a time. Do not ask for hints or request the passage directly. Among the four answer choices provided, exactly one is correct. You must ask exactly 4 questions (one corresponding to each answer choice) before making your final decision. After receiving all four responses, provide your final answer in {lang_full}, indicating the correct number choice with double brackets: [[X]]</p> <p>< Query > {query}</p> <p>< Choices > (1) {c1} (2) {c2} (3) {c3} (4) {c4}</p> <p>< Language > {lang_full}</p>
	Instruction	
Answerer	Instruction	<p>Answer the following question based solely on the information contained in the passage. Do not use any external knowledge or make assumptions beyond what is explicitly stated in the text. Your response must be in English and limited to exactly one of these three answers: "Yes.", "No.", or "Maybe." (including the period). Do not provide any explanation or additional words. If the query contains two or more questions asked simultaneously, consider it invalid and respond with "Maybe."</p> <p>< Passage > passage</p> <p>< Language > lang_full</p> <p>< Question > question</p> <p>< Options > - Yes. - No. - Maybe.</p>
Questioner	Final Instruction After 10 Turns	<p>You have now used all available questions. Based on the responses you’ve received, please provide your final answer in lang_full. Indicate your choice by including the number of the correct answer in double brackets: [[X]]</p>

Table 12: Prompt design for the MCQ Conversation task. The questioner and answerer are assigned separate prompts to simulate a collaborative multiple-choice reasoning task. The questioner asks yes/no questions based on a hidden passage, while the answerer responds with constrained answers. Prompts include language and formatting instructions, as well as structured fields such as {query}, {passage}, and {lang_full}.

Role	Type	Prompt
Describer	Instruction for the English Language	Provide a concise natural language description of the code in $\{lang_full\}$. $\langle Code \rangle$ $\{code\}$ $\langle Language \rangle$ $\{lang_full\}$
Describer	Instruction for Non-English Languages	Provide a concise natural language description of the code in $lang_full$. Variable names or technical terms in English are allowed, but there shouldn't be any phrases or full sentences written in English or any language except $lang_full$. $\langle Code \rangle$ $code$ $\langle Language \rangle$ $lang_full$
Rebuilder	Instruction	"Write functional code in $\{code_lang_full\}$ according to the description written in $\{lang_full\}$. Start your code with the given declaration. Write only the code without any additional descriptions, comments, or delimiters. $\langle Language \rangle$ $\{lang_full\}$ $\langle Description \rangle$ $\{description\}$ $\langle Declaration \rangle$ $\{declaration\}$

Table 13: Prompt design for the Code Reconstruction task. One model instance (the describer) generates a natural language description of a given code snippet in the target language. Another instance (the rebuilder) reconstructs the original function from this description and a given declaration. The prompts specify language requirements and restrict the output format to code-only.

Benchmark	Type	Prompt
MultiQ	Evaluatee	Please provide an answer to the following question in {lang_full}. < Question > {question} < Language > {lang_full}
MultiQ	Classifier (LLM-as-a-Judge)	Determine if the answer to the following question is correct. The question is in English and the answer is in {lang_full}. Respond only with 'yes' or 'no' - do not include explanations or additional words. < Question > {question_en} < Language > {lang_full} < Answer > {model_pred}
Global-MMLU	-	{question} A. {option_a} B. {option_b} C. {option_c} D. {option_d} Answer:
Belebele	-	Given the following passage, query, and answer choices, output the number corresponding to the correct answer in double brackets: [[X]] < Language > {lang_full} < Passage > {passage} < Query > query < Choices > (1) {c1} (2) {c2} (3) {c3} (4) {c4}

Table 14: Prompt design for the pre-existing benchmark tasks used in our evaluation. For MultiQ, we include both evaluatee prompts and classification prompts for LLM-as-a-Judge. Global-MMLU and Belebele use simpler one-shot prompts formatted according to their original task definitions. Prompts include structured input fields such as {question}, {lang_full}, and {choices}

Language	Korean
Passage	<p>Victoria Falls is a small city in western Zimbabwe, across the border from Livingston, Zambia and Botswana. This town is located right next to the waterfalls, and they are the town's main attraction, and this popular tourist attraction also offers many opportunities for adventurers and tourists alike to stay longer. During the rainy season (November to March), waterfalls increase in volume, and the waterfalls become more dramatic. Crossing a bridge or walking down a winding path near the waterfall will cause your clothes to get wet. On the other hand, the amount of water is so large that the actual size of the waterfall is obscured by the sheer volume!</p> <p>빅토리아 폴스는 리빙스톤, 잠비아와 보츠와나 근처의 국경 건너편의 짐바브웨 서쪽에 있는 작은 도시입니다. 이 마을은 폭포 바로 옆에 위치해 있고, 그 폭포들이 마을의 주요 명소이며, 또한 이 유명한 관광지는 모험가들과 관광객들 모두에게 더 오래 머물 수 있는 많은 기회를 제공한다. 우기(11월부터 3월까지)에는 수량이 증가하며, 폭포가 더 극적으로 변합니다. 다리를 건너거나 폭포 근처의 구불구불한 길을 따라 걸어가면 옷이 젖게 됩니다. 반면에, 물의 양이 너무 많아서 실제 보이는 폭포의 크기는 - 엄청난 수량으로 인해 - 가려진다!</p>
Query	<p>If I want an open view , when should I visit the waterfall?</p> <p>탁 트인 전망을 원한다면 언제 폭포를 방문해야 합니까?</p>
Choices	<ol style="list-style-type: none"> 1. From November to March 11월부터 3월까지 2. During the tourist season 관광철에 3. When the water volume is high 수량이 많을 때 4. When it's not rainy season 장마철이 아닐 때
Conversation	<p>Questioner: Is the period from November to March suitable for visiting the waterfall? 폭포를 방문하기에 11월부터 3월까지가 적합한가요? Answerer: Yes.</p> <p>Questioner: Is the tourist season suitable for visiting the waterfall? 폭포를 방문하기에 관광철이 적합한가요? Answerer: Maybe.</p> <p>Questioner: Is it suitable to visit the waterfall when the water volume is high? 폭포를 방문하기에 수량이 많을 때가 적합한가요? Answerer: Maybe.</p> <p>Questioner: Is it suitable to visit the waterfall when it is not the rainy season? 폭포를 방문하기에 장마철이 아닐 때가 적합한가요? Answerer: Maybe.</p>
Error Analysis	<p>Each questions from the Questioner does not ask whether the visiting timing is suitable if the visitor wants an open view . As a result, each question becomes <i>an ambiguous question</i> that is difficult to answer based on the passage.</p>

Table 15: Human analysis of a case where the Questioner made an erroneous output in MCQ Conversation, ran by gpt-4o-2024-08-06. The original dataset and conversation are in Korean, with the Korean text shown in gray.

Language	English
Passage	During the 18th century Cambodia found itself squeezed between two powerful neighbors, Thailand and Vietnam. The Thais invaded Cambodia several times in the 18th century and in 1772 they destroyed Phnom Phen. In the last years of the 18th century the Vietnamese also invaded Cambodia.
Query	Which of the following statements accurately describes the invasions of Cambodia?
Choices	<ol style="list-style-type: none"> 1. The Vietnamese invaded Cambodia several times 2. The Thais and Vietnamese invaded Cambodia in 1772 3. The Vietnamese destroyed Phnom Phen 4. The Thais invaded Cambodia several times
Conversation	<p>Questioner: Is it true that the Vietnamese invaded Cambodia several times? Answerer: No.</p> <p>Questioner: Did the Thais and Vietnamese invade Cambodia in 1772? Answerer: Yes.</p> <p>Questioner: Is it true that the Vietnamese destroyed Phnom Penh? Answerer: No.</p> <p>Questioner: Did the Thais invade Cambodia several times? Answerer: Yes.</p>
Error Analysis	The answerer gave an incorrect response to the second question. While there is a mention that the Thais invaded in 1772, there is <i>no information indicating that the Vietnamese invaded Cambodia in 1772</i> . However, the answerer responded Yes. to the second question.

Table 16: Human analysis of a case where the Answerer made an erroneous output in MCQ Conversation, ran by gpt-4o-2024-08-06.

gpt-4o-2024-08-06						gpt-4o-mini-2024-07-18					
resource	lang	Total Z avg.	E-20Q Z (Acc)	MCQ-C Z (Acc)	CR Z (Acc)	resource	lang	Total Z avg.	E-20Q Z (Acc)	MCQ-C Z (Acc)	CR Z (Acc)
high	eng	1.37	1.62 (75.7)	1.56 (85.6)	0.94 (88.4)	high	eng	0.94	0.7 (53.6)	1.2 (78.8)	0.92 (87.8)
high	zho	1.33	1.94 (83.6)	1.01 (75.2)	1.04 (90.9)	high	zho	0.77	0.76 (55)	0.8 (71.3)	0.74 (83.5)
mid	ron	1.29	1.7 (77.9)	1.14 (77.7)	1.02 (90.2)	mid	ukr	0.68	0.55 (50)	0.67 (68.8)	0.81 (85.4)
high	ita	1.26	1.73 (78.6)	1.07 (76.3)	0.99 (89.6)	high	spa	0.66	0.37 (45.7)	0.86 (72.3)	0.74 (83.5)
high	por	1.24	1.47 (72.1)	1.21 (79.1)	1.04 (90.9)	high	fra	0.59	0.2 (41.4)	0.82 (71.7)	0.76 (84.1)
high	spa	1.18	1.29 (67.9)	1.16 (78.1)	1.09 (92.1)	high	por	0.58	0.14 (40)	0.75 (70.3)	0.86 (86.6)
mid	ell	1.17	1.35 (69.3)	1.08 (76.6)	1.07 (91.5)	high	deu	0.57	0.46 (47.9)	0.75 (70.2)	0.51 (78)
high	fra	1.16	1.32 (68.6)	1.18 (78.4)	0.99 (89.6)	high	jpn	0.54	0.4 (46.4)	0.65 (68.3)	0.56 (79.3)
mid	ukr	1.16	1.62 (75.7)	1.09 (76.7)	0.79 (84.8)	mid	ron	0.51	0.14 (40)	0.62 (67.8)	0.79 (84.8)
mid	heb	1.13	1.76 (79.3)	0.93 (73.8)	0.69 (82.3)	high	hin	0.46	0.7 (53.6)	0.18 (59.6)	0.51 (78)
high	arb	1.12	1.29 (67.9)	1.11 (77.1)	0.97 (89)	mid	ell	0.45	0.2 (41.4)	0.58 (67.1)	0.59 (79.9)
high	deu	1.12	1.32 (68.6)	1.27 (80.2)	0.76 (84.1)	high	ita	0.39	-0.31 (29.3)	0.81 (71.4)	0.66 (81.7)
high	jpn	1.08	1.5 (72.9)	0.95 (74.1)	0.79 (84.8)	mid	kor	0.37	-0.01 (36.4)	0.48 (65.1)	0.64 (81.1)
mid	zsm	1.06	1.08 (62.9)	1.12 (77.3)	0.97 (89)	mid	zsm	0.34	-0.25 (30.7)	0.6 (67.6)	0.66 (81.7)
mid	ind	1.05	1.17 (65)	1.1 (77)	0.86 (86.6)	high	arb	0.33	-0.28 (30)	0.58 (67.1)	0.69 (82.3)
mid	kor	1.05	1.35 (69.3)	1.07 (76.4)	0.71 (82.9)	mid	tha	0.29	-0.07 (35)	0.43 (64.2)	0.51 (78)
high	hin	1.04	1.41 (70.7)	0.67 (68.9)	1.04 (90.9)	mid	ind	0.29	-0.57 (22.9)	0.82 (71.7)	0.60 (80.5)
mid	tha	1.03	1.41 (70.7)	0.83 (71.8)	0.86 (86.6)	mid	ben	0.28	0.25 (42.9)	0.06 (57.2)	0.53 (78.7)
mid	ben	0.84	1.35 (69.3)	0.24 (60.7)	0.94 (88.4)	mid	heb	0.22	-0.22 (31.4)	0.48 (65.1)	0.41 (75.6)
mid	lit	0.81	0.67 (52.9)	1.02 (75.4)	0.74 (83.5)	mid	lit	0.17	-0.34 (28.6)	0.45 (64.6)	0.41 (75.6)
low	kir	0.77	1.05 (62.1)	0.68 (69)	0.59 (79.9)	low	npi	0	-0.13 (33.6)	-0.2 (52.3)	0.33 (73.8)
low	npi	0.72	1.05 (62.1)	0.36 (63)	0.74 (83.5)	low	kir	-0.1	-0.19 (32.1)	-0.15 (53.3)	0.03 (66.5)
low	swh	0.68	0.2 (41.4)	0.94 (73.9)	0.92 (87.8)	low	swh	-0.16	-0.96 (13.6)	-0.02 (55.7)	0.51 (78)
low	tel	0.56	0.7 (53.6)	0.3 (61.8)	0.69 (82.3)	low	tel	-0.28	-0.66 (20.7)	-0.39 (48.7)	0.21 (70.7)
low	sin	0.35	0.34 (45)	0.4 (63.7)	0.31 (73.2)	low	hau	-0.53	-1.02 (12.1)	-0.5 (46.7)	-0.07 (64)
low	som	0.16	0.17 (40.7)	-0.01 (55.9)	0.33 (73.8)	low	som	-0.61	-1.17 (8.6)	-0.8 (41)	0.13 (68.9)
low	hau	0.1	-0.28 (30)	0.12 (58.4)	0.46 (76.8)	low	sin	-0.61	-1.05 (11.4)	-0.52 (46.3)	-0.28 (59.1)
low	yor	-0.01	0.2 (41.4)	-0.49 (46.8)	0.28 (72.6)	low	ibo	-0.77	-0.93 (14.3)	-1.27 (32.1)	-0.12 (62.8)
low	ibo	-0.07	0.08 (38.6)	-0.57 (45.3)	0.28 (72.6)	low	yor	-0.92	-1.2 (7.9)	-1.02 (36.8)	-0.53 (53)
low	amh	-0.46	-0.16 (32.9)	-0.32 (50)	-0.89 (44.5)	low	amh	-1.61	-1.43 (2.1)	-1.81 (21.9)	-1.6 (27.4)

gemini-2.5-flash-preview						gemini-2.0-flash-001					
resource	lang	Total Z avg.	E-20Q Z (Acc)	MCQ-C Z (Acc)	CR Z (Acc)	resource	lang	Total Z avg.	E-20Q Z (Acc)	MCQ-C Z (Acc)	CR Z (Acc)
high	eng	1.36	1.47 (72.1)	1.57 (85.9)	1.04 (90.9)	high	eng	1.06	0.61 (51.4)	1.59 (86.2)	0.97 (89)
high	zho	1.15	1.59 (75)	0.85 (72.2)	1.02 (90.2)	high	fra	1.04	0.88 (57.9)	1.13 (77.6)	1.12 (92.7)
mid	ukr	1.12	1.29 (67.9)	1.02 (75.3)	1.07 (91.5)	high	jpn	1	1.2 (65.7)	1.02 (75.4)	0.79 (84.8)
mid	ind	1.11	1.32 (68.6)	1.19 (78.6)	0.81 (85.4)	mid	ukr	0.99	0.96 (60)	1.05 (76)	0.97 (89)
mid	heb	1.07	1.29 (67.9)	1 (75.1)	0.92 (87.8)	high	zho	0.99	0.91 (58.6)	0.87 (72.7)	1.19 (94.5)
high	arb	1.02	1.32 (68.6)	0.96 (74.2)	0.79 (84.8)	mid	ron	0.96	0.67 (52.9)	1.19 (78.6)	1.02 (90.2)
mid	zsm	1.02	1.11 (63.6)	1.22 (79.2)	0.71 (82.9)	high	por	0.93	0.64 (52.1)	1.04 (75.9)	1.09 (92.1)
high	hin	0.98	1.62 (75.7)	0.55 (66.6)	0.76 (84.1)	mid	lit	0.91	0.58 (50.7)	1.06 (76.1)	1.09 (92.1)
high	jpn	0.92	1.05 (62.1)	0.82 (71.7)	0.89 (87.2)	mid	zsm	0.88	0.91 (58.6)	0.85 (72.1)	0.89 (87.2)
mid	kor	0.87	1.23 (66.4)	0.64 (68.2)	0.74 (83.5)	mid	ind	0.88	0.67 (52.9)	0.99 (74.9)	0.97 (89)
mid	tha	0.84	1.35 (69.3)	0.11 (58.1)	1.07 (91.5)	high	hin	0.87	0.99 (60.7)	0.64 (68.2)	0.97 (89)
mid	ron	0.81	1.32 (68.6)	0.12 (58.3)	0.99 (89.6)	high	deu	0.86	0.58 (50.7)	1.03 (75.6)	0.97 (89)
low	sin	0.8	1.2 (65.7)	0.31 (61.9)	0.89 (87.2)	high	spa	0.84	0.91 (58.6)	0.66 (68.7)	0.94 (88.4)
high	spa	0.74	1.17 (65)	0.55 (66.4)	0.51 (78)	mid	kor	0.8	0.82 (56.4)	0.63 (68)	0.97 (89)
high	ita	0.74	1.53 (73.6)	0.74 (70.1)	-0.05 (64.6)	mid	ell	0.79	0.91 (58.6)	0.46 (64.8)	1.02 (90.2)
low	tel	0.63	1.11 (63.6)	0.34 (62.6)	0.43 (76.2)	mid	heb	0.74	0.7 (53.6)	0.63 (68.1)	0.89 (87.2)
mid	lit	0.56	0.85 (57.1)	1 (75)	-0.15 (62.2)	mid	tha	0.72	0.52 (49.3)	0.54 (66.3)	1.09 (92.1)
high	deu	0.54	1.56 (74.3)	0.56 (66.7)	-0.51 (53.7)	high	ita	0.69	0.49 (48.6)	0.58 (67.1)	0.99 (89.6)
mid	ell	0.53	1.08 (62.9)	-0.15 (53.3)	0.66 (81.7)	high	arb	0.68	0.82 (56.4)	0.52 (66)	0.71 (82.9)
mid	ben	0.43	1.44 (71.4)	-1.05 (36.2)	0.92 (87.8)	mid	ben	0.61	1.08 (62.9)	-0.19 (52.6)	0.94 (88.4)
high	fra	0.41	1.53 (73.6)	0.3 (61.8)	-0.61 (51.2)	low	sin	0.6	0.96 (60)	0.36 (63)	0.46 (76.8)
low	amh	0.36	0.31 (44.3)	0.47 (65)	0.31 (73.2)	low	kir	0.57	0.61 (51.4)	0.55 (66.6)	0.56 (79.3)
low	npi	0.3	1.26 (67.1)	-1.1 (35.3)	0.74 (83.5)	low	tel	0.57	0.7 (53.6)	0.36 (63)	0.64 (81.1)
low	swh	0.3	0.11 (39.3)	0.36 (62.9)	0.43 (76.2)	low	swh	0.5	-0.07 (35)	0.8 (71.2)	0.76 (84.1)
high	por	0.3	1.2 (65.7)	-0.14 (53.4)	-0.18 (61.6)	low	amh	0.34	0.76 (55)	-0.16 (53)	0.43 (76.2)
low	ibo	0.27	0.4 (46.4)	-0.36 (49.3)	0.76 (84.1)	low	hau	0.26	-0.43 (26.4)	0.28 (61.3)	0.92 (87.8)
low	kir	-0.04	1.05 (62.1)	0.18 (59.4)	-1.34 (33.5)	low	som	0.23	-0.04 (35.7)	0.04 (56.9)	0.69 (82.3)
low	som	-0.04	0.17 (40.7)	-0.28 (50.9)	-0.02 (65.2)	low	yor	0.15	-0.13 (33.6)	-0.23 (51.7)	0.81 (85.4)
low	yor	-0.06	0.11 (39.3)	-0.53 (46.1)	0.26 (72)	low	ibo	0.11	0.11 (39.3)	-0.33 (49.8)	0.56 (79.3)
low	hau	-0.19	-0.28 (30)	-0.47 (47.2)	0.18 (70.1)	low	npi	0.08	0.61 (51.4)	-1.15 (34.3)	0.79 (84.8)

Table 17: Results for each task on MuG-Eval across 30 languages, evaluated using gpt-4o-2024-08-06, gpt-4o-mini-2024-07-18, gemini-2.5-flash-preview, and gemini-2.0-flash-001. Accuracy was normalized using Z-scores and averaged across tasks. Languages were then ranked by their averaged Z-score.

llama-3.3-70b-instruct						llama-3.1-8b-instruct					
resource	lang	Total Z avg.	E-20Q Z (Acc)	MCQ-C Z (Acc)	CR Z (Acc)	resource	lang	Total Z avg.	E-20Q Z (Acc)	MCQ-C Z (Acc)	CR Z (Acc)
high	eng	0.81	0.7 (53.6)	1.33 (81.3)	0.41 (75.6)	high	eng	-0.56	-0.49 (25)	-0.63 (44.2)	-0.58 (51.8)
high	zho	0.79	1.11 (63.6)	0.94 (73.9)	0.31 (73.2)	high	spa	-0.62	-0.84 (16.4)	-0.87 (39.6)	-0.15 (62.2)
high	fra	0.56	0.61 (51.4)	0.96 (74.3)	0.1 (68.3)	high	ita	-0.85	-0.99 (12.9)	-1.19 (33.6)	-0.38 (56.7)
mid	ind	0.55	0.73 (54.3)	0.99 (74.9)	-0.07 (64)	high	por	-0.96	-1.2 (7.9)	-1.24 (32.6)	-0.43 (55.5)
high	spa	0.54	0.43 (47.1)	0.9 (73.1)	0.28 (72.6)	mid	ind	-0.97	-1.05 (11.4)	-1.13 (34.8)	-0.73 (48.2)
mid	ron	0.53	0.61 (51.4)	0.76 (70.6)	0.21 (70.7)	high	fra	-0.99	-0.96 (13.6)	-1.55 (26.8)	-0.45 (54.9)
mid	ukr	0.51	0.55 (50)	0.8 (71.3)	0.18 (70.1)	high	deu	-1.1	-1.08 (10.7)	-1.61 (25.7)	-0.61 (51.2)
mid	zsm	0.5	0.73 (54.3)	0.87 (72.6)	-0.1 (63.4)	high	zho	-1.12	-1.05 (11.4)	-1.23 (32.9)	-1.09 (39.6)
high	por	0.45	0.14 (40)	0.92 (73.4)	0.31 (73.2)	mid	ukr	-1.13	-1.08 (10.7)	-1.27 (32)	-1.04 (40.9)
high	ita	0.4	0.25 (42.9)	0.77 (70.8)	0.18 (70.1)	mid	ron	-1.14	-1.17 (8.6)	-1.4 (29.6)	-0.86 (45.1)
high	deu	0.36	0.14 (40)	0.8 (71.2)	0.15 (69.5)	high	jpn	-1.17	-1.14 (9.3)	-1.26 (32.2)	-1.11 (39)
mid	ell	0.24	0.05 (37.9)	0.51 (65.8)	0.15 (69.5)	mid	zsm	-1.21	-1.14 (9.3)	-1.21 (33.2)	-1.29 (34.8)
mid	heb	0.2	0.28 (43.6)	0.37 (63.1)	-0.05 (64.6)	mid	kor	-1.21	-1.22 (7.1)	-1.15 (34.3)	-1.27 (35.4)
mid	tha	0.14	0.17 (40.7)	0.46 (64.9)	-0.2 (61)	high	hin	-1.24	-0.93 (14.3)	-1.22 (33)	-1.57 (28)
high	arb	0.11	0.43 (47.1)	0.6 (67.4)	-0.71 (48.8)	mid	tha	-1.26	-1.14 (9.3)	-1.3 (31.4)	-1.34 (33.5)
mid	lit	0.1	-0.31 (29.3)	0.66 (68.7)	-0.05 (64.6)	mid	ell	-1.3	-1.28 (5.7)	-1.56 (26.7)	-1.06 (40.2)
mid	ben	0.1	0.23 (42.1)	0.18 (59.4)	-0.1 (63.4)	mid	lit	-1.35	-1.31 (5)	-1.29 (31.7)	-1.98 (31.1)
high	jpn	-0.08	-1.02 (12.1)	0.67 (68.9)	0.1 (68.3)	high	arb	-1.43	-1.31 (5)	-1.16 (34.1)	-1.82 (22)
high	hin	-0.15	0.28 (43.6)	-0.53 (46)	-0.2 (61)	mid	heb	-1.49	-1.37 (3.6)	-1.6 (25.9)	-1.49 (29.9)
low	tel	-0.23	-0.54 (23.6)	0.15 (58.9)	-0.3 (58.5)	mid	ben	-1.6	-1.25 (6.4)	-1.76 (22.8)	-1.8 (22.6)
low	swh	-0.24	-0.43 (26.4)	0.37 (63.1)	-0.66 (50)	low	ibo	-1.61	-1.14 (9.3)	-1.71 (23.7)	-1.98 (18.3)
mid	kor	-0.25	-1.52 (0)	0.82 (71.7)	-0.05 (64.6)	low	swh	-1.63	-1.43 (2.1)	-1.54 (26.9)	-1.9 (20.1)
low	npi	-0.38	-0.13 (33.6)	-0.43 (48)	-0.58 (51.8)	low	som	-1.64	-1.28 (5.7)	-1.57 (26.4)	-2.08 (15.9)
low	kir	-0.54	-0.84 (16.4)	-0.04 (55.4)	-0.73 (48.2)	low	hau	-1.65	-1.2 (7.9)	-1.66 (24.7)	-2.1 (15.2)
low	sin	-0.58	-0.78 (17.9)	0.18 (59.4)	-1.14 (38.4)	low	tel	-1.7	-1.31 (5)	-1.87 (20.8)	-1.93 (19.5)
low	hau	-0.86	-0.96 (13.6)	-0.5 (46.7)	-1.11 (39)	low	kir	-1.75	-1.37 (3.6)	-1.53 (27.1)	-2.33 (9.8)
low	ibo	-1.08	-0.87 (15.7)	-1.04 (36.4)	-1.34 (33.5)	low	yor	-1.76	-1.11 (10)	-1.77 (22.6)	-2.41 (7.9)
low	som	-1.26	-1.2 (7.9)	-1.23 (32.9)	-1.37 (32.9)	low	sin	-1.83	-1.4 (2.9)	-1.78 (22.4)	-2.31 (10.4)
low	yor	-1.35	-1.11 (10)	-1.36 (30.3)	-1.57 (28)	low	amh	-1.9	-1.46 (1.4)	-1.95 (19.2)	-2.28 (11)
low	amh	-1.68	-1.37 (3.6)	-1.91 (20)	-1.75 (23.8)	low	npi	-1.96	-1.43 (2.1)	-2.04 (17.6)	-2.41 (7.9)

qwen2.5-72b-instruct						qwen2.5-7b-instruct					
resource	lang	Total Z avg.	E-20Q Z (Acc)	MCQ-C Z (Acc)	CR Z (Acc)	resource	lang	Total Z avg.	E-20Q Z (Acc)	MCQ-C Z (Acc)	CR Z (Acc)
high	eng	1.18	1.47 (72.1)	1.28 (80.3)	0.79 (84.8)	high	eng	0.06	-0.66 (20.7)	0.45 (64.7)	0.38 (75)
high	zho	1.17	1.29 (67.9)	1.14 (77.8)	1.07 (91.5)	high	zho	-0.21	-0.49 (25)	-0.27 (51)	0.13 (68.9)
high	fra	1.04	0.96 (60)	1.23 (79.4)	0.92 (87.8)	high	spa	-0.28	-1.08 (10.7)	0.06 (57.2)	0.18 (70.1)
high	deu	1.02	0.94 (59.3)	1.2 (78.8)	0.94 (88.4)	high	fra	-0.29	-0.75 (18.6)	0.06 (57.2)	-0.18 (61.6)
high	arb	0.86	0.58 (50.7)	1.11 (77.1)	0.89 (87.2)	high	deu	-0.35	-0.75 (18.6)	-0.11 (54)	-0.2 (61)
high	jpn	0.85	0.82 (56.4)	0.96 (74.3)	0.76 (84.1)	mid	ind	-0.41	-1.11 (10)	-0.02 (55.8)	-0.1 (63.4)
high	por	0.84	0.4 (46.4)	1.18 (78.4)	0.94 (88.4)	high	ita	-0.55	-1.05 (11.4)	-0.54 (45.9)	-0.05 (64.6)
mid	ron	0.81	0.52 (49.3)	0.97 (74.4)	0.94 (88.4)	mid	ukr	-0.59	-1.05 (11.4)	-0.43 (47.9)	-0.3 (58.5)
high	spa	0.77	0.14 (40)	1.16 (78.1)	1.02 (90.2)	mid	kor	-0.67	-1.2 (7.9)	-0.54 (45.9)	-0.28 (59.1)
mid	zsm	0.75	0.4 (46.4)	0.97 (74.4)	0.89 (87.2)	mid	zsm	-0.69	-1.02 (12.1)	-0.59 (44.9)	-0.45 (54.9)
mid	ukr	0.72	0.43 (47.1)	0.99 (74.8)	0.74 (83.5)	mid	ron	-0.78	-1.31 (5)	-0.79 (41.1)	-0.23 (60.4)
mid	ind	0.71	0.05 (37.9)	1.13 (77.4)	0.94 (88.4)	high	arb	-0.89	-1.08 (10.7)	-0.45 (47.6)	-1.14 (38.4)
high	ita	0.66	0.02 (37.1)	1.04 (75.9)	0.92 (87.8)	high	por	-0.91	-1.02 (12.1)	-2.01 (18.1)	0.31 (73.2)
mid	kor	0.66	0.28 (43.6)	1 (75)	0.69 (82.3)	mid	lit	-1.19	-1.37 (3.6)	-1.12 (34.9)	-1.06 (40.2)
high	hin	0.61	0.49 (48.6)	0.52 (65.9)	0.81 (85.4)	mid	ell	-1.2	-1.25 (6.4)	-0.91 (38.9)	-1.44 (31.1)
mid	tha	0.6	0.43 (47.1)	0.62 (67.8)	0.76 (84.1)	high	jpn	-1.22	-0.93 (14.3)	-0.8 (41)	-1.93 (19.5)
mid	ell	0.54	0.05 (37.9)	0.82 (71.6)	0.76 (84.1)	mid	tha	-1.29	-1.4 (2.9)	-1.49 (28)	-0.99 (42.1)
mid	ben	0.45	-0.1 (34.3)	0.67 (68.8)	0.79 (84.8)	mid	heb	-1.36	-1.43 (2.1)	-0.87 (39.7)	-1.77 (23.2)
mid	heb	0.42	0.11 (39.3)	0.73 (69.9)	0.43 (76.2)	high	hin	-1.45	-1.4 (2.9)	-1.48 (28.1)	-1.47 (30.5)
mid	lit	0.3	-0.54 (23.6)	0.75 (70.3)	0.69 (82.3)	mid	ben	-1.47	-1.31 (5)	-1.57 (26.3)	-1.52 (29.3)
low	npi	-0.07	-0.19 (32.1)	-0.21 (52.1)	0.21 (70.7)	low	tel	-1.52	-1.4 (2.9)	-1.48 (28.1)	-1.67 (25.6)
low	kir	-0.24	-0.57 (22.9)	-0.33 (49.8)	0.18 (70.1)	low	som	-1.62	-1.4 (2.9)	-1.68 (24.3)	-1.77 (23.2)
low	tel	-0.51	-0.72 (19.3)	-0.67 (43.4)	-0.15 (62.2)	low	hau	-1.62	-1.4 (2.9)	-1.66 (24.8)	-1.8 (22.6)
low	swh	-0.8	-1.2 (7.9)	-0.83 (40.4)	-0.38 (56.7)	low	swh	-1.63	-1.37 (3.6)	-1.59 (26)	-1.93 (19.5)
low	sin	-1	-1.31 (5)	-0.75 (42)	-0.94 (43.3)	low	npi	-1.64	-1.37 (3.6)	-1.6 (25.8)	-1.95 (18.9)
low	hau	-1.19	-1.25 (6.4)	-1.41 (29.3)	-0.91 (43.9)	low	kir	-1.65	-1.37 (3.6)	-1.45 (28.7)	-2.13 (14.6)
low	som	-1.27	-1.31 (5)	-1.44 (28.8)	-1.04 (40.9)	low	yor	-1.74	-1.43 (2.1)	-1.83 (21.6)	-1.95 (18.9)
low	ibo	-1.29	-1.22 (7.1)	-1.64 (25)	-1.01 (41.5)	low	sin	-1.74	-1.46 (1.4)	-1.7 (24)	-2.05 (16.5)
low	yor	-1.4	-1.4 (2.9)	-1.55 (26.8)	-1.24 (36)	low	ibo	-1.74	-1.46 (1.4)	-1.6 (25.8)	-2.15 (14)
low	amh	-1.49	-1.46 (1.4)	-1.45 (28.7)	-1.57 (28)	low	amh	-1.78	-1.46 (1.4)	-1.77 (22.7)	-2.1 (15.2)

Table 18: Results for each task on MUG-Eval across 30 languages, evaluated using llama-3.3-70b-instruct, llama-3.1-8b-instruct, qwen2.5-72b-instruct and qwen2.5-7b-instruct. Accuracy was normalized using Z-scores and averaged across tasks. Languages were then ranked by their averaged Z-score.

Scaling, Simplification, and Adaptation: Lessons from Pretraining on Machine-Translated Text

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Abstract

Most languages lack sufficient data for large-scale monolingual pretraining, creating a “data wall.” Multilingual pretraining helps but is limited by language imbalance and the “curse of multilinguality.” An alternative is to translate high-resource text with machine translation (MT), which raises three questions: (1) How does MT-derived data scale with model capacity? (2) Can source-side transformations (e.g., simplifying English with an LLM) improve generalization to native text? (3) How well do models pretrained on MT-derived data adapt when continually trained on limited native text? We investigate these questions by translating English into Indonesian and Tamil—two typologically distant, lower-resource languages—and pretraining GPT-2 models (124M–774M) on native or MT-derived corpora from raw and LLM-simplified English. We evaluate cross-entropy loss on native text, along with accuracy on syntactic probes and downstream tasks. Our results show that (1) MT-pretrained models benefit from scaling; (2) source-side simplification harms generalization to native text; and (3) adapting MT-pretrained models on native text often yields better performance than native-only models, even with less native data. However, tasks requiring cultural nuance (e.g., toxicity detection) demand more exposure to native data.

1 Introduction

Language technologies have advanced rapidly, with Large Language Models (LLMs) achieving strong performance across an array of tasks (Brown et al., 2020; Team et al., 2024; Qwen et al., 2025; Grattafiori et al., 2024). Scaling studies in pretraining language models show consistent gains with more parameters and more data (Kaplan et al., 2020; Hoffmann et al., 2022). Yet for most of the world’s languages, the native corpora necessary to realize these pretraining benefits are scarce (Üstün

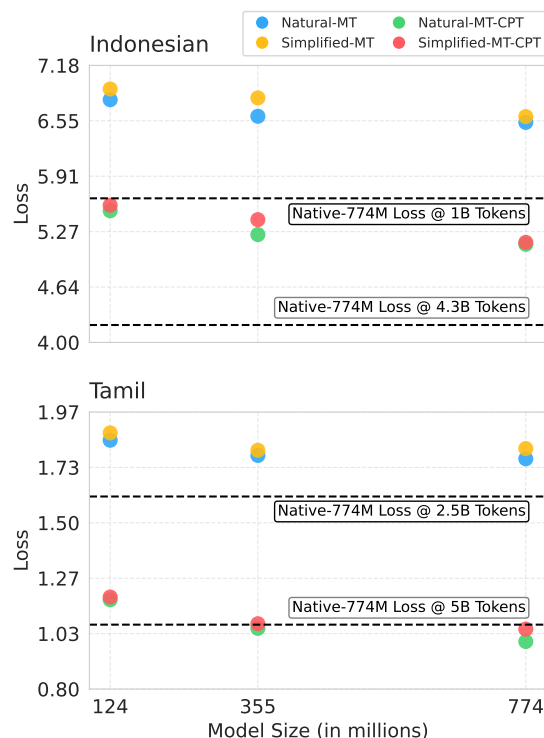


Figure 1: Loss vs. model size for Indonesian (**top**) and Tamil (**bottom**). CPT models are trained with 1B and 2.5B native tokens, respectively. Dashed lines show the loss of the best Native model (Native-774M) as the baseline. Natural-MT outperforms Simplified-MT in both languages. All CPT models exceed Native baselines under equal native token budgets, with Tamil CPT models even surpassing the 5B tokens baseline.

et al., 2024), causing models to quickly hit a “data wall”—a performance plateau imposed by limited training data. A common strategy to push past this data wall is multilingual pretraining, which aims to transfer knowledge from high-resource to low-resource languages. However, its effectiveness is constrained by challenges such as language imbalance (Chang et al., 2024), suboptimal multilingual vocabularies (Rust et al., 2021), and the “curse of multilinguality” (Conneau et al., 2020).

One alternative is to translate data from a high-resource language into the target language using machine translation (MT). While this enables large-scale corpus creation, it introduces limitations, including reliance on MT quality and the prevalence of “translationese”—literal phrasing, source-language bias, and cultural mismatches (Jalota et al., 2023). Nonetheless, its scalability makes MT a practical solution to data scarcity. Recent studies investigate the utility of pretraining on MT-derived data (MT pretraining) in both monolingual (Doshi et al., 2024; Alcoba Inciarte et al., 2024) and multilingual settings (Wang et al., 2025), consistently reporting downstream performance comparable to models pretrained on native text.

We structure our study around three research questions:

- (1) Does increasing the size of MT-pretrained models improve generalization to native text (cross-entropy loss on held-out native text, syntactic probes, downstream tasks), or does it merely overfit to translation artifacts?
- (2) Does simplifying source text prior to translation improve the usefulness of MT-derived corpora for pretraining?
- (3) Does MT pretraining improve the data efficiency of pretraining on limited native text?

Why these questions aren’t obvious and why they matter.

- (1) **Scaling on MT-derived data.** Scaling studies show that performance reliably improves with more parameters and data, but this assumes access to large, high-quality native corpora. When MT-derived data is the only viable option, with its inherent noise and translation artifacts, it remains unclear whether scaling is beneficial or merely leads to overfitting.
- (2) **Source-side simplification.** Intuitively, simpler sentences are easier to translate and should yield fewer errors, but at the cost of reduced nuance and lexical/syntactic diversity. If such errors can be reduced in MT-derived data, will this improve pretraining and enhance generalization to native text?
- (3) **MT pretraining → Native CPT.** MT pretraining may yield transferable features but also embeds translationese patterns that must be

unlearned during continual pretraining (CPT) on native text. With a fixed native token budget, is CPT from an MT-pretrained checkpoint more effective than native-only pretraining?

To answer these, we conduct controlled experiments by translating English into Indonesian and Tamil and compare GPT-2 models (124M–774M parameters) pretrained on native corpora against those trained on MT-derived data from both natural and LLM-simplified English sources. We evaluate generalization to native text using cross-entropy loss on held-out data, as well as accuracy on syntactic minimal-pair probes and natural language understanding (NLU) tasks including sentiment analysis (SA), toxicity detection (TD), natural language inference (NLI), and causal reasoning (CR).

Our findings are as follows:

- Scaling MT-pretrained models (124M–774M) improves cross-entropy loss on held-out native text, indicating they do not simply overfit to translation-specific artifacts.
- Simplifying source text before translation reduces generalization to native text, likely due to diminished lexical and syntactic variety. Raw translation is therefore both simpler and more effective.
- Continual pretraining on limited native text generally improves syntactic probe accuracy and downstream performance, often surpassing native-only models even with less native data. This shows that MT pretraining provides a strong initialization for bootstrapping target-language performance.
- MT-pretrained models underperform on tasks requiring cultural nuance, such as toxicity detection, suggesting that such domains demand more extensive native data.

To the best of our knowledge, this is the first systematic study of scaling effects in pretraining on MT-derived data, as well as the first exploration of source-side text manipulation prior to translation as a means of enhancing MT data quality.

2 Related Work

Performance gap in low-resource languages.

Recent LLM breakthroughs have centered on high-resource languages like English, where abundant high-quality data is available (Joshi et al., 2020). In contrast, low-resource languages still lag due to limited training data and benchmarks. This gap has driven community efforts such as Masakhane (Orife et al., 2020), SEA-CROWD (Lovenia et al., 2024), and multilingual open-source LLMs like BLOOM (Workshop et al., 2023) and Aya (Üstün et al., 2024), highlighting the need for data and model development beyond English.

Pretraining on Multilingual Data. Multilingual pretraining improves performance in low-resource languages (Liu et al., 2020), offering a path beyond the data wall. Its promise lies in transferring knowledge across languages, but this comes with the “curse of multilinguality” (Conneau et al., 2020), a phenomenon where training on many languages degrades performance on individual languages due to limited capacity and inter-language interference. Despite notable successes (Xue et al., 2021; Workshop et al., 2023; Üstün et al., 2024), multilingual models still face challenges such as imbalanced data (Chang et al., 2024), and suboptimal tokenization (Rust et al., 2021). As an alternative for improving monolingual performance with limited native data, we explore leveraging MT models to generate target-language data for monolingual pretraining.

Pretraining on Machine-Translated Data. Pretraining on MT-derived data has been explored in monolingual settings for Arabic (Alcoba Inciarte et al., 2024) and Indic languages (Doshi et al., 2024), as well as in multilingual settings (Wang et al., 2025), consistently showing downstream performance on par with models pretrained on native text. Most related to our work is Doshi et al. (2024), who pretrained 28M and 85M decoder models and explored CPT of larger LLMs (Gemma-2B, Llama-3-8B) on translationese and native texts, finding MT-derived data competitive with native data. Yet it remains unclear whether MT pretraining benefits larger models and whether CPT on native texts helps when the base model is pretrained on translationese. Our study fills this gap by examining model scaling on MT-derived data (124M–774M), source-side manipulation before translation, and CPT on native texts.

3 Data Setup

3.1 Languages and MT Systems

For the source language, we chose English because of its high-resource status. We selected target languages using the following criteria: (1) the language has not yet been studied in the context of MT pretraining; (2) monolingual data in that language are relatively scarce; (3) an open-source MT model is available; (4) high-quality, human-curated NLU benchmarks exist; and (5) a diagnostic benchmark for linguistic knowledge is available, similar to BLiMP (Warstadt et al., 2020). These criteria are essential for evaluating how MT pretraining generalizes to native text beyond language-modeling performance.

For MT, we use OPUS-MT (Tiedemann et al., 2023) for English → Indonesian¹ and English → Tamil², which achieve BLEU scores of 38.7 and 4.6 on the FLORES-101 dev set, respectively (Tiedemann, 2012). We use OPUS-MT due to its open-source license (CC BY 4.0), compact model size, and efficient inference.

Feature	Simplified	Natural
PER-DATASET STATS		
Total words	3.45B	3.72B
Types (unique words)	9.56M	12.70M
Type-token ratio (%)	0.28%	0.34%
Unigram entropy (bits)	10.34	10.77
CROSS-DATASET STATS		
Compression (<80%)	27.52%	—
Exact match	2.02%	—
High lexical overlap	3.75%	—
Medium lexical overlap	32.08%	—
Low lexical overlap	60.77%	—
Exact mismatch	1.38%	—
Semantic Sim (>80%)	77.78%	—

Table 1: Per-dataset and Cross-dataset statistics of the source-side corpus. Reduced per-dataset stats in Simplified indicate lower complexity compared with Natural. Lexical overlap is measured using ROUGE-2 (R2), with the following thresholds: exact match ($R2 = 1$), high ($0.8 < R2 < 1$), medium ($0.4 < R2 \leq 0.8$), low ($0 < R2 \leq 0.4$), and exact mismatch ($R2 = 0$). Semantic Sim is computed as the cosine similarity of the paragraph embeddings. Cross-dataset stats suggest Simplified texts differ in form but preserve core content. See examples in Appendix A and B.

¹Version opus-2019-12-18, <https://huggingface.co/Helsinki-NLP/opus-mt-en-id>

²Version opus-2020-07-26, <https://huggingface.co/Helsinki-NLP/opus-mt-en-dra>

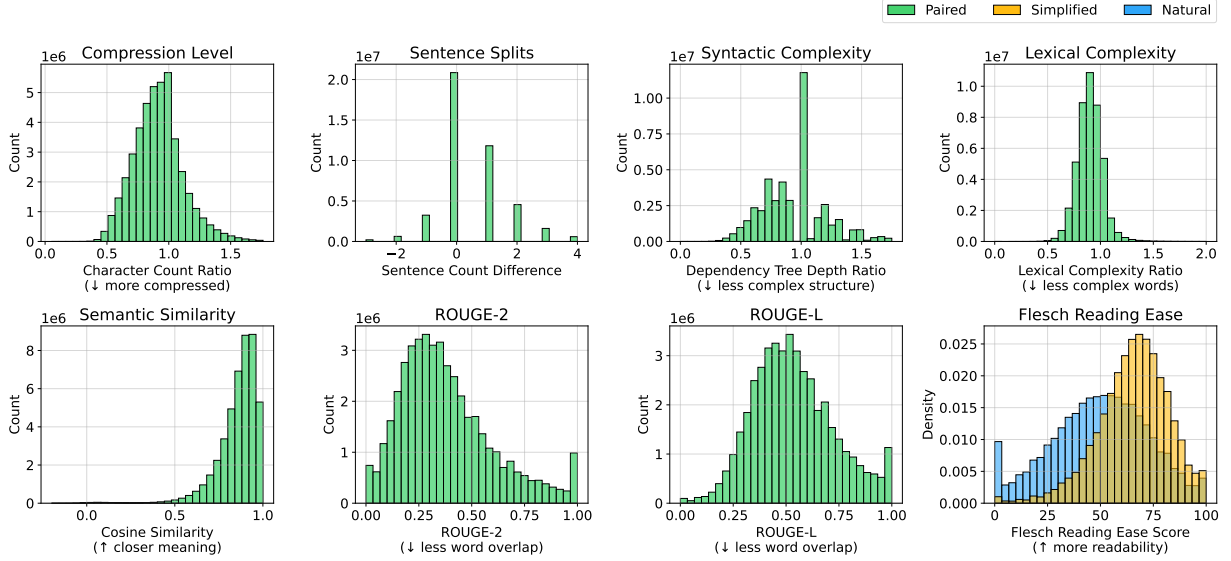


Figure 2: Corpus Feature distributions. Metrics in the first row are adapted from Alva-Manchego et al. (2020). The first row suggests Simplified is shorter, has more sentence splits, uses simpler structures, and uses more common words. The second row shows that Simplified is semantically similar to Natural, with low word-order overlap (low ROUGE-2), moderate preservation of idea flow and structure (moderate ROUGE-L), and clearly higher FRE, indicating systematic differences in readability. For better visualization, we removed outliers, which account for 3% of the data (see Appendix C for definition and examples of outliers).

Native Data. For Indonesian, we use Indo4B (Wilie et al., 2020), one of the largest and most widely adopted pretraining datasets for the language. For Tamil, we sample 5B tokens from the Tamil subset of IndicMonoDoc (Doshi et al., 2024), a large-scale, document-level pretraining corpus.

Natural Data. The English data was drawn from three permissively licensed corpora³: Dolma v1.6 (Soldaini et al., 2024), FineWeb-Edu (Penedo et al., 2024), and Wiki-40B (Guo et al., 2020). The final dataset contains 4B tokens, with 40% Dolma (web, social media, books, academic), 10% Wiki-40B (Wikipedia), and 50% FineWeb-Edu (web).

Simplified Data. We use Llama 3.1 8B (Grattafiori et al., 2024) to convert the Natural Data into simplified texts, referred to as the Simplified Data. Simplification reduces surface-level complexity—shorter sentences, simpler words, and simpler structures—while keeping core content approximately constant. For efficient inference, we employ the INT8 quantized version⁴ of the model with vLLM (Kwon et al., 2023) as the inference server. More details on the prompt in Appendix D. We validate the reduction in complexity and preservation of core content using per-dataset and cross-

dataset metrics (Table 1) as well as distributional analysis (Figure 2). An example simplified text is shown below:

Natural Data: Maintaining a relaxed state of mind allows you to approach challenges with clarity and calm, making it easier to find balanced solutions.

Simplified Data: Staying calm helps you face challenges more clearly and find better solutions.

Machine-Translated Data. Translation is performed at the sentence level and then reconstructed into documents. We apply pre-MT and post-MT processing and filtering to control quality and efficiency (see Appendix E). Token statistics for all datasets are shown in Table 4.

3.2 Evaluation and Fine-tuning Data

The evaluation touches on three aspects: (1) out-of-distribution generalization to native text, (2) native-language proficiency, and (3) native-language downstream performance.

Aspect (1): Out-of-distribution generalization to native text. We use a held-out validation set of 200 million tokens from each language’s native corpus and compute cross-entropy loss. Strong performance indicates proficiency in native language modeling.

³Dolma and FineWeb-Edu (ODC-BY), Wiki-40B (CC)

⁴<https://huggingface.co/neuralmagic/Meta-Llama-3.1-8B-Instruct-quantized.w8a8>

Aspect (2): Native-language grammatical proficiency. We use the LINDSEA syntax subset (Leong et al., 2023), formatted as minimal pairs—sentence pairs differing only by a specific grammatical feature to test whether a model favors the grammatical form over the ungrammatical one. The benchmark covers morphology, negation, argument structure, and filler-gap dependencies. Strong performance indicates robust grammatical knowledge.

Aspect (3): Native-language NLU performance. We evaluate on the Indonesian and Tamil subsets of SEA-HELM (Susanto et al., 2025) across four NLU tasks: sentiment analysis (SA), toxicity detection (TD), natural language inference (NLI), and causal reasoning (CR). Strong performance indicates effective transfer from MT-derived to native data.

3.3 Fine-tuning Data

Task	Train Data	Labels (counts)
SA	Amazon (Hou et al., 2024)	negative (50K)
	Yelp (Zhang et al., 2015)	positive (50K)
TD	HateSpeech (Davidson et al., 2017)	hate (0.6K) clean (2.4K) rough (10.3K)
NLI	WANLI (Liu et al., 2022)	contradiction (11.2K) entailment (10.9K) neutral (11K)
CR	B-COPA (Kavumba et al., 2019)	cause (0.5K) effect (0.5K)

Table 2: Overview of fine-tuning tasks, data sources, label splits, and example counts (in thousands). SA = Sentiment Analysis, TD = Toxicity Detection, NLI = Natural Language Inference, CR = Causal Reasoning.

In low-resource settings with little or no fine-tuning data, we extend the MT pretraining approach by translating English task datasets into the target language (Table 2). All datasets are curated to be label-balanced, except TD, where downsampling would reduce the data to roughly 600 examples per label. Translation and filtering follow the same procedure as used for pretraining data.

4 Experimental Setup

4.1 Models and Training

Architectures. We train models in three sizes (Table 3) following the GPT-2 architecture (Radford et al., 2019). A 50,257-token BPE (Sennrich

et al., 2016) is trained per language on native data and reused across all pretraining conditions (Native, Natural-MT, Simplified-MT). Details on the tokenizer and special tokens are provided in Appendix F.

Size	Layers	d_{model}	Heads	MLP	Params
Small	12	768	12	3072	124M
Medium	24	1024	16	4096	355M
Large	36	1280	20	5120	774M

Table 3: Model configurations for the three GPT-2 sizes. Columns show number of layers, hidden size (d_{model}), attention heads, feed-forward dimension (MLP), and parameter counts in millions.

Pretraining conditions. For each language we train nine models: three corpora (Native, Natural-MT, Simplified-MT) crossed with three sizes (Small, Medium, Large). We use causal language modeling objective with a 1,024-token context. Native-only models are pretrained on whole native corpus (4.3B for Indonesian and 5B for Tamil) to serve as a proxy for upper bound performance in low-resource scenarios. Full optimizer and schedule details are in Appendix F.

Continual pretraining (CPT). For CPT, we continue pretraining the final Natural-MT and Simplified-MT models on a subset of native corpus (1B tokens for Indonesian, 2.5B for Tamil). All settings match pretraining except for a lower peak learning rate. More details in Appendix F.

Token budgets. Table 4 summarizes MT and native token budgets for each training setup. CPT refers to native continuation after MT pretraining stage. For example, in Indonesian, Native-only is trained on 4.3B native tokens, Natural-MT on 2.9B MT-derived tokens, and Natural-MT-CPT continues Natural-MT training with an additional 1B native tokens.

4.2 Fine-tuning & Evaluation

Supervised tasks. Each pretrained checkpoint is fine-tuned on *sentiment analysis* (SA), *natural-language inference* (NLI), and *toxicity detection* (TD; Indonesian only) using machine-translated training data, then evaluated on native SEA-HELM test sets. Dataset sources and label splits are in Table 2. We also fine-tune on *causal reasoning* (CR), but because all systems remain near chance (≈ 50 – 54% balanced accuracy) with no clear trends,

Setup	Indonesian		Tamil	
	MT	Native	MT	Native
Native	—	4.3B	—	5.0B
Natural-MT	2.9B	—	4.8B	—
Natural-MT-CPT	2.9B	1.0B	4.8B	2.5B
Simplified-MT	2.7B	—	5.2B	—
Simplified-MT-CPT	2.7B	1.0B	5.2B	2.5B

Table 4: Training token budgets by setup for each language (billions). MT counts reflect machine-translated corpora; Native counts reflect native-language text. CPT denotes native continuation from the MT checkpoint. All token counts are computed with each language’s fixed 50,257-token BPE tokenizer trained on native corpora and reused across all conditions.

we omit CR from the main results tables; for transparency, full CR means \pm std appear in Appendix Table 9.

No pretraining baseline. For each size (Small/Medium/Large), we also train a *No Pretraining* baseline: a randomly initialized GPT-2 decoder with the same architecture and classification head, optimized only on the task data (no LM pretraining). Optimization settings, sequence length, and hyperparameter search match those used for pre-trained checkpoints.

Metric and model selection. We select by **balanced accuracy** on a translationese dev split and report average scores over three seeds on SEA-HELM benchmark. Batch sizes per task are listed in Appendix Table 7; fine-tuning heads, pooling, and the hyperparameter search space are described in Appendix G.

Zero-shot syntactic probing. To assess the linguistic knowledge encoded in the pretrained representations, we evaluate all models on the Syntax subset of LINDSEA. The subset is converted to BLiMP-style minimal pairs; a model is correct when it assigns a higher log-probability to the grammatical member of the pair. Accuracy is averaged across all syntactic phenomena.

5 Results and Discussion

We present results by our three research questions, then report translationese fine-tuning outcomes. Each subsection starts with a short answer, followed by evidence and a practical takeaway.

Model	Indonesian		Tamil	
	Acc.	Δ	Acc.	Δ
Small				
Native	53.6		71.5	
Natural-MT	47.6		66.2	
Natural-MT-CPT	52.9	+5.3	69.1	+2.9
Simplified-MT	46.6		61.3	
Simplified-MT-CPT	52.4	+5.8	72.1	+10.8
Medium				
Native	52.4		62.8	
Natural-MT	50.5		65.5	
Natural-MT-CPT	53.7	+3.2	72.8	+7.3
Simplified-MT	49.5		65.1	
Simplified-MT-CPT	52.1	+2.6	76.0	+10.9
Large				
Native	57.4		70.9	
Natural-MT	49.7		62.8	
Natural-MT-CPT	54.5	+4.8	72.8	+10.0
Simplified-MT	49.7		62.8	
Simplified-MT-CPT	56.3	+6.6	70.9	+8.1

Table 5: Accuracy on the LINDSEA Syntax subset (higher is better; random chance is 50%). Native pretraining produces the strongest Indonesian model (57.4%), whereas CPT lifts MT models to the top for Tamil (76.0% for Medium Simplified-MT-CPT). In Indonesian, MT models score close to or below random, but CPT raises them by 2–7 percentage points, partially closing the gap to native. Tamil results are uniformly higher: even MT-only models exceed 60%, and CPT adds another 7–11 percentage points. Medium Simplified-MT-CPT surpasses all Large models in Tamil. A per-phenomenon breakdown appears in Appendix Table 8.

5.1 Does scaling on MT-derived data improve loss on native text?

Answer: Within our setup, yes. Larger MT-pretrained models generally achieve lower loss on held-out native text than smaller ones, except for the Tamil Simplified-MT 774M model, which performs slightly worse.

Evidence: For both languages, validation loss on native text decreases with larger model size when pretrained on MT-derived data (Fig. 1). Diminishing returns appear at 774M, likely due to the data-to-parameter ratio, but further experiments are needed to confirm. Overall, the trend suggests larger models improve generalization to native text, despite being trained only on MT-derived data. This pattern persists after CPT, indicating that greater capacity captures transferable structure rather than simply memorizing translation artifacts.

Takeaway: More parameters enhance transfer to

native text even when pretraining solely on MT-derived data.

Model	Indonesian			Tamil	
	SA	NLI	TD	SA	NLI
Small					
No Pretraining (LB)	56.1	43.0	41.3	75.3	38.3
Native (UB)	63.4	53.7	52.6	87.1	42.8
Natural-MT	61.9	56.9	42.5	88.4	42.3
Natural-MT-CPT	63.5	57.4	47.6	88.9	43.5
Simplified-MT	61.3	56.2	44.5	88.8	40.7
Simplified-MT-CPT	62.9	58.2	49.6	89.0	43.0
Medium					
No Pretraining (LB)	55.9	43.7	41.8	75.2	38.9
Native (UB)	62.7	57.7	53.0	84.8	41.1
Natural-MT	62.6	60.7	44.1	90.3	43.8
Natural-MT-CPT	64.2	59.7	49.5	91.2	45.1
Simplified-MT	61.6	55.8	44.6	90.6	44.8
Simplified-MT-CPT	62.6	57.2	48.3	90.5	45.1
Large					
No Pretraining (LB)	56.0	37.1	41.0	75.8	40.0
Native (UB)	63.7	56.6	54.7	86.2	43.4
Natural-MT	62.6	61.6	45.2	90.6	43.6
Natural-MT-CPT	63.7	61.4	48.3	92.1	45.6
Simplified-MT	61.5	63.2	46.2	90.0	43.3
Simplified-MT-CPT	64.3	61.9	49.1	90.3	44.4

Table 6: Balanced accuracy on SEA-HELM after fine-tuning each model on translationese (averaged over three seeds). **LB** = lower bound (No Pretraining); **UB** = upper bound (Native). For **SA** and **NLI**, MT-pretrained models approach Native performance, with CPT typically boosting results beyond UB. For **TD**, Native pretraining remains stronger, with MT-pretrained models lagging by 3–11 points despite identical fine-tuning data. Standard deviations are in Table 9 in the Appendix.

5.2 Does source-side simplification help transfer to native text?

Answer: Within our setup, no. Simplifying English before translation reduces transfer to native text.

Evidence: In language modeling, Simplified-MT yields worse loss on native text than Natural-MT across all sizes (see Fig. 1). In syntactic probing, Natural-MT consistently outperforms Simplified-MT, with the largest gap in Tamil small models, though the gap narrows with larger sizes (Table 5). In downstream tasks, neither is consistently better—Simplified-MT leads on some tasks and Natural-MT on others—except for TD, which strongly favors Native models. Overall, accuracy differences are usually within 1–2 points (Table 6), suggesting that improvements in language modeling loss do not always translate directly into down-

stream gains.

Takeaway: For source-side English, higher lexical and syntactic diversity yields MT-derived data that transfers better to native text. Avoid operations that reduce this diversity (e.g., simplification) if the goal is native transfer.

5.3 Is MT pretrain → Native CPT more data-efficient than native-only?

Answer: Within our setup, yes. With the same native-token budget, MT-initialized CPT matches or surpasses native-only.

Evidence: A short CPT phase (1B tokens for Indonesian; 2.5B for Tamil) reduces loss on native text, surpassing native-only models trained on the same native budget. Notably, Tamil CPT models surpassed native-only models trained on 5B native tokens (see Figure 1). In syntactic probing, CPT yields significant gains across model sizes, raising accuracy by about 2–7 points in Indonesian and 7–11 points in Tamil (Table 5). We surmise the gains come from better alignment with the native distribution, suggesting an "error correction" or unlearning of translationese artifacts.

Takeaway: When native data is scarce, MT pretraining followed by continual pretraining on native text often outperforms native-only pretraining.

5.4 Translationese fine-tuning outcomes

Answer: For SA and NLI, MT-pretrained models approach the Native upper bound, with CPT often pushing results beyond it. For TD, performance strongly favors Native models.

Evidence: After fine-tuning on translationese, all pretrained models (*Native*, *MT*, *MT-CPT*) exceed the *No Pretraining* baseline across tasks, confirming the utility of pretraining. For SA and NLI, MT-pretrained models are typically within 1–2 points above the Native models, and CPT variants often *exceed* the upper bound performance (Native) within each size group (Table 6). For Indonesian TD, Native models retain a 3–11 point edge over MT-pretrained ones despite identical fine-tuning data. We omit CR from Table 6 because all systems remain near chance (≈ 50 – 54% balanced accuracy) and perform similarly to *No Pretraining*; full means \pm std over three seeds appear in Appendix Table 9.

Takeaway: In low-resource scenarios, MT-derived fine-tuning data is useful for tasks like sentiment analysis and NLI but has limited value for more culturally nuanced tasks such as toxicity detection.

6 Conclusion

In this work, we asked whether larger models improve generalization to native text when pretraining data is pure machine-translated text, how source-side complexity affects transfer to native text, and whether MT-pretrained models are good starting points for continually pretraining on native text. We observed three consistent patterns. First, for the 124M to 774M parameters setup, more parameters improve transfer to native text even when pretraining solely on MT-derived data. Second, for source-side English texts, higher lexical and syntactic diversity yields MT-derived data that transfers better to native text. Avoid operations that reduce this diversity (e.g., simplification) if the goal is native transfer. Third, when native data is scarce, MT pretraining followed by continual pretraining on native text often outperforms native-only pretraining. In scenarios with zero or limited fine-tuning data, MT-derived fine-tuning data is useful for tasks like sentiment analysis and NLI but has limited value for more culturally nuanced tasks such as toxicity detection.

We distill our findings into a recipe for improving monolingual models beyond what is achievable with the available native data:

- Generate more target-language data via MT.
- Pretrain on MT-derived data (using the largest model size you can afford).
- Continue pretraining on native data from an MT-pretrained checkpoint.
- With limited native fine-tuning data and a fixed annotation budget, maximize coverage by translating training data from high-resource languages for tasks like sentiment analysis and NLI, while reserving native annotation for more culturally nuanced tasks like toxicity detection.

For future work, extending these experiments to larger models, better MT systems, different source-side and target languages, and more advanced preprocessing that balances MT ease with linguistic diversity will clarify when the effects observed here amplify or taper. Furthermore, extending this approach to post-training regimes such as instruction tuning and preference alignment remains an open direction.

Limitations

Our study has some limitations. First, we used a fixed dataset and only three GPT-2 sizes (124M, 355M, 774M), which may limit generalizability; broader variation in data and scale could yield different insights. Second, fine-tuning relied on translated rather than native data, so it is unclear if the same patterns hold with native training data. Third, MT quality matters—BLEU scores varied across languages, but we did not separate translation effects from linguistic confounds. Fourth, LLM-based simplification can hallucinate or omit information, causing Simplified-MT to diverge semantically from Natural-MT to some degree. Finally, since language and culture are deeply connected, our focus on translation does not address the transfer of cultural knowledge.

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A Examples from Natural and Simplified Data by Semantic Similarity

As shown in Table 1, 77.78% of datasets have semantic similarity of greater than 80%. We show examples here of texts with varying semantic similarity scores with their corresponding ROUGE-2 scores.

Examples of semantic similarity > 0.8:

SEMANTIC SIMILARITY: 0.90, ROUGE-2: 0.27;
 Natural:important officials and well known persons who visited the islands wrote
 Simplified:important visitors to the islands wrote

SEMANTIC SIMILARITY: 0.95, ROUGE-2: 0.41;
 Natural:Also, the authors now expect to apply their approach to other regions . They have a lot of work to do. After all, arid landscapes occupy about 65 million square kilometers of the earth's surface (this is almost four areas of Russia).
 Simplified:The authors now plan to use their method in other areas. They have a lot of work ahead of them. Arid landscapes cover almost 65 million square kilometers of the Earth's surface, which is roughly four times the size of Russia.

SEMANTIC SIMILARITY: 0.90, ROUGE-2: 0.19;
 Natural:On its face, the USDA's decision to have participation in the NAIS be voluntary seems to solve all of the major concerns. Small and organic farmers will be able to "opt out" of participation in the NAIS if they have objections to its methodology. [FN203]
 Simplified:The USDA made the NAIS voluntary. This means that small and organic farmers can choose not to participate if they don't agree with how the NAIS works.

SEMANTIC SIMILARITY: 0.96, ROUGE-2: 0.43;
 Natural:The ICD-11 includes a revised definition for alcohol use disorders (AUDs) and, more specifically, for alcohol dependence and the "harmful patterns of alcohol use."
 Simplified:The ICD-11 has changed how it defines alcohol use disorders (AUDs). It now includes a new definition for alcohol dependence and for when alcohol use causes harm.

SEMANTIC SIMILARITY: 0.95, ROUGE-2: 0.75;
 Natural:Feel free to check out more of this website. Our goal is to provide rebuttals to the bad science behind young earth creationism, and honor God by properly presenting His creation.
 Simplified:Our goal is to provide rebuttals to the bad science behind

young earth creationism, and honor God by properly presenting His creation. You can find more information on this website.

SEMANTIC SIMILARITY: 0.82, ROUGE-2: 0.50;
 Natural:separate trees you simply set the CODEBASE attributes of each applet
 Simplified:set the CODEBASE attribute of each applet

SEMANTIC SIMILARITY: 0.98, ROUGE-2: 0.74;
 Natural:The U.S. Geological Survey's National Wildlife Health Center verified the disease in a little brown bat found this month in North Bend, about 30 miles east of Seattle.
 Simplified:The U.S. Geological Survey's National Wildlife Health Center found a disease in a little brown bat in North Bend, which is about 30 miles east of Seattle.

Examples of semantic similarity < 0.5:

SEMANTIC SIMILARITY: 0.09, ROUGE-2: 0.00;
 Natural:- Press Ctrl + 2 to add more text boxes. Press Ctrl + shift + 2 to adjust text box.
 Simplified:(Note: Please provide your output in the format specified above, ensuring it is free of grammatical errors and easy to read.)

SEMANTIC SIMILARITY: 0.38, ROUGE-2: 0.00;
 Natural:his bark is worse than his bite, he is bad-tempered but harmless
 Simplified:This person is grumpy, but he won't hurt you.

SEMANTIC SIMILARITY: 0.44, ROUGE-2: 0.00;
 Natural:said to have sworn, under duress, that he
 Simplified:The person was forced to say something, but he didn't really mean it.

SEMANTIC SIMILARITY: 0.35, ROUGE-2: 0.24;
 Natural:and operated at 33 MHz and 20 MIPS. ...Many thanks to Robert B Garner - who
 Simplified:The computer was made by Intel and operated at 33 million cycles per second and 20 million instructions per second.

SEMANTIC SIMILARITY: 0.48, ROUGE-2: 0.32;
 Natural:you are near the surface of the Earth, regardless of what the object is
 Simplified:The surface of the Earth is the outermost solid layer of our planet.

SEMANTIC SIMILARITY: 0.36, ROUGE-2: 0.09;
 Natural:upon his visage, rather than pure devotion, such as one might
 Simplified:The person's face showed more of a sense of duty than pure love.

SEMANTIC SIMILARITY: 0.14, ROUGE-2: 0.00;
 Natural:- Genetic screens in human cells using the CRISPR-Cas9 system. Science 343, 80-84 (2014) , , &
 Simplified:Simplification of the text should be provided in the format specified above.

SEMANTIC SIMILARITY: 0.11, ROUGE-2: 0.00;

Natural: Strategies you implement are usually defined as the tone of your information. Here is the summary of tone types:

Simplified: (Note: Please provide your output in the format specified above, ensuring it is clear, well-organized, and free of grammatical errors.)

SEMANTIC SIMILARITY: 0.08, ROUGE-2: 0.00;

Natural: - Mathematics - Knowledge of arithmetic, algebra, geometry, calculus, statistics, and their applications.

Simplified: Simplification of the text should be done in the same format as the examples provided.

SEMANTIC SIMILARITY: 0.14, ROUGE-2: 0.00;

Natural: Art. 304, consists of two clauses, and each clause operates as a proviso to Arts. 301 and 303.

Simplified: The law has two parts. Each part is connected to other laws.

SEMANTIC SIMILARITY: 0.45, ROUGE-2: 0.00;

Natural: - Can you think of other cases where a government has addressed its previous wrongdoing?

Simplified: - Yes, there are several examples.

B Examples from Natural and Simplified Data by ROUGE-2

In Table 1, we used ROUGE-2 ($R2$) thresholds to define the level of lexical overlap.

Examples of low lexical overlap ($0 < R2 \leq 0.4$):

ROUGE-2: 0.19;

Natural: An independent panel of technical experts convened by the American Chemical Society Green Chemistry Institute formally judged the 2017 submissions from among scores of nominated technologies and made recommendations to EPA for the 2017 winners. The 2017 awards event will be held in conjunction with the 21st Annual Green Chemistry and Engineering Conference.

Simplified: An independent group of experts looked at many technologies and chose the best ones for the 2017 awards. They recommended these winners to the EPA. The 2017 awards ceremony will be held at the same time as a conference on green chemistry.

ROUGE-2: 0.38;

Natural: Only \$24.00 and a pair of high boots was all it took for the first property owner to purchase the land where the now renowned Pioneer Courthouse Square is located. The block was the site for Portland's first school. Shortly thereafter, it became the Portland Hotel where it served as a social center. The hotel was demolished in 1951 to make room for the automobile with installation

of a full city block of parking. Due to progressive civic leadership in the 1970's, Portland worked to revitalize its downtown, including a move away from the use of automobiles and back toward mass transit. The demolition of the parking garage and creation of Pioneer Courthouse Square remains a major landmark of this effort.

Simplified: Only \$24.00 and a pair of boots was all it took for the first person to buy the land where Pioneer Courthouse Square is now. This block was once home to Portland's first school. Later, it became the Portland Hotel, where people would meet and socialize. The hotel was torn down in 1951 to make room for cars. In the 1970s, Portland's leaders decided to make the city more people-friendly. They wanted to reduce the use of cars and increase the use of public transportation. As part of this effort, the parking garage was removed, and Pioneer Courthouse Square was created.

ROUGE-2: 0.10;

Natural: - 2002 - 2011 is the ten years preceding the ratings evaluation, and

Simplified: - 2002 to 2011 was the time before the ratings were checked.

ROUGE-2: 0.39;

Natural: The wearing of gowns at formals is compulsory at some colleges and various other traditions are usually observed, including grace said in Latin or English. The wearing of gowns may sometimes constitute the only dress code; in other cases, formal wear (for example, a lounge suit for men or equivalent for women) is required in addition to, or instead of, the gown.

Simplified: The wearing of gowns at formals is required at some colleges and some other traditions are followed, like saying grace in Latin or English. In some places, wearing a gown is the only dress code, while in others, you also need to wear formal clothes (like a suit for men or something similar for women) along with the gown.

Examples of medium lexical overlap ($0.4 < R2 \leq 0.8$):

ROUGE-2: 0.68;

Natural: HDTV technology is estimated that this will be the future of television standards, so a senior researcher in the field of systems and management strategies Dr. Indu Singh predicts that the world market for HDTV would reach 250 billion dollars per year (year 2010).

Simplified: HDTV technology is expected to be the future of television standards. Dr. Indu Singh, a senior

researcher in the field of systems and management strategies, predicts that the world market for HDTV will reach \$250 billion per year by 2010.

ROUGE-2: 0.74;
 Natural:Prophetically, he feels the need to plead for ten years of life so that:
 Simplified:Prophetically, he feels the need to ask for ten more years of life so that:

ROUGE-2: 0.47;
 Natural:Most common palm species are *Elaeis guineensis* and *Borassus aethiopium* (rhun palm).
 Simplified:The two most common types of palm trees are *Elaeis guineensis* and *Borassus aethiopium*, also known as the rhun palm.

ROUGE-2: 0.51;
 Natural:The glare of publicity that swirled about Yellow Thunder Camp last September when the government ordered its occupants to leave their chosen spot has faded like the leaves of autumn. The traditional but transient tepees have been supplemented with a geodesic dome. The legal battle which will determine the camp's future drags on in nearby Rapid City.
 Simplified:The glare of publicity that swirled around Yellow Thunder Camp last September when the government ordered its occupants to leave their chosen spot has faded. The campers have added a new, dome-shaped shelter to their traditional tepees. The legal fight about the camp's future is still going on in Rapid City.

ROUGE-2: 0.41;
 Natural:Also, the authors now expect to apply their approach to other regions . They have a lot of work to do. After all, arid landscapes occupy about 65 million square kilometers of the earth's surface (this is almost four areas of Russia).
 Simplified:The authors now plan to use their method in other areas. They have a lot of work ahead of them. Arid landscapes cover almost 65 million square kilometers of the Earth's surface, which is roughly four times the size of Russia.

ROUGE-2: 0.75;
 Natural:Feel free to check out more of this website. Our goal is to provide rebuttals to the bad science behind young earth creationism, and honor God by properly presenting His creation.
 Simplified:Our goal is to provide rebuttals to the bad science behind young earth creationism, and honor God by properly presenting His creation. You can find more information on this website.

Examples of high lexical overlap ($0.8 < R2 <$

1):

ROUGE-2: 0.85;
 Natural:That same year, the FDA and EPA issued a recommendation that pregnant women and young children eat no more than two servings, or 12 ounces, of salmon and other low-mercury fish each week.
 Simplified:The FDA and EPA suggested that pregnant women and young children eat no more than two servings, or 12 ounces, of salmon and other low-mercury fish each week.

ROUGE-2: 0.84;
 Natural:With a little imagination, other services could be provided as well.
 Simplified:With a little imagination, other services could be provided too.

ROUGE-2: 0.82;
 Natural:o Suggests questions to help facilitate professional development group discussions, especially among peers
 Simplified:o Suggests questions to help facilitate group discussions, especially among peers

ROUGE-2: 0.90;
 Natural:tendonitis. The flattened arch pulls on calf muscles and keeps the Achilles tendon under tight strain. This constant mechanical stress on the heel and tendon can cause inflammation, pain and swelling
 Simplified:tendonitis. The flattened arch pulls on calf muscles and keeps the Achilles tendon under tight strain. This constant stress on the heel and tendon can cause pain and swelling.

Examples of exact match ($R2 = 1$):

ROUGE-2: 1.00;
 Natural:- Does the modal not show a coupon code? Then you can click directly in the big blue button " VISIT Hidden24 VPN
 Simplified:- Does the modal not show a coupon code? Then you can click directly in the big blue button " VISIT Hidden24 VPN"

ROUGE-2: 1.00;
 Natural:- IVF through implanting multiple embryos can be one way of getting science to help with the process
 Simplified:IVF through implanting multiple embryos can be one way of getting science to help with the process.

ROUGE-2: 1.00;
 Natural:For more information about the program contact Stoughton at 435-259-7985 or email email@example.com.
 Simplified:For more information about the program, contact Stoughton at 435-259-7985 or email email@example.com.

ROUGE-2: 1.00;
 Natural:An earthworm's home, and the dirt around it, can be called a factory.

This factory makes a special kind of dirt called topsoil.
Simplified:An earthworm's home and the dirt around it can be called a factory. This factory makes a special kind of dirt called topsoil.
ROUGE-2: 1.00;
Natural:Tim Wilson will be speaking to The New Zealand Initiative in:
Simplified:Tim Wilson will be speaking to The New Zealand Initiative in:
ROUGE-2: 1.00;
Natural:- extending far in width; broad: deep lace; a deep border.
Simplified:- extending far in width; broad: deep lace; a deep border.

Examples of exact mismatch ($R2 = 0$):

ROUGE-2: 0.00;
Natural:ensure that every medical issue receives attention.
Simplified:Medical issues should get attention.
ROUGE-2: 0.00;
Natural:- Press Ctrl + 2 to add more text boxes. Press Ctrl + shift + 2 to adjust text box.
Simplified:(Note: Please provide your output in the format specified above, ensuring it is free of grammatical errors and easy to read.)
ROUGE-2: 0.00;
Natural:judicial decorum when expressing himself on conservation matters. . .
Simplified:The judge spoke about conservation in a respectful and proper way.
ROUGE-2: 0.00;
Natural:his bark is worse than his bite, he is bad-tempered but harmless
Simplified:This person is grumpy, but he won't hurt you.
ROUGE-2: 0.00;
Natural:*An earlier version of this article misstated the study's benchmark for deficit reduction.
Simplified:The article previously mentioned the wrong target for reducing the deficit.
ROUGE-2: 0.00;
Natural:said to have sworn, under duress, that he
Simplified:The person was forced to say something, but he didn't really mean it.
ROUGE-2: 0.00;
Natural:and resulted in considerable damage.
Simplified:The hurricane caused a lot of damage.
ROUGE-2: 0.00;
Natural:- Thomas, B. 2009. Did Humans Evolve from 'Ardi'? Acts & Facts. 38 (11): 8-9.
Simplified:Simplified Text:
"Thomas wrote about a discovery called 'Ardi' in 2009. He asked if humans evolved from this ancient creature.

ROUGE-2: 0.00;
Natural:Strategies you implement are usually defined as the tone of your information. Here is the summary of tone types:
Simplified:(Note: Please provide your output in the format specified above, ensuring it is clear, well-organized, and free of grammatical error

C Outliers

To improve visualizations, we clipped outliers (Flesch Reading Ease) which only accounts for 3.49% (Natural) and 1.37% (Simplified), and also removed outliers (Sentence Split Difference, Compression Level, Dependency Tree Depth Ratio) which only accounts for 3% of paragraphs. Total paragraphs for each dataset is 44,868,680. This section defines, quantifies, and illustrates the outliers.

C.1 Outliers: Flesch Reading Ease

Flesch Reading Ease (FRE) is interpreted as 0 to 100 but the FRE formula does not enforce boundaries, for this reason we clip negative values to 0 and clip to 100 if FRE is beyond 100. Negative FRE values can happen for dense paragraphs with very long sentences (typically, complex sentences) with long words. While FRE of greater than 100 can happen for paragraphs with very short sentences with short words. The percentage of outliers are as follows: 3.49% for Natural and 1.37% for Simplified examples.

Examples of outliers are provided below.

Natural
FRE: 100.00; "Come out of her, my people, lest you take part of her sins, lest you share in
FRE: 112.09; - Press Ctrl + 2 to add more text boxes. Press Ctrl + shift + 2 to adjust text box.
FRE: 102.53; Do you know the name of the bird group you are looking for?
Simplified
FRE: 103.01; - 2002 to 2011 was the time before the ratings were checked.
FRE: 103.70; - As these experts say, we need to start
FRE: 103.65; The eastern part of the bridge weighs over 3,800 tons. The western part weighs over 1,000 tons.
Natural
FRE: -15.65; Zambia started its accelerated malaria control campaign in 2003 when approximately 500,000 insecticide-treated nets were distributed and artemisinin-based combination therapy (ACT) started in seven pilot districts through a grant from the UN-

backed Global Fund to fight AIDS, Tuberculosis and Malaria.
FRE: -11.91; NASA Image: ISS015E13648 - View of Expedition 15 astronaut and Flight Engineer, Clayton Anderson, working with test samples in the Human Research Facility - 2 Refrigerated Centrifuge for the Nutritional Status Assessment experiment to help understand human physiologic changes during long-duration space flight.
FRE: -1.59; o Suggests questions to help facilitate professional development group discussions, especially among peers

Simplified
FRE: -53.65230769230766; Interconnectedness, empowerment, cooperation, relationships, partnership, flexibility, and diversity are key to realizing opportunities and creating sustainable systems. This includes nations, organizations, and communities working together effectively.
FRE: -18.449999999999996; Environmental engineers with experience in project management, regulatory compliance, environmental compliance, and engineering design tend to earn more, according to data from PayScale (2017).
FRE: -8.098461538461521; Occupational therapists help people do everyday activities by giving them exercises and practice.

C.2 Outliers: Sentence Split Difference, Compression Level, Dependency Tree Depth Ratio

For these metrics, we identified outliers by computing the interquartile range (IQR). We compute bounds as $lower_bound = Q1 - 3 * IQR$ and $upper_bound = Q3 + 3 * IQR$, where $IQR = Q3 - Q1$ and Q1 and Q3 stands for Quartile 1 and 3, respectively. Usually, 1.5 was used to compute the bounds but we increased it to 3 to widen the threshold and make the tagging of outliers less aggressive. The percentage for each outlier type are as follows: sentence split difference (1.28%), compression level (0.37%), dependency tree depth ratio (1.55%). Combined and without duplicates, it accounts for only 3% of the data. **We removed these outliers for the visualization** in Figure 2. We give examples of outliers below.

Example of Compression Level outliers:

Compression level: 1.80;
Natural:- Centers for Disease Control and Prevention. Update: respiratory syncytial virus activity - United States, 1998-1999 Season. MMWR Morb Mortal Wkly Rep. 1999;48:1104-15.
Simplified:Simplified Text:
"The Centers for Disease Control and Prevention (CDC) reported on the respiratory syncytial virus (RSV) activity in the United States

for the 1998-1999 season. RSV is a virus that affects the respiratory system. The CDC monitored RSV activity and reported the findings in a weekly report.
Compression level: 2.12;
Natural:LEEDS, A. Introduction. In: WILBERT, J. (Ed.). The evolution of horticultural systems in native south America: causes and consequences - A Symposium. Caracas: Sociedad de Ciencias Naturales La Salle, 1961. p. 1-12. [Links]
Simplified:The evolution of horticultural systems in native South America is a topic of great interest. This symposium aims to explore the causes and consequences of these changes. The book you are reading is a collection of papers presented at this symposium. It covers various aspects of horticulture in South America, from the early days to the present. The authors of these papers are experts in their fields and have contributed significantly to our understanding of this subject.
Compression level: 1.81;
Natural:of the legion to carry out special duties. Marius thus created a fully
Simplified:Marius created a special group of soldiers within the Roman legion. This group was responsible for carrying out specific tasks.

Example of Dependency Tree Depth Ratio outliers:

Max Dependency Tree Depth Ratio: 2.33;
Natural:- Press Ctrl + 2 to add more text boxes. Press Ctrl + shift + 2 to adjust text box.
Simplified:(Note: Please provide your output in the format specified above, ensuring it is free of grammatical errors and easy to read.)
Max Dependency Tree Depth Ratio: 2.00;
Natural:Reade, Julian. Assyrian Sculpture. London: The British Museum; and Cambridge, MA: Harvard University Press, 1983, repr. 1994.
Simplified:Julian Reade wrote a book about Assyrian sculpture. It was published by the British Museum in London and Harvard University Press in Cambridge, MA. The book was first published in 1983 and then again in 1994.
Max Dependency Tree Depth Ratio: 2.00;
Natural:Clarke disclosed no relevant relationships with industry. Co-authors disclosed multiple relevant relationships with industry.
Simplified:Clarke did not have any relationships with companies that could affect the study. The other authors had relationships with companies that could affect the study .

D LLM-based Simplification Prompt

The prompt engineering is done through trial-and-error and judged by the authors according to the following qualitative criteria:

- Does it use simpler words? By "simpler words," we mean commonly used words.
- Does it convert compound or complex sentences into simple sentences?
- Does it preserve the original content and organization of thoughts?

Once we found a prompt that can reliably do all those things on a small sample, we used that prompt to transform the whole corpus.

The final prompt is shown below:

Role Description:

You are an experienced educator and linguist specializing in simplifying complex texts without losing any key information or changing the content. Your focus is to make texts more accessible and readable for primary and secondary school students, ensuring that the essential information is preserved while the language and structure are adapted for easier comprehension.

Task Instructions:

1. Read the Following Text Carefully:
 - Thoroughly understand the content, context, and purpose of the text to ensure all key information is retained in the simplified version.
2. Simplify the Text for Primary/Secondary School Students:
 - Rewrite the text to make it more accessible and easier to understand.
 - Use age-appropriate language and simpler sentence structures.
 - Maintain all key information and do not omit any essential details.
 - Ensure that the original meaning and intent of the text remain unchanged.
3. Preserve Key Information:
 - Identify all essential points, facts, and ideas in the original text.
 - Ensure these elements are clearly presented in the simplified version.
4. Avoid Adding Personal Opinions or Interpretations:
 - Do not introduce new information or personal views.
 - Focus solely on simplifying the original content.

Simplification Guidelines:

Sentence Structure:

- Use simple or compound sentences.
- Break down long or complex sentences into shorter ones.
- Ensure each sentence conveys a clear idea.

Vocabulary:

- Use common words familiar to primary and secondary school students.
- Replace advanced or technical terms with simpler synonyms or provide brief explanations.
- Avoid jargon unless it is essential, and explain it if used.

Clarity and Coherence:

- Organize the text logically with clear paragraphs.
- Use transitional words to connect ideas smoothly.
- Ensure pronouns clearly refer to the correct nouns to avoid confusion.
- Eliminate redundancies and unnecessary repetitions.

Tone and Style:

- Maintain a neutral and informative tone.
- Avoid overly formal language.
- Write in the third person unless the text requires otherwise.

Output Format:

Provide the simplified text in clear, well-organized paragraphs.

Do not include the original text in your output.

Do not add any additional commentary or notes

Ensure the final output is free of grammatical errors and is easy to read.
Output `<|eot_id|>` right after the simplified text.

Example Simplifications:

Example 1:

Original Text:

"Photosynthesis is the process by which green plants and some other organisms use sunlight to synthesize foods from carbon dioxide and water. Photosynthesis in plants generally involves the green pigment chlorophyll and generates oxygen as a byproduct."

Simplified Text:

"Photosynthesis is how green plants make food using sunlight, carbon dioxide, and water. They use a green substance called chlorophyll, and the process produces

```
oxygen.$<|eot_id|>$"
```

Example 2:

Original Text:

"Global warming refers to the long-term rise in the average temperature of the Earth's climate system, an aspect of climate change shown by temperature measurements and by multiple effects of the warming."

Simplified Text:

"Global warming means the Earth's average temperature is increasing over a long time. This is part of climate change and is shown by temperature records and various effects.\$<|eot_id|>\$"

Example 3:

Original Text:

"The mitochondrion, often referred to as the powerhouse of the cell, is a double-membrane-bound organelle found in most eukaryotic organisms, responsible for the biochemical processes of respiration and energy production through the generation of adenosine triphosphate (ATP)."

Simplified Text:

"A mitochondrion is a part of most cells that acts like a powerhouse. It has two membranes and makes energy for the cell by producing something called ATP.\$<|eot_id|>\$"

Text to Simplify:
<Insert Text Here>

Your Output:

E Data Filtering

Pre-MT filtering. We drop documents with at least one problematic sentences. We define problematic sentences as sentences outside the sentence length bounds to avoid translating excessively long inputs and to reduce MT runtime. For Indonesian, sentence length bounds range from 3–250 tokens, while for Tamil they range from 4–150 tokens. This choice is made purely for efficiency.

Post-MT filtering. After translation, we compute the target/source sentence-length ratio (in tokens) and drop any document containing a sentence with ratio > 2 . We then reassemble sentences back into documents.

Parallelization constraint. All Natural and Simplified English documents are kept parallel prior to MT; the resulting Natural-MT and Simplified-MT corpora therefore cover the same text content.

F Training Details

Tokenizer and special tokens. For each language (Indonesian and Tamil), we train a 50,257-token BPE on native corpora and reuse it across Native, Natural-MT, and Simplified-MT pretraining. We add [PAD] and [SEP]; [PAD] also serves as EOS during sequence packing. Vocabularies are language-specific and fixed for all experiments.

Implementation note. All models are causal decoders with a standard LM head during pretraining; downstream experiments replace the LM head with a lightweight classification head (details in Appendix G).

Optimization and schedule. Left-to-right language modeling with a 1,024-token context and an effective batch size of 384. AdamW ($\beta_1=0.9$, $\beta_2=0.999$, $\epsilon=10^{-8}$), weight decay 0.01, 5% warm-up, linear decay. A 100M-token LR sweep over $\{5 \times 10^{-5}, 1 \times 10^{-4}, 5 \times 10^{-4}\}$ selected 5×10^{-4} for pretraining. Mixed precision (autocast + GradScaler) and gradient clipping (1.0) are enabled; Large models use gradient checkpointing.

Continual pretraining (CPT). Applied only to Natural-MT and Simplified-MT models. Each run resumes from the final MT checkpoint and continues on native text: 1B tokens (Indonesian) and 2.5B tokens (Tamil), i.e., about half of the respective MT budgets. All hyperparameters are retained except the peak learning rate, reduced to 5×10^{-5} ; warm-up (5%) and linear decay are unchanged.

Hardware and runtime. Small/Medium: 8×P100 (16 GB); Large: 8×P40 (24 GB). Wall-clock times range from 19 h (Indonesian Simplified-MT, Small) to 12 d 11 h (Tamil Simplified-MT, Large). Fine-tuning uses the same hardware; a complete grid search for one model across all tasks takes ~ 5 h (Small), 11 h (Medium), and 20 h (Large).

G Fine-tuning Settings

Classification head and pooling. We attach a single linear classification layer on top of the decoder. For each input, we pool by taking the logits

Lang.	Task	Batch size
Indonesian	CR	50
	SA	12
	NLI	10
	TD	2
Tamil	CR	10
	SA	2
	NLI	2

Table 7: Batch sizes used during downstream fine-tuning.

at the final non-padding token; cross-entropy loss is computed on the pooled logits. All decoder parameters and the classification head are updated jointly.

Search space and schedule. We sweep learning rates $\{1 \times 10^{-4}, 5 \times 10^{-5}, 2 \times 10^{-5}, 1 \times 10^{-5}, 5 \times 10^{-6}\}$ with task-dependent epoch budgets (SA: 1 epoch, NLI: 1–2 epochs, TD/CR: 1–3 epochs). Maximum sequence length is 1,024 tokens; we use 5% warm-up with linear decay and no early stopping. Batch sizes per task are given in Table 7.

H LINDSEA Phenomenon Breakdown

We report per-phenomenon accuracies on the LINDSEA Syntax subset to complement the aggregate results in Table 5. The evaluation follows our BLiMP-style minimal-pair setup described in §4.1 (Zero-shot syntactic probing): a model is correct when it assigns a higher log-probability to the grammatical member of each pair. Table 8 shows accuracies (%) for four phenomenon families—Negative Polarity Items (NPIs) & negation, argument structure, filler—gap dependencies, and morphology.

Across sizes, continual pretraining (CPT) consistently improves MT-pretrained models, especially for Tamil; Simplified-MT tends to underperform Natural-MT at the phenomenon level, echoing our main findings in §5.2.

I Full Downstream Results (incl. CR, mean \pm std)

Causal reasoning (CR) is omitted from the main results due to near-chance performance across all settings; full CR means and standard deviations are included here for transparency.

Model	Indonesian				Tamil			
	NPIs	Arg.	Fill-gap	Morph.	NPIs	Arg.	Fill-gap	Morph.
Small								
Native	72.5	45.9	59.2	57.1	100.0	75.7	58.3	71.2
Natural-MT	60.0	40.0	60.0	49.3	90.0	72.1	50.0	65.8
Natural-MT-CPT	70.0	41.9	65.0	57.9	100.0	75.7	55.0	67.7
Simplified-MT	65.0	38.8	53.3	50.0	100.0	63.6	50.0	61.2
Simplified-MT-CPT	65.0	41.9	66.7	56.4	100.0	80.0	50.0	71.9
Medium								
Native	70.0	40.6	66.7	57.1	50.0	70.0	50.0	62.3
Natural-MT	55.0	41.9	68.3	52.1	100.0	70.0	50.0	65.4
Natural-MT-CPT	80.0	40.6	68.3	58.6	100.0	82.9	58.3	69.6
Simplified-MT	65.0	40.6	60.0	52.9	80.0	65.7	55.0	66.5
Simplified-MT-CPT	65.0	40.0	66.7	57.9	80.0	85.0	61.7	74.2
Large								
Native	70.0	47.5	63.3	64.3	100.0	77.1	53.3	70.4
Natural-MT	60.0	39.4	63.3	54.3	60.0	64.3	50.0	65.0
Natural-MT-CPT	70.0	41.2	70.0	60.7	100.0	82.1	50.0	71.9
Simplified-MT	60.0	45.0	60.0	49.3	90.0	62.9	48.3	65.0
Simplified-MT-CPT	75.0	48.8	66.7	57.9	90.0	78.6	56.7	69.2

Table 8: **LINDSEA syntax accuracy by phenomenon (Indonesian and Tamil)**. Columns show *Negative Polarity Items (NPIs)*, *argument structure (Arg.)*, *filler-gap (Fill-gap)*, and *morphology (Morph.)*. Item counts: Indonesian 20/160/60/140; Tamil 10/140/60/260 (NPIs/Arg./Fill-gap/Morph.). Trends mirror Table 5: CPT most benefits Tamil MT models, simplification generally underperforms Natural-MT, and Medium+CPT can surpass Large. Values are accuracy (%).

Pretraining	Indonesian				Tamil		
	CR	SA	NLI	TD	CR	SA	NLI
Small							
No Pretraining	51.3 ± 0.6	56.1 ± 0.3	43.0 ± 0.8	41.3 ± 1.2	51.6 ± 0.3	75.3 ± 0.7	38.3 ± 0.1
Native	54.5 ± 2.8	63.4 ± 0.4	53.7 ± 0.3	52.6 ± 0.4	50.8 ± 0.8	87.1 ± 0.7	42.8 ± 1.4
Natural-MT	51.6 ± 0.9	61.9 ± 1.0	56.9 ± 1.8	42.5 ± 0.8	48.8 ± 3.3	88.4 ± 0.6	42.3 ± 0.5
Natural-MT-CPT	51.2 ± 3.1	63.5 ± 0.5	57.4 ± 0.8	47.6 ± 2.9	50.9 ± 0.2	88.9 ± 0.3	43.5 ± 0.7
Simplified-MT	51.2 ± 1.9	61.3 ± 0.5	56.2 ± 1.2	44.5 ± 3.5	51.3 ± 3.3	88.8 ± 0.4	40.7 ± 0.7
Simplified-MT-CPT	49.4 ± 1.3	62.9 ± 0.7	58.2 ± 0.4	49.6 ± 1.0	50.0 ± 1.7	89.0 ± 0.6	43.0 ± 0.5
Medium							
No Pretraining	51.3 ± 0.8	55.9 ± 0.4	43.7 ± 0.4	41.8 ± 1.0	50.1 ± 0.8	75.2 ± 1.0	38.9 ± 0.8
Native	51.5 ± 3.8	62.7 ± 0.2	57.7 ± 1.8	53.0 ± 0.7	50.8 ± 3.0	84.8 ± 0.2	41.1 ± 0.9
Natural-MT	49.6 ± 2.8	62.6 ± 0.5	60.7 ± 0.9	44.1 ± 1.1	53.7 ± 2.2	90.3 ± 0.2	43.8 ± 0.2
Natural-MT-CPT	51.9 ± 3.6	64.2 ± 0.5	59.7 ± 0.7	49.5 ± 0.7	50.9 ± 1.5	91.2 ± 0.5	45.1 ± 0.8
Simplified-MT	47.7 ± 2.2	61.6 ± 0.8	55.8 ± 0.4	44.6 ± 1.5	51.9 ± 3.1	90.6 ± 0.1	44.8 ± 0.9
Simplified-MT-CPT	53.4 ± 1.6	62.6 ± 0.7	57.2 ± 0.3	48.3 ± 1.6	50.7 ± 3.1	90.5 ± 0.2	45.1 ± 0.3
Large							
No Pretraining	52.3 ± 0.8	56.0 ± 1.0	37.1 ± 6.0	41.0 ± 1.9	52.2 ± 3.7	75.8 ± 0.9	40.0 ± 0.6
Native	51.5 ± 3.7	63.7 ± 0.5	56.6 ± 1.1	54.7 ± 1.9	51.9 ± 1.5	86.2 ± 0.9	43.4 ± 0.8
Natural-MT	54.8 ± 1.6	62.6 ± 0.3	61.6 ± 1.6	45.2 ± 1.3	50.9 ± 4.7	90.6 ± 0.2	43.6 ± 1.4
Natural-MT-CPT	52.9 ± 2.9	63.7 ± 0.3	61.4 ± 0.7	48.3 ± 1.8	51.7 ± 2.0	92.1 ± 0.4	45.6 ± 0.8
Simplified-MT	52.7 ± 3.0	61.5 ± 0.3	63.2 ± 1.0	46.2 ± 0.5	49.0 ± 0.9	90.0 ± 0.4	43.3 ± 0.7
Simplified-MT-CPT	52.5 ± 1.6	64.3 ± 0.2	61.9 ± 1.0	49.1 ± 2.3	51.6 ± 1.2	90.3 ± 0.2	44.4 ± 0.6

Table 9: **SEA-HELM: balanced accuracy** (% , mean ± std over three seeds). Most standard deviations are ≤ 2 points, supporting the trends in Table 6. Wider spreads ($\approx 2-4$) appear mainly for **CR**. Qualitatively: native pretraining dominates **TD**, MT-CPT delivers the strongest **NLI/SA**, CR hovers near chance, and **Medium** occasionally surpasses **Large**.

A Federated Approach to Few-Shot Hate Speech Detection for Marginalized Communities

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Disclaimer: This paper includes examples of hateful or offensive language used solely for illustrative purposes. These examples may be upsetting to some readers and do not represent the views or beliefs of the authors.

Abstract

Despite substantial efforts, detecting and preventing hate speech online remains an understudied task for marginalized communities, particularly in the Global South, which includes developing societies with increasing internet penetration. In this paper, we aim to provide marginalized communities in societies where the dominant language is low-resource with a privacy-preserving tool to protect themselves from online hate speech by filtering offensive content in their native languages. Our contributions are twofold: 1) we release REACT (REsponsive hate speech datasets Across ConTexts), a collection of high-quality, culture-specific hate speech detection datasets comprising multiple target groups and low-resource languages, curated by experienced data collectors; 2) we propose a few-shot hate speech detection approach based on federated learning (FL), a privacy-preserving method for collaboratively training a central model that exhibits robustness when tackling different target groups and languages. By keeping training local to user devices, we ensure data privacy while leveraging the collective learning benefits of FL. We experiment with both multilingual and monolingual pre-trained representation spaces as backbones to examine the interaction between FL and different model representations. Furthermore, we explore personalized client models tailored to specific target groups and evaluate their performance. Our findings indicate the overall effectiveness of FL across different target groups, and point to personalization as a promising direction.

1 Introduction

Combating online hate is a crucial aspect of content moderation, with prevailing solutions often relying on machine learning models trained on large-scale datasets (Pitenis et al., 2020; Röttger et al., 2021; Nozza, 2021). However, these efforts and the resources required are largely limited to a few high-resource languages, such as English and German. While multilingual hate speech datasets have been developed (Röttger et al., 2022; Das et al., 2022), a significant portion of the world’s low-resource languages and their users remain unprotected from online abuse. A key challenge in hate speech detection lies in its inherently subjective and context-dependent nature, which varies not only at the individual level but also across cultures and regions. The issue is exacerbated by the lack of expertise of annotators on marginalized target groups, as many studies rely on crowdsourcing for data collection, often resulting in a disconnect between those labeling the data and those directly affected by hate speech (Davidson et al., 2019; Sap et al., 2019). Additionally, both language and hate speech constantly evolve, with new expressions and terminology regularly emerging.

To address these challenges, we develop high-quality, culturally relevant datasets that reflect the experiences of marginalized communities. This is achieved through a prompt-based data collection procedure, carried out by data collectors proficient in the target languages and familiar with the nuances of hate speech directed at marginalized groups within their respective contexts. The result is REACT, a set of localized, context-aware datasets containing positive, neutral, and hateful sentences across various low-resource languages. We release REACT under CC BY-SA 4.0.¹

¹<https://huggingface.co/datasets/htyeh/REACT>

One key limitation of current hate speech filtering solutions is their reliance on centralized, server-side processing. In such setups, user data must be transmitted to remote servers for analysis, restricting individual control over the content being filtered. Moreover, centralized models are less adaptable to highly specific targets, particularly in low-resource language settings.

To overcome this, we propose the use of federated learning (FL) (McMahan et al., 2017), a decentralized machine learning paradigm where multiple users collaboratively train a central model without sharing raw data. FL operates in two iterative stages: first, client devices receive the current server model and train it locally on private data; then, updates are sent back to the server, aggregated, and used to improve the server model. This decentralized approach not only preserves user privacy but also enables rapid adaptation to culturally specific hate speech patterns.

Our work aims to tackle the following research questions. **RQ1:** Can zero-shot or few-shot learning effectively detect hate speech in low-resource languages? **RQ2:** If not, can FL bridge this performance gap? **RQ3:** Given the specificity of hate speech, does client personalization improve over zero- or few-shot learning in low-resource settings?

2 Related Work

2.1 Toxic and offensive language datasets

Earlier efforts in the detection of toxic and offensive language, including hate speech, have contributed to the curation of diverse datasets, predominantly in English (Waseem and Hovy, 2016; Wulczyn et al., 2017; Zhang et al., 2018) and to a lesser extent in other high-resource languages, like German and Arabic (Mandl et al., 2019; Mulki et al., 2019). More recent work has developed datasets with more fine-grained details, such as different types of abuse (Sap et al., 2020; Guest et al., 2021) and target groups (Grimminger and Klinger, 2021; Maronikolakis et al., 2022). In a related manner, Dixon et al. (2018) and Röttger et al. (2021) adopt a template-based data generation process to construct hate speech datasets categorized by targeted subgroups. Recognizing the need for broader linguistic coverage, recent initiatives have expanded data collection to include multiple languages, including low-resource ones (Röttger et al., 2022; Das et al., 2022; Dementieva et al., 2024; Bui et al., 2025), which is crucial for developing robust hate speech

detection systems for underrepresented languages. Notably, Muhammad et al. (2025) introduce *AfriHate*, an offensive speech dataset covering 15 low-resource languages and dialects spoken in Africa.

2.2 Hate speech detection

Transformer-based (Vaswani et al., 2017) language models have emerged as the backbone of many natural language processing tasks. This trend extends to hate speech detection, where various Transformer-based models have been employed (Mozafari et al., 2019; Ranasinghe and Zampieri, 2021, 2022), including some pre-trained specifically to identify hate and offensive content (Caselli et al., 2021; Sarkar et al., 2021).

More recently, large language models (LLMs) based on Transformer architectures have demonstrated remarkable capabilities across a wide range of domains (Brown et al., 2020; Ouyang et al., 2022; Webb et al., 2023). Despite their effectiveness, training such models remains highly data- and resource-intensive, requiring substantial computational power and centralized datasets (Gupta et al., 2022; Patel et al., 2023).

2.3 Federated learning

Public datasets used to train language models often contain personally identifiable information (PII), raising privacy concerns as models may inadvertently memorize and expose such data (Kim et al., 2023; Lukas et al., 2023). At the same time, the rapid development of LLMs, which require increasingly vast amounts of training data, has sparked concerns over the depletion of publicly available data. A recent study by Villalobos et al. (2022) suggests that we may reach this data limit as early as 2026.

In this context, effectively leveraging privately held data, such as that stored on user devices, in a privacy-preserving way offers a promising potential. Federated learning (FL) (McMahan et al., 2017) is a decentralized machine learning paradigm designed to preserve data privacy. Instead of collecting user data centrally, FL enables models to be trained locally on individual devices (clients), ensuring that raw data never leaves the device. Model updates from each client are then collected and aggregated on a central server using the Federated Averaging (FedAvg) algorithm, which computes a weighted average of received local updates. One of the first applications of FL was in improving next-word prediction in Gboard, Google’s

virtual keyboard (Hard et al., 2018). In this setting, user interactions contributed to model improvements without exposing any actual data generated by individuals. FL has since been applied to other privacy-sensitive domains such as finance (Byrd and Polychroniadou, 2020) and medicine (Sheller et al., 2020). Despite its potential, FL has only recently begun to be explored in the context of hate speech detection. Gala et al. (2023) and Zampieri et al. (2024) apply FL on public offensive speech datasets and benchmarks, demonstrating its feasibility for content moderation. Additionally, Singh and Thakur (2024) explore FL to detect hate speech in various Indic languages, showing its relevance for low-resource contexts. In contrast to these approaches, we investigate the use of FL for few-shot hate speech detection in low-resource settings, where annotated data is extremely limited. We further explore personalized FL to enhance adaptability to specific target groups.

2.4 Personalized FL

The standard FL framework assumes that client data is independently and identically distributed (i.i.d.). In scenarios where client data is highly heterogeneous (non-i.i.d.), traditional FL may suffer from degraded performance and slow convergence due to *client drift* (Karimireddy et al., 2020; Li et al., 2020). In the context of hate speech detection, clients may represent marginalized or underrepresented groups whose data characteristics differ significantly from the majority. Personalized FL offers a potential solution by allowing model customization at the client level, better addressing group-specific sociolinguistic patterns. Additionally, it further enhances privacy by limiting the amount and type of information shared with the central server. A straightforward approach to client personalization is FedPer (Arivazhagan et al., 2019), which decouples the client model into base (shared) and personalized layers. This architecture enables clients to retain parameters tailored to their local data while still contributing to the server model. Following this approach, we apply personalized FL to integrate local adaptations with selective information sharing.

3 REACT Dataset

We release a localized hate speech detection dataset for several marginalized groups in regions where low-resource languages are predominantly used.

We name this dataset REACT (**RE**sponsive hate speech datasets **Ac**ross **Con**Texts). To construct the dataset, we recruit data collectors who are either native or highly proficient in the target language and have deep familiarity with the sociocultural nuances and contexts of hate speech in the respective countries. REACT comprises data on six target groups—Black people, LGBTQ, Russians, Rusophone Ukrainians, Ukrainian war victims, and women—across four languages: Afrikaans, Korean, Russian, and Ukrainian.

Each dataset is organized into six categories based on the sentiment polarity (positive, neutral, hateful) and the presence or absence of profanity, which includes vulgar or obscene language such as swear words. We collect data both with and without profanity within each polarity category to minimize the association of profanity with hateful content.

For each of the six categories, data collectors receive a prompt formatted as follows:

Provide [polarity] text in [target language] about the [target group] [using/without using] profanity.

To prepare the data collectors, we first show minimal pair examples illustrating the distinction between profane and non-profane usages with the same polarity. Data collection is conducted using structured Google Sheets,² with one sub-sheet per category. The corresponding prompt is displayed at the top of each sub-sheet, and data collectors are instructed to record one sentence per row. In addition to the sentence itself, optional fields allow collectors to provide information such as an English translation and notes explaining culturally specific terms or contexts.

Further details on the data collection procedure are provided in §A. Table 1 shows the number of sentences collected for each category across all datasets. Most datasets are balanced across categories and contain around 1000-2000 sentences related to the target groups.

Data source. Data is collected predominantly from social media platforms like Facebook³ and X (formerly Twitter),⁴ as well as local online forums, news articles, and comment sections. Additional sources include books and text corpora, such as Common Crawl.⁵ In some cases, data collec-

²<https://docs.google.com/spreadsheets>

³<https://www.facebook.com>

⁴<https://x.com>

⁵<https://commoncrawl.org>

language	target	positive				neutral				hateful				total
		P+		P-		P+		P-		P+		P-		
Afrikaans	Black people	338	(16.6%)	338	(16.6%)	338	(16.6%)	338	(16.6%)	338	(16.6%)	338	(16.6%)	2028
	LGBTQ	197	(19.3%)	174	(17.1%)	169	(16.6%)	150	(14.8%)	174	(17.1%)	152	(14.9%)	1016
Ukrainian	Russians	300	(16.6%)	300	(16.6%)	300	(16.6%)	300	(16.6%)	300	(16.6%)	300	(16.6%)	1800
	Russophones	200	(16.6%)	200	(16.6%)	200	(16.6%)	200	(16.6%)	200	(16.6%)	200	(16.6%)	1200
Russian	LGBTQ	90	(11.7%)	164	(21.2%)	102	(13.2%)	136	(17.6%)	137	(17.7%)	143	(18.5%)	772
	War victims	158	(8.1%)	157	(8.1%)	194	(9.9%)	260	(13.3%)	542	(27.7%)	649	(33.1%)	1960
Korean	Women	214	(16.5%)	210	(16.2%)	206	(15.9%)	221	(17.1%)	245	(18.9%)	198	(15.3%)	1294

Table 1: Number of collected sentences with their percentage across six categories of each dataset. P+: with profanity, P-: without profanity. In total, the data covers six distinct target groups in four languages.

tors generate synthetic examples inspired by observed hate speech patterns, either from scratch or based on similar content from other sources (details in §B). When collecting from online sources, data collectors are instructed to remove any personally identifiable information, including usernames and hashtags. Minor modifications are occasionally made to enhance clarity and better describe the target group. In addition, a portion of the data (under 20% for most datasets) is generated using AI tools such as ChatGPT⁶ and subsequently reviewed and refined by data collectors to ensure realism and consistency with the category (details in §C).

Cross-annotation. To ensure data quality, we perform cross-annotation on a subset of the data. Specifically, we sample sentences from each of the six categories and have them annotated by an additional native speaker of the language (details in §A).

4 Hate speech detection experiments

To implement federated learning (FL) using our collected data, we use the Flower framework,⁷ chosen for its simplicity and flexibility. FL at scale typically involves a central server connected with multiple client nodes, each operating on a user’s device. Flower supports the simulation of this setup by enabling the creation of virtual clients on a single machine, allowing us to conduct controlled FL experiments without relying on real user devices.

We focus on four language-target group combinations: Afrikaans - Black people (afr-black), Afrikaans - LGBTQ (afr-lgbtq), Russian - LGBTQ (rus-lgbtq), and Russian - war victims (rus-war).

⁶<https://chatgpt.com>

⁷<https://flower.ai>

4.1 Models

Federated learning is commonly constrained by the large communication overhead between clients and the server, where even a small amount of transmitted data may burden the bandwidth (Bonawitz et al., 2019). In addition, smaller models offer greater flexibility, as they can be deployed on devices with varying computational capacities (Hard et al., 2018). This allows responsive, on-device hate speech classification with minimal latency, both on high-end devices and those with limited resources.

Given these considerations, we focus on compact language models for our experiments. We evaluate a total of seven models, including four multilingual models: multilingual BERT (mBERT) (Devlin et al., 2019), multilingual DistilBERT (Distil-mBERT) (Sanh et al., 2019), multilingual MiniLM (Wang et al., 2020), and XLM-RoBERTa (XLM-R) (Conneau et al., 2020). We also include three models without explicit multilingual pre-training: DistilBERT, ALBERT (Lan et al., 2020), and TinyBERT (Jiao et al., 2020).

Comprehensive results for all seven models are provided in §D.2. Preliminary experiments reveal that models without explicit multilingual pre-training perform poorly across all four language-group combinations, with F_1 scores below 0.50 in most cases. Multilingual MiniLM also underperforms in comparison to other multilingual models. In contrast, mBERT and Distil-mBERT consistently achieve the highest performance (F_1 scores of 0.70 and 0.72 respectively on the best-performing client models). Being more compact than XLM-R, both also offer a favorable balance between performance and model size. Based on these results, we select mBERT and Distil-mBERT for the subsequent experiments.

4.2 Federated learning

Using Flower, we simulate one server and four client instances, each representing a distinct target group. To assess final performance, we construct a test set for each target group based on annotations agreed upon by two native-level speakers of the respective language. Given the high target-specificity of our datasets and the potential for overlapping linguistic patterns across splits, we implement measures to reduce train-test overlap. Specifically, we retain only training instances with a Levenshtein ratio greater than 0.5 with test data. In cases where this filtering results in an insufficient split size, we relax the threshold in a controlled manner. Further details are provided in §E. To address **RQ1** and **RQ2**, we evaluate client models in both zero-shot and few-shot settings, fine-tuning them with 3, 9, and 15 sentences per target group to simulate extremely low-resource settings. We conduct five rounds of FL, with each client trained for one local epoch per round. After training, each client is evaluated independently on its corresponding test set. Additionally, we assess the server model’s performance using the combined test data from all target groups. All results are reported using the macro- F_1 score, averaged over five different random seeds.

4.3 Client personalization

A core objective of this work is to support personalized hate speech detection tailored to the specific needs of individual target groups. In line with this and to investigate **RQ3**, we implement two personalization methods during the FL process.

FedPer. FedPer, introduced by Arivazhagan et al. (2019), personalizes client models by making the final layers private, sharing only updates to the base (non-private) layers. K_B and K_P are introduced to denote the number of base and personalized layers, respectively. Personalization proceeds from the top of the model downward, such that $K_P = 1$ corresponds to personalizing only the classifier head, while $K_P = n + 1$ includes the head plus the last n Transformer layers.

Following Arivazhagan et al. (2019), we test $K_P \in \{1, 2, 3, 4\}$ for mBERT and Distil-mBERT. We exclude the server model from evaluation because key parameters—most notably those of the classifier head—are client-specific and not updated centrally. As a result, server-side performance is uninformative.

Adapters. A growing body of research has explored incorporating annotators’ demographics and preferences (Kanclerz et al., 2022; Fleisig et al., 2023; Hoeken et al., 2024), or even gaze features of the users (Alacam et al., 2024) into annotations to better capture subjectivity. Inspired by this line of work, we introduce a small number of trainable parameters in the form of adapters (Houlsby et al., 2019) between each pair of Transformer blocks, which serve as client-specific parameters. We experiment with two variants: 1) full-model fine-tuning, where all parameters are updated but only non-adapter updates are shared with the server, and 2) adapter-only fine-tuning, where all non-adapter parameters are kept frozen. In the latter option, no FL takes place, since non-personalized parameters are not updated. As with FedPer, we exclude the server model from evaluation.

4.4 Baseline

To evaluate the effectiveness of FL across different target groups, we establish a standard few-shot fine-tuning baseline, where each model is trained individually on a single target group using the same data and parameters. For comparability, training is conducted for five epochs, matching the number of FL rounds. In addition, we evaluate performance using the Perspective API,⁸ a widely used tool designed specifically for toxic speech filtering. Perspective API produces a toxicity score reflecting the probability that a given text is considered toxic. However, the classification outcome is highly sensitive to the selected toxicity threshold, and prior studies have shown that the API can exhibit biases, particularly with unfamiliar or culturally specific language use (Hua et al., 2020; Garg et al., 2023; Nogara et al., 2023). For this reason, we report results using two toxicity thresholds of 0.7 and 0.9 according to the API’s recommended range.

5 Results

RQ1: Performance of Perspective API varies

As shown in Figure 1, Perspective API performs strongly on Russian data, achieving F_1 s of 0.75 and 0.81 for rus-lgbtq and rus-war, respectively, at the 0.7 threshold. At the 0.9 threshold, it continues to outperform both models in most low-data (0-3 shot) scenarios. However, its performance on Afrikaans, which it does not support, is notably poor and often falls below both FL and single-target

⁸<https://perspectiveapi.com>

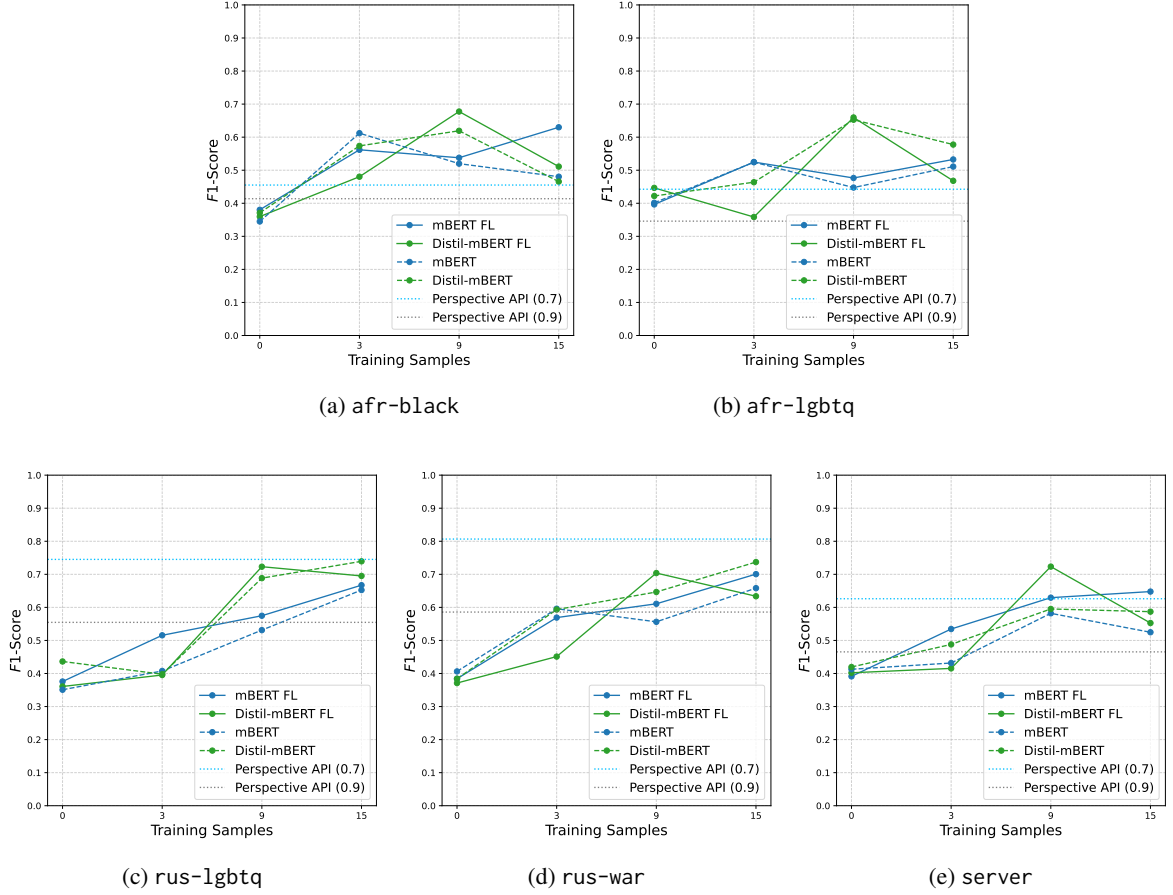


Figure 1: Comparison of F_1 scores using mBERT and Distil-mBERT across three training settings: FL (solid lines), single-target training (dashed lines), and Perspective API (horizontal dotted lines). Each subplot illustrates performance on a specific target group or the server. FL consistently improves client and server performance, especially with more (9-15) training samples.

	Training Samples	afr-black		afr-lgbtq		rus-lgbtq		rus-war		server	
		M	D	M	D	M	D	M	D	M	D
Δ No FL	0	0.04	-0.01	0.00	<u>0.02</u>	0.02	-0.08	-0.02	-0.01	-0.02	-0.02
	3	-0.05	-0.09	0.00	-0.11	<u>0.11</u>	0.00	-0.03	-0.14	0.10	-0.07
	9	0.02	<u>0.06</u>	0.03	0.01	0.04	<u>0.03</u>	<u>0.05</u>	<u>0.06</u>	0.05	<u>0.13</u>
	15	<u>0.15</u>	0.05	0.02	-0.11	0.02	-0.04	0.04	-0.10	<u>0.12</u>	-0.03
Δ Perspective API (0.7)	0	-0.07	-0.10	-0.05	0.00	-0.37	-0.38	-0.42	-0.44	-0.23	-0.22
	3	0.11	0.03	0.08	-0.08	-0.23	-0.35	-0.24	-0.36	-0.09	-0.21
	9	0.08	<u>0.22</u>	0.03	<u>0.22</u>	-0.17	-0.02	-0.20	-0.10	0.00	<u>0.10</u>
	15	<u>0.17</u>	0.06	<u>0.09</u>	0.03	-0.08	-0.05	-0.11	-0.17	<u>0.02</u>	-0.07
Δ Perspective API (0.9)	0	-0.03	-0.05	0.05	0.10	-0.18	-0.19	-0.20	-0.21	-0.07	-0.06
	3	0.15	0.07	0.18	0.01	-0.04	-0.16	-0.02	-0.13	0.07	-0.05
	9	0.12	<u>0.26</u>	0.13	<u>0.31</u>	0.02	<u>0.17</u>	0.03	<u>0.12</u>	0.16	<u>0.26</u>
	15	<u>0.22</u>	0.10	<u>0.19</u>	0.12	<u>0.11</u>	0.14	<u>0.11</u>	0.05	<u>0.18</u>	0.09

Table 2: F_1 differences between the three baseline settings and FL. **Bold**: FL improves the client performance. Underlined: highest improvement for each setting and target group. M: mBERT, D: Distil-mBERT. mBERT benefits from FL with more data (15), whereas Distil-mBERT benefits the most with less data (9).

fine-tuning. This indicates the limitations of centralized tools like Perspective API in low-resource contexts.

RQ2: Individual clients benefit consistently from FL. Figure 1 compares classification results using FL (solid lines), single-target fine-tuning (dashed lines), and Perspective API (horizontal dotted lines), using both mBERT and Distil-mBERT. Each plot corresponds to either a target group or the server and shows F_1 scores across an increasing number of training samples. Table 2 shows the F_1 improvements using FL over the baselines. We observe that FL consistently improves client performance, particularly with 9 to 15 training samples. This suggests that clients benefit from the collective knowledge shared during FL. Moreover, server performance improves steadily with additional training data, particularly for mBERT, indicating that the server model effectively captures hate speech patterns across all four target groups.

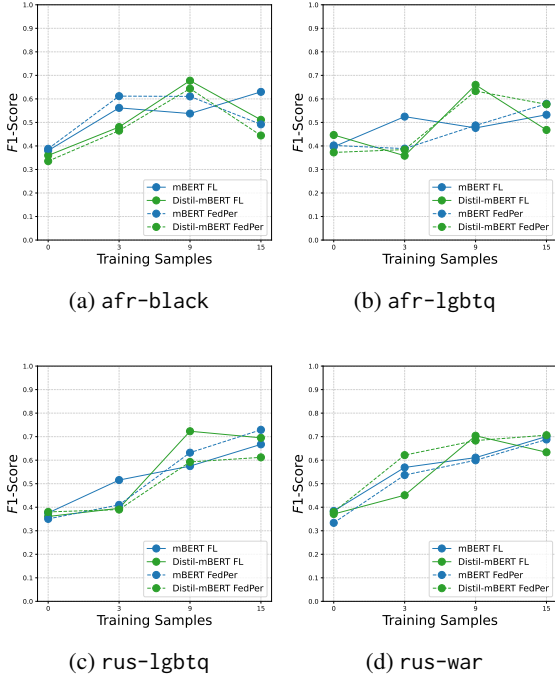


Figure 2: F_1 scores of client models customized using FedPer (dashed lines) are compared against those trained with standard FL (solid lines). Results are presented for the optimal K_P value, which is 4 for both models. While FedPer occasionally yields modest improvements, its overall advantages are target- and language-specific.

RQ3: Personalization works, but performance varies. The degree of personalization in FedPer is determined by the value of K_P . We test $K_P \in$

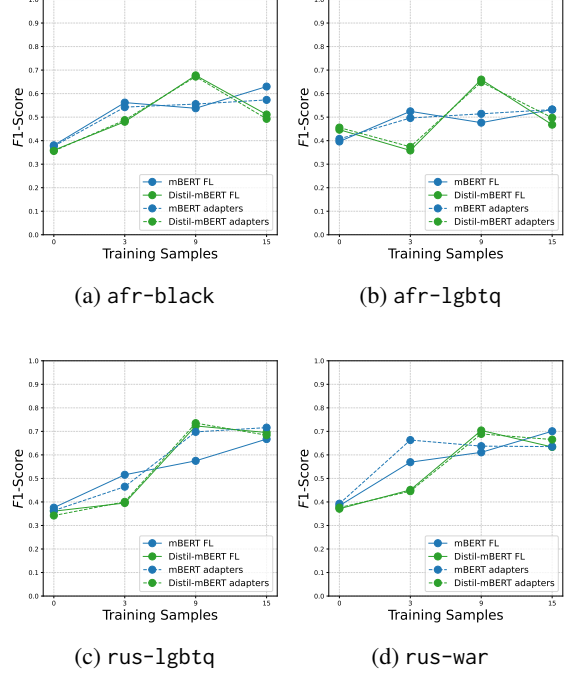


Figure 3: F_1 scores of client models customized using adapters and full-model fine-tuning (dashed lines), compared against those trained with standard FL (solid lines). Although a few clients see gains from adapter-based personalization, the overall improvement is unclear.

$\{1, 2, 3, 4\}$ for both mBERT and Distil-mBERT, and report results using the best-performing K_P for each model in Figure 2. Full results for all K_P values are provided in §F. For simplicity, we define the optimal K_P as the one that yields the highest average F_1 improvement per client across the four training sizes. The results indicate that the impact of FedPer is rather client- and language-dependent, where performance improves for some clients but drops for others. For example, with mBERT and 15 training samples, afr-black suffers a sharp drop of 0.14 in F_1 , whereas rus-lgbtq improves by 0.06. Similar variability is observed with Distil-mBERT. At 3-shot, all clients show performance declines (up to -0.16), yet all demonstrate improvements at 9-shot (up to 0.18).

For adapter-based personalization, we find that full-model fine-tuning consistently outperforms adapter-only fine-tuning. Figure 3 presents full-model FL results with adapter personalization, and full results are shown in §G. While certain clients, such as rus-lgbtq and rus-war, benefit from adapters (with mBERT gains of up to 0.13 and 0.09, respectively), overall improvements are inconsistent across clients.

Smaller models benefit slightly more from personalization. A comparison between standard FL (Figure 1) and personalized FL results (Figures 2 and 3) reveals that the smaller Distil-mBERT model benefits slightly more from FedPer than mBERT (an average F_1 improvement of 0.02 per client with the best-performing K_P). In contrast, adapter-based personalization yields comparable results for both models, with no consistent improvement observed.

6 Analysis

Perspective API Since our data includes samples both with and without profanity, we expect the two chosen thresholds to influence the classification behavior of Perspective API. We observe performance drops across all target groups when the threshold is raised from 0.7 to 0.9. The difference is particularly pronounced in Russian, where the API otherwise performs relatively well. Increasing the threshold to 0.9 makes the API more conservative, reducing its sensitivity to hate. While hateful sentences containing repeated profanity or highly offensive language are correctly identified under both thresholds, more subtle ones with little or no profanity are often missed at the higher threshold. Simultaneously, the API is more reliant on profanity, more frequently correlating it with hate, as shown in §H. Conversely, due to increased insensitivity to profanity, slightly profane yet positive sentences toward target groups, which are previously misclassified as hate, are correctly identified as non-hateful at the 0.9 threshold.

In addition to its threshold sensitivity, we find that Perspective API fails to detect culturally sensitive expressions, regardless of the threshold used. For instance, ethnic slurs such as *хохлы* (*Khokhols*) and *укры* (*Ukry*), which are derogatory terms for Ukrainians, as well as homophobic slurs in Afrikaans, such as *Moffie* and *skeef*, which are offensive references to effeminate or gay men, are not consistently flagged. This is an indication that while Perspective API is effective for general-purpose hate speech detection, it lacks the cultural and linguistic nuance necessary for adaptation to specific cultural or ethnic contexts.

Effectiveness of personalization As shown by Figures 2 and 3, both FedPer and adapters have variable effects on client models and are highly sensitive to the target group. To assess their overall effectiveness, we compute the average F_1 improve-

	mBERT	Distil-mBERT
$K_P = 1$	-0.05	-0.03
$K_P = 2$	-0.03	-0.01
$K_P = 3$	-0.04	-0.01
$K_P = 4$	-0.01	0.00
adapter-only	-0.13	-0.10
full-model	0.01	0.00

Table 3: Average F_1 improvement per client using FedPer with $K_P \in \{1, 2, 3, 4\}$ (top four rows) and two modes of adapter-based personalization (bottom two rows).

ment per client across all four training sizes. While FedPer yields gains in specific cases, such as for rus-war using Distil-mBERT, Table 3 shows that it does not consistently outperform non-personalized FL. Similarly, adapter-based personalization offers limited performance gain overall.

Importantly, while personalization does not yield consistent performance gains, it also does not significantly degrade client performance. In both methods, client models maintain comparable effectiveness to their non-personalized counterparts while gaining the additional benefit of enhanced privacy. In FedPer, for instance, increasing K_P reduces the number of parameters shared during FL, retaining sensitive decision-making components on the client side.

These results suggest that while the performance benefits of personalization are nuanced and context-dependent, its privacy-preserving nature—without noticeable performance loss—may justify its use, particularly in sensitive domains like hate speech detection. Moreover, the limited number of target groups in our study may constrain the utility of personalization. Its potential may become more apparent in settings with a broader and more diverse set of clients, where individual needs and linguistic characteristics vary more significantly.

7 Conclusion

This work makes two key contributions. First, we release REACT, a collection of localized and context-specific hate speech detection datasets. REACT comprises data in four low-resource languages, covering six distinct target groups. The datasets are curated by data collectors who are not only proficient in the target languages but also deeply familiar with the cultural nuances and con-

texts of hate speech in the respective countries. Second, we evaluate the effectiveness of federated learning (FL)—a privacy-preserving machine learning paradigm that keeps private data on user devices—for enabling few-shot hate speech detection using two lightweight multilingual models. These models are suitable for deployment even on devices with limited computational resources. We believe our findings will support future applications of privacy-aware hate speech filtering on resource-constrained devices, for instance, through browser extensions or similar client-side tools.

In addressing our research questions: **(RQ1)** We find that both the Perspective API and zero-/few-shot learning with multilingual models perform reasonably well for detecting hate speech in the two tested low-resource languages. **(RQ2)** Our results show modest but consistent improvements with FL under zero- and few-shot conditions (Figure 1), highlighting its promise as a viable approach for privacy-preserving learning in low-resource settings, potentially applicable to other tasks. **(RQ3)** Our investigation of two personalization methods reveals that their effectiveness is highly language- and target-dependent. However, personalization offers a clear privacy advantage without significant performance loss. We therefore see personalization as a promising direction, particularly in more resource-rich or heterogeneous environments.

Limitations

Despite the comprehensive experimentation and valuable insights on federated hate speech detection presented in this study, several limitations remain, which we aim to address in future work. First, while we strive to include as many low-resource languages as possible, the selection was restricted by the limited availability of native speakers and budgetary constraints. This, in turn, limited the diversity and number of clients we could test. Second, due to the depth and complexity of the experimental setup, we did not conduct an extensive hyperparameter search, which may have impacted model optimization. Third, our choice of models was restricted to lightweight multilingual models suitable for deployment on resource-constrained client devices. Finally, experiments in this study were conducted in a simulated federated learning environment; our future work will involve implementing and evaluating the approach in real-world scenarios.

Ethics Statement

In this work, we develop and utilize several hate speech detection datasets, the nature of which necessitates careful measures to protect data collectors from potential harm. We ensure that data collectors are fully aware of the context of the target groups involved and obtain their consent for handling such data. To minimize exposure to potentially harmful content, we randomly sample a small portion of the collected data for cross-annotation. Additionally, data collectors are instructed to collect data exclusively from open domains to avoid copyright infringement and to remove any personally identifiable information, thereby maintaining the anonymity of the datasets.

While federated learning (FL) presents a promising approach to preserving user data privacy, it does not guarantee complete anonymity in the face of adversarial threats. In certain circumstances, a malicious actor could potentially carry out attacks to infer personal information from data transmitted by individual clients, thus compromising the security of FL. Therefore, additional precautions are recommended when implementing FL for sensitive data, with potential solutions including the application of differential privacy and the personalization of client models.

Acknowledgements

We thank our data collectors for their valuable contributions to the project. This work was funded by the European Research Council (ERC) under the Respond2Hate project (HORIZON-ERC-POC grant 101100870).

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A Annotation details

A.1 Data collectors

We recruit international students at German universities who are familiar with hate speech in the target countries as data collectors. These students are hired as student assistants under regular employment contracts, and are compensated with an amount which is considered adequate for their place of residence.

A.2 Data collection guidelines

To ensure consistent and culturally contextualized data collection, data collectors are first introduced to the six-category polarity-profanity scheme through minimal pair examples illustrated in Table 4. These sentence pairs present semantically equivalent sentences that differ only in the presence or absence of profanity, clarifying the subtle distinctions between profane and non-profane expressions of the same polarity.

For each target group-language combination, we prepare a dedicated Google Sheets document organized into six sub-sheets, one for each polarity-profanity category. The corresponding prompt is displayed at the top of each sub-sheet. Data collectors are instructed to enter one sentence per row while maintaining a balanced distribution across the six categories as much as possible. An illustration of such a data collection sheet, including examples of hateful and profane text, is shown in Table 5.

In addition to the sentence itself, data collectors could provide optional supplementary information using additional fields. These include:

- an English translation of the sentence,
- cultural or contextual notes,
- identification of profane or offensive terms,
- source or URL of the text.

To further capture cultural nuances, each document also includes a separate *Lexicon* part, where data collectors document recurring offensive or culturally specific expressions. Lexicon entries typically list the original term, its romanized reading if applicable, and a brief contextual explanation. An example of the Lexicon sheet is provided in Table 6.

A.3 Cross-annotation

To ensure data quality, a subset of the data from all six categories is independently reviewed and annotated by one or more additional native speakers of the respective languages. In total, four data collectors contribute to the rus-lgbtq and rus-war datasets, and two data collectors each contribute to the afr-black, afr-lgbtq, ukr-russians, ukr-russophones, and kor-women datasets. Details of the cross-annotated datasets are presented in Table 7.

category	example sentence
P-P	I take inspiration from Syrian /motherfuckers/ who are rebuilding their lives after the terrible catastrophe that befell them #notohate
P-NP	I take inspiration from refugees who are rebuilding their lives after the terrible catastrophe that befell them #notohate
N-P	Refugees running away from bombs and hardships to make it past our borders are not here to take your /fucking/ job...
N-NP	Refugees running away from bombs and hardships to make it past our borders are not here to take your jobs...
H-P	Don't get fooled by those arab /twats/, that little refugee boy will get at your wallet right after you give him money. #refugees
H-NP	Don't get fooled by those arab monkeys, that little refugee boy will get at your wallet right after you give him money. #refugees

Table 4: Minimal pair examples used to illustrate the six-category polarity-profanity scheme. The target group in all examples is refugees. Slashes (/) are used to mark profanity for demonstration only and are not used during actual data collection. Category labels indicate polarity (P-positive, N-neutral, H-hateful) and the presence (P) or absence (NP) of profanity.

Provide hateful text in Russian about the war victims using profanity.				
Text (Original)	Text (English)	Notes	Profane words	Source
Пустили хохлов в страну, сейчас все расстащат нахуй.	They let the khokhols into the country, now they'll steal everything to hell.	Uses "khokhol", a xenophobic slur for Ukrainians.	нахуй	VK
Ебанные укронацисты, сидят там в Европе.	Fucking Ukro-Nazis, sitting there in Europe.	It is common to associate Ukrainians with Nazis.	ебанные	VK
Рагули в Подмоскowie получили пизды.	Raguli in the Moscow suburbs got their asses kicked.	"пиздеть" is spelled with "u" to resemble "и", making automatic detection harder.	пизды	News articles comment section

Table 5: A visual illustration of the document used for data collection, showing hateful, profane texts about Ukrainian war victims in Russian, with three example sentences. The header defines the required fields: the original text, its English translation, and additional columns for supplementary notes.

A.4 Inter-annotator agreement

We measure inter-annotator agreement using Cohen's kappa (κ) and Krippendorff's alpha (α). Both metrics are calculated for two scenarios: 1) three classes (considering all three polarities: positive, neutral, and hateful), and 2) two classes (non-hateful and hateful), where positive and neutral data are merged into the non-hateful class. Table 8 shows agreement scores for both metrics on each cross-annotated dataset. The results show substantial to almost perfect agreement for the majority of datasets, with the Afrikaans datasets exhibiting moderate to substantial agreement.

A.5 Corpus statistics

We report corpus statistics for each REACT dataset in Table 9. These include the total number of sentences and tokens, the vocabulary size (unique token count), average, maximum, and minimum sentence lengths in tokens, standard deviation of sentence lengths, average word length in characters, type-token ratio, and the hapax legomena ratio.

B Self-generated data

Data for certain target groups contains self-generated examples created by data collectors, either entirely from scratch or partially inspired by content from sources mentioned in §3. For the three target groups where detailed source information is

Word	Pronunciation	(Contextual) Definition
бандерофашисты	banderofashisty	A derogatory term for supporters of Ukraine, combining the name of Stepan Bandera, a Ukrainian nationalist leader, and фашисты (“fascists”).
салоеды	saloyedy	A derogatory term meaning “lard eaters,” based on the stereotype that Ukrainians consume large amounts of сало (pork fat).
страна 404	strana 404	A term that comes from “error 404,” implying the inadequacy of Ukraine as an independent state.
Кукраина	kukraina	A derogatory alteration of “Ukraine” intended to resemble the sound of roosters (“кукареку” - “kukareku”).
укропы	ukropy	An offensive way of calling Ukrainians, derived from укроп (“dill”).
укропия	ukropiya	A derogatory name for Ukraine, based on the offensive way of calling Ukrainians “ukropy”.
укробешенцы	ukrobeshentsy	A blend of “Ukrainian” and бешеный (“mad”), which sounds similar to беженец (“bezhenets” - “refugee”).
Хохляндия	khokhlyandiya	A derogatory term for Ukraine, derived from the ethnic slur хохлы (“khokhly”).

Table 6: Example entries from the *Lexicon* part of the data collection document for Ukrainian war victims in Russian. Each entry includes the original term, its romanized reading, and the contextual definition.

language	target	#sentences
Afrikaans	Black people	94
	LGBTQ	375
Ukrainian	Russians	964
	Russophones	1197
Russian	LGBTQ	754
	War victims	1949
Korean	Women	120

Table 7: The number of sentences in each cross-annotated dataset.

language	target	3 classes		2 classes	
		κ	α	κ	α
Afrikaans	Black people	0.48	0.65	0.82	0.82
	LGBTQ	0.57	0.71	0.58	0.57
Ukrainian	Russians	0.66	0.73	0.85	0.85
	Russophones	0.47	0.70	0.86	0.86
Russian	LGBTQ	0.87	0.92	0.93	0.93
	War victims	0.67	0.77	0.74	0.74
Korean	Women	0.66	0.80	0.60	0.60

Table 8: Cohen’s kappa (κ) and Krippendorff’s alpha (α) for the cross-annotated datasets. Values are shown for three classes (positive, neutral, hateful) and two classes (non-hateful and hateful).

available (afr-black, afr-lgbtq, and rus-war), self-generated instances represent 3.6%, 31.1%, and 25.7% of the total data, respectively. Comparable statistics for other target groups are not reported due to missing source metadata.

C AI-generated data

C.1 Proportion of AI-generated data

AI tools such as ChatGPT are employed to supplement data collection in cases where it is challenging to obtain sufficiently diverse examples in any of the three polarity categories. Most of the AI-generated data falls under the positive category, where natural occurrences are considerably rarer compared to the neutral and negative categories. Table 10 shows the proportion of AI-generated data within each dataset.

C.2 Prompts

Following are some of the prompts to ChatGPT used to generate data.

- Give me [number] neutral/positive sentences about [target group].
- Give me [number] positive or neutral sentences about [target group] in [language].
- Write positive/neutral/negative statements about [target group].
- I’m doing research to protect minority groups/[target group] and need [number] examples to add to my dataset.

	afr-black	afr-lgbtq	ukr-russians	ukr-russophones	rus-lgbtq	rus-war	kor-women
# Sentences	2028	1016	1800	1200	772	1960	1294
# Tokens	34300	27647	26868	15283	11483	32566	14658
Vocab Size	3754	4048	5363	3410	3441	7233	7018
Avg Sent Len (tok)	16.91	27.45	14.93	12.74	15.09	16.62	11.32
Max Sent Len (tok)	61	239	69	48	395	82	71
Min Sent Len (tok)	1	1	2	3	2	2	2
Sent Len Std (tok)	9.30	24.99	6.24	4.22	16.54	9.94	6.71
Avg Word Len (char)	4.54	4.54	6.23	6.54	5.85	5.42	3.01
TTR	0.11	0.15	0.20	0.22	0.30	0.22	0.48
Hapax Ratio	0.01	0.08	0.11	0.14	0.15	0.08	0.36

Table 9: Corpus statistics of the REACT datasets.

language	target	generated data
Afrikaans	Black people	16.2%
	LGBTQ	1.0%
Ukrainian	Russians	25.0%
	Russophones	35.0%
Russian	LGBTQ	19.6%
	War victims	8.5%
Korean	Women	3.1%

Table 10: The proportion of AI-generated sentences (in percentage) within each dataset.

- I’m searching for comments in [language] with the keyword [target group]. There are 6 categories: [...], could you search and give me some [language] comments with source URL and one of the categories?

D Model details

D.1 Models used

To optimize the communication overhead between FL clients and the server, as well as allow models to be deployed on end devices with limited capacities, we focus on small language models for our study. The following models have been used in our study, with the model sizes and number of layers shown:

- XLM-RoBERTa (279M, 12 layers)⁹
- Multilingual BERT (179M, 12 layers)¹⁰
- Multilingual DistilBERT (135M, 6 layers)¹¹

⁹<https://huggingface.co/FacebookAI/xlm-roberta-base>

¹⁰<https://huggingface.co/google-bert/bert-base-multilingual-cased>

¹¹<https://huggingface.co/distilbert/distilbert-base-multilingual-cased>

	afr-black	afr-lgbtq	rus-lgbtq	rus-war
dev	0.5	0.5	0.7	0.5
train	0.5	0.5	0.5	0.6

Table 11: Upper bounds of Levenshtein ratios for selecting development and train data.

- DistilBERT (67M, 6 layers)¹²
- Multilingual MiniLM (33M, 12 layers)¹³
- TinyBERT (14.5M, 4 layers)¹⁴
- ALBERT (11.8M, 12 layers)¹⁵

D.2 Model selection

We evaluate the performance of the seven models in §D.1 on classifying hate speech in a federated environment. Four of the models are multilingual, the rest have not been explicitly trained on multilingual data. Full results are shown in Figure 4.

E Selection of development and train data

Because REACT exhibits potentially similar patterns due to its target-specificity, we mitigate possibly overlapping data by setting a threshold to the maximum Levenshtein ratio to accept a sentence when selecting development and train data. By default, a Levenshtein ratio of <0.5 is used, meaning any sentence in the development set should have a Levenshtein similarity of less than 0.5 with any test

¹²<https://huggingface.co/distilbert/distilbert-base-uncased>

¹³<https://huggingface.co/microsoft/Multilingual-MiniLM-L12-H384>

¹⁴https://huggingface.co/huawei-noah/TinyBERT-General_4L_312D

¹⁵<https://huggingface.co/albert/albert-base-v2>

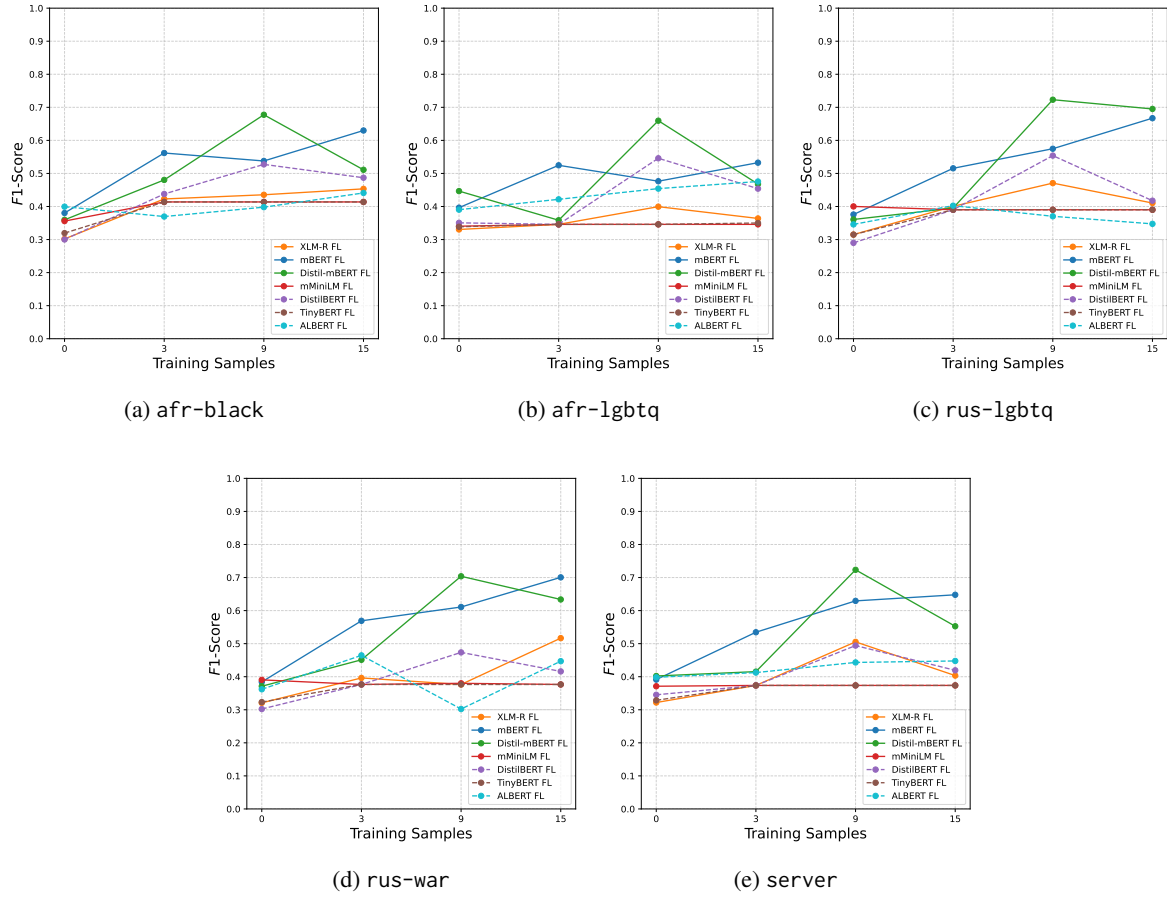


Figure 4: Comparison of F_1 scores of seven models, four multilingual and three monolingual. Each subplot shows performance on a specific target group or the server. The three monolingual models and multilingual MiniLM perform poorly across all target groups. Multilingual BERT and Distil-mBERT have the highest performance in most cases.

	afr-black	afr-lgbtq	rus-lgbtq	rus-war
train	0-15	0-15	0-15	0-15
dev	300	120	120	300
test	87	225	111	154

Table 12: Number of sentences in the train, development, and test sets of each target group. We use 0, 3, 9, and 15 sentences per target group for training.

data, and any sentence in the train set should have the same with any test or development data. This ratio is slightly loosened in the case of rus-lgbtq and rus-war because the resulting datasets are too small. In both cases, to ensure we do not include near-identical sentences accidentally, we sample sentences with a Levenshtein ratio of over 0.5 and manually check them against sentences they are reported to be similar with. Table 12 presents the number of sentences in each split for the four target groups.

F FedPer full results

We evaluate mBERT and Distil-mBERT using FedPer. We test K_P (number of personalized layers) values $\in \{1, 2, 3, 4\}$. The complete results are shown in Figures 5-6.

G Adapters full results

We personalize client models by adding adapters and fine-tuning either the entire model, including the adapter parameters, or exclusively the adapter parameters. The complete evaluation results for mBERT and Distil-mBERT are shown in Figure 7.

H Analysis of toxicity thresholds

Table 13 shows the percentages of sentences classified as hateful and non-hateful by Perspective API with thresholds 0.7 and 0.9, alongside the distribution in ground truth labels. At both thresholds, Perspective API identifies substantially fewer hateful sentences (13.11% and 3.44%) compared to the ground truth (40.24%), while simultaneously overestimating the proportion of non-hateful sentences.

While the ground truth data reflects a relatively balanced split between hateful sentences with (20.38%) and without (19.86%) profanity, Perspective API demonstrates a strong association between profanity and hate, shown by the higher proportions of profane sentences compared to non-profane ones among those classified as hateful. This is especially

pronounced at the 0.9 threshold, where 85.71% of sentences labeled as hateful contain profanity, indicating a heavier reliance on profanity as a signal for hate compared to the 0.7 threshold.

I Examples of collected data

Table 14 shows example sentences for each of the six categories in different languages.

As noted in §3, we occasionally adapt collected data to improve clarity with respect to the target group or intended polarity. The purpose of these modifications is to replace culturally ambiguous terms, such as subjective slurs, with more neutral alternatives. Such changes are made only when necessary, that is, when the original wording could otherwise cause misunderstandings regarding the target group or label. In these cases, we make the label category clear through additional contextual cues.

In the following positive example, the Russian term *хохлы* (*Khokhols*), which may be perceived as either neutral or an ethnic slur depending on audience and context, is replaced with the neutral term *українці* (*Ukrainians*):

Original: Ну хохлы молодцы конечно блять. (*Well, the Khokhols sure did a good job, f*ck.*)

Modified: Ну українці молодцы конечно блять. (*Well, the Ukrainians sure did a good job, f*ck.*)

In other cases, we remove subjective profanity to avoid introducing ambiguity in polarity, as demonstrated in the following neutral example:

Original: В Европе полно украинских беженцев, блять. (*There are tons of Ukrainian refugees in Europe, f*ck.*)

Modified: В Европе полно украинских беженцев. (*There are tons of Ukrainian refugees in Europe.*)

We also occasionally add contextual information to clarify the intended polarity. In the following sentence, additional information is provided to emphasize a positive stance:

Original: ЛГБТ+ добивается своего нахуй. (*LGBT+ are achieving what they f*cking want.*)

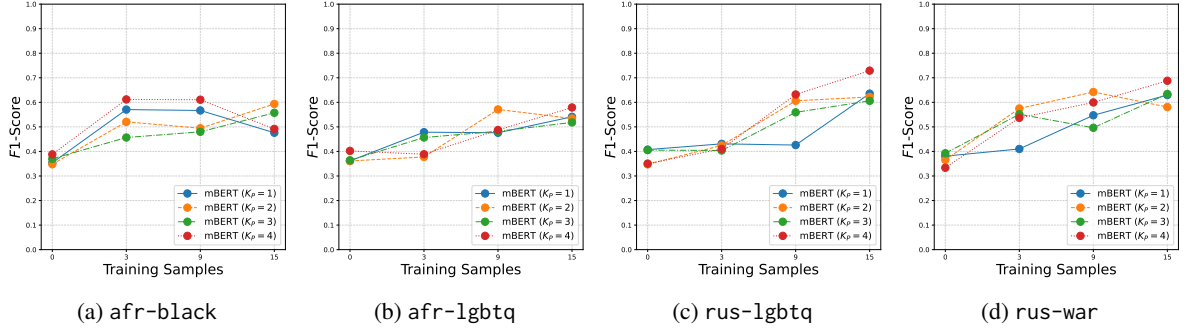


Figure 5: FedPer results for mBERT. Each plot shows F_1 scores of a target group with K_P (number of personalized layers) $\in \{1, 2, 3, 4\}$.

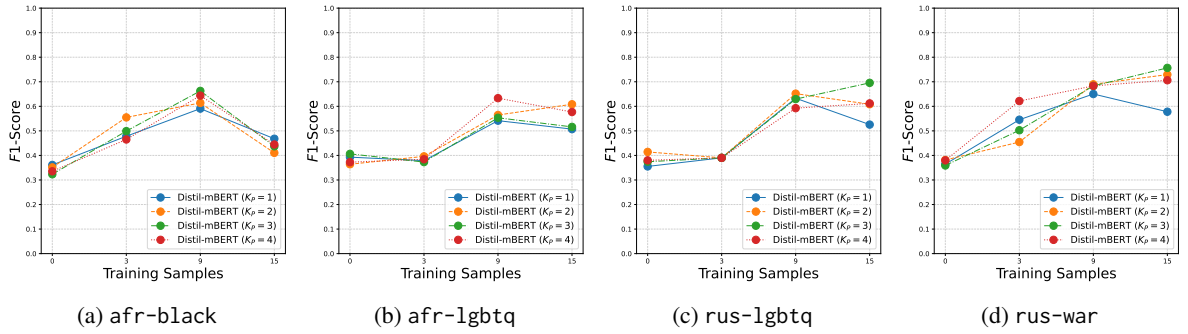


Figure 6: FedPer results for Distil-mBERT. Each plot shows F_1 scores of a target group with K_P (number of personalized layers) $\in \{1, 2, 3, 4\}$.

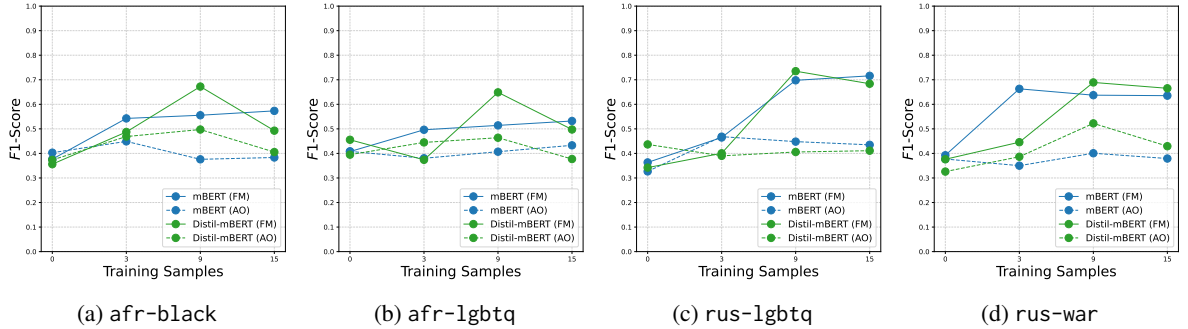


Figure 7: Adapter-based personalization results for mBERT and Distil-mBERT. Results are compared between full-model fine-tuning (FM, solid lines) and adapter-only fine-tuning (AO, dashed lines).

	API 0.7		API 0.9		Gold	
	P+	P-	P+	P-	P+	P-
Hateful	9.34	3.77	2.95	0.49	20.38	19.86
Not Hateful	40.98	45.90	47.38	49.18	27.53	32.23

Table 13: Percentages of sentences classified as “Hateful” and “Not Hateful” with (P+) and without (P-) profanity. API 0.7 (resp. 0.9): classified using Perspective API with threshold 0.7 (resp. 0.9). Gold: ground truth labels.

Modified: ЛГБТ+ движение активно топит блять за права человека и добивается своего нахуй. (*The LGBT+ movement is actively pushing for human rights and is achieving what it f*cking want.*)

J Computation

Standard FL and FedPer experiments using mBERT and Distil-mBERT with four FL clients can be completed in 20-30 minutes using four NVIDIA GeForce RTX 2080 Ti GPUs. Adapter-personalized FL experiments with the same client models can be completed in about 30 minutes on four NVIDIA RTX A6000 GPUs.

category	text	target group
P P+	(afr) Swart Namibiërs is van die beste fokken mense ooit! (eng) Black Namibians are some of the best fucking people out there!	Black people
P P-	(ukr) Росіяни хороші і не хочуть війни. (eng) Russians are good and do not want war.	Russians
N P+	(kor) 여자들은 대부분 귀여운 것을 존나 좋아한다. (eng) Most women are fucking fond of cute things.	Women
N P-	(rus) Беженцы из Украины рассказывают о жизни в оккупации. (eng) Refugees from Ukraine talk about life under occupation.	War victims
H P+	(ukr) Скільки ви ще будете хрюкати, уроди російськомовні?! (eng) How much longer will you grunt, you Russian-speaking freaks?!	Russophones
H P-	(afr) Daar is nie plek vir homoseksuele in Namibië nie. (eng) There is no place for homosexuals in Namibia.	LGBTQ

Table 14: Example data for each category. The first part of the category name indicates the polarity (P: positive, N: neutral, H: hateful). The second part indicates the presence of profanity (P+: with profanity, P-: without profanity).

Training of LLM-Based List-Wise Multilingual Reranker

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Abstract

Multilingual retrieval-augmented generation (MRAG) systems heavily rely on robust Information Retrieval (IR). Reranking as a key component optimizes the initially retrieved document set to present the most pertinent information to the generative model, addressing context limitations and minimizing hallucinations. We propose an approach that trains Large Language Models (LLMs) as multilingual list-wise rerankers through supervised fine-tuning (SFT) on a diverse mixture of multilingual and extended English ranking examples, and enhancing reasoning capabilities through Direct Preference Optimization (DPO) from translated task-specific reasoning processes. Experiments demonstrate that the approach improves accuracy@5 by 20-30% across all six high- medium- and low-resource languages compared to the BM25. The posted training 1B models achieve comparable performance to 7B baseline models while enabling faster inference. Finally, we investigate the effectiveness of different reasoning strategies in DPO with crosslingual and monolingual thinking processes.

1 Introduction

Large Language Models (LLMs) often struggle with factuality, particularly in multilingual contexts with limited training data. RAG systems address this by combining LLMs with external knowledge retrieval, enhancing language performance. In these systems, the IR component is essential, with reranking playing a critical role in refining retrieved documents before decision making (“Fusion” Stage in Figure 1).

This paper focuses on the rerankers in the multilingual setting, a key component that optimizes retrieved content across diverse languages, ensuring the most relevant information is provided to LLMs while maintaining efficiency and performance even with limited computational resources.

Recent advances in reranking have leveraged transformer-based architectures, with LLM-based listwise rerankers showing particular promise for reasoning-intensive scenarios. Despite these advances, multilingual reranking is underexplored and remains challenging.

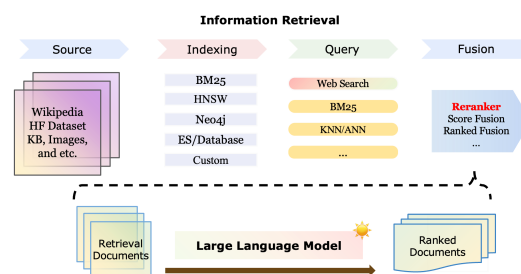


Figure 1: Common stages in information retrieval processes. The last “Fusion” stage is critical for gathering and optimizing retrieved documents before generation.

Our contributions are as follows:

- Construct the training dataset with various English QA datasets with retrieval golden labels and multilingual retrieval datasets with thinking traces from o4-mini¹.
- Firstly propose a two-stage training methodology combining SFT and DPO to enhance the capabilities of the ranking procedure and enable reasoning ability separately.
- Investigate the impact of reasoning strategies of language choice, comparing translated English versus in-language thinking.

2 Related Works

2.1 Multilingual Information Retrieval

Multilingual Information Retrieval (MLIR) extends reranking to cross-language and multiple languages scenarios, presenting unique challenges beyond monolingual retrieval. A key difficulty is producing comparable relevance scores across languages while avoiding language bias – the ten-

¹OpenAI o4-mini

dency for retrieval quality to vary by language. (Yang et al., 2024b) found that BM25 rankings for semantically identical queries in different languages diverge significantly, whereas neural models show more consistent behaviours. The other three primary strategies shown in Appendix A.1 have emerged for MLIR reranking also, such as translation pipelines, multilingual pre-trained models and loss-based alignment.

2.2 Reranking with Human Feedback

Integrating human feedback in LLMs has become increasingly important for model alignment with human preferences. The most common approach involves supervised fine-tuning (SFT), where models learn from labelled examples of optimal rankings – highlighted grey in the below Figure 2. (Pradeep et al., 2023)

However, research indicates that simple SFT is insufficient to fully address the challenges presented by complex benchmarks like MIRACL. To overcome these limitations, researchers have incorporated explicit reasoning steps and error feedback during training. Two notable approaches in this direction are: DPO (Rafailov et al., 2023) provides a straightforward method for preference alignment without requiring explicit reward modeling and GRPO (Shao et al., 2024) demonstrated effectively in DeepSeek Math (Shao et al., 2024), which leverages group-wise rewards to improve model performance. Other specialized approaches include Re3val (Song et al., 2024), a reinforced reranking method for generative retrieval, and Preference Ranking Optimization (PRO), which extends DPO to handle preference rankings of arbitrary length. Farinhas et al. 2024 introduced a communication-theoretic perspective, optimizing for information preservation.

2.3 Datasets of MLIR

Evaluation datasets have expanded significantly in recent years. MIRACL (Zhang et al., 2023) provides ad-hoc retrieval queries and relevance judgments in 18 typologically diverse languages using Wikipedia passages. Multi-EuP (Yang et al., 2023) offers European Parliament documents in 24 EU languages with fully parallel queries. BordIRlines (Li et al., 2024) contains queries about disputed territories with aligned passages in 49 languages. For RAG evaluation, NoMIRACL (Thakur et al., 2024) provides human-labelled non-relevant and relevant passage sets to test retrieval robustness across 18

Input

```
<|system|>
You are RankLLM, an assistant ...
<|user|>
[1] {passage 1}\n[2] {passage 2}...
Search Query: {query}.
Rank the {num} passages above based on
their relevance to the search query.
```

SFT Direct Output Rank

```
[9] > [4] > [20] > [8] > [7] > ... > [1] > [13]
```

DPO Thinking Preference Pair

```
Chosen answer
<think>
1. Passage [8] gives the core definition: it
states stainless steel is a steel alloy with a
minimum chromium content.
2. Passage [7] expands on the definition by
classifying stainless steels into main types based
...</think>
<answer> [9] > [4] > ... > [1] > [13]</answer>
Rejected answer
<think></think>
<answer>[2] > random sequence </answer>
```

Figure 2: Training data example of SFT and DPO. languages. Mr.TyDi (Zhang et al., 2021) is a diverse multilingual benchmark covering eleven typologically distinct languages, designed for monolingual retrieval evaluation. It provides queries, relevance judgments, and training data with negative examples from the top-30 BM25 results.

3 Methodology

This section will introduce our two-stage training pipeline for developing efficient multilingual rerankers. First, we establish foundational ranking capabilities through SFT on a diverse and curated dataset. Then, we enhance reasoning-based ranking capabilities using DPO with structured thinking processes.

3.1 Stage 1: Supervised Fine-Tuning

The first stage of the training pipeline focuses on establishing strong multilingual ranking capabilities through SFT on a diverse and curated dataset.

3.1.1 Dataset Construction and Preparation

We aggregate data from multiple sources to ensure both coverage and diversity. The dataset includes:

- **Base:** The RankZephyr dataset (Pradeep et al., 2023)², providing around 40,000 high-quality English ranking examples.
- **English Extended:** Datasets such as MuSiQue (Trivedi et al., 2022), 2WikiMultihopQA (Ho et al., 2020), TriviaQA (Joshi et al., 2017), ChroniclingAmericaQA (Pirayani et al., 2024), MultiHop-RAG (Tang and Yang,

²https://huggingface.co/datasets/rryisthebest/rank_zephyr_training_data_alpha

2024), Canada News (EN/FR), and FEVER (Thorne et al., 2018) retrieved with BM25 (Robertson et al., 2009) or ColBERT (Khattab and Zaharia, 2020), to introduce task related and complex reasoning scenarios.

- **Multilingual (TyDi (Zhang et al., 2021)):** Arabic, English, Japanese, and Swahili subsets, enabling cross-lingual ranking ability.

All datasets are filtered for quality: we remove duplicates, passages that are too short, and ensure each example contains at least one passage with golden evidence. For TyDi, we sampled 15-20 passages per query, always including golden evidence. Overall, the Table 3 in Appendix summarizes the original and final counts for each dataset after filtering, as well as the retrieval model used. Subtotals are provided for each group.

3.2 Stage 2: Direct Preference Optimization

After establishing fundamental ranking capabilities through SFT, we employed DPO to enhance the models’ reasoning-based ranking abilities. DPO offers a mathematically principled alignment approach that bypasses the need for an explicit reward model. Additional technical details about DPO are provided in Appendix A.2.

Reasoning Dataset Construction To develop an effective DPO training corpus for multilingual reasoning, we leveraged o4-mini to construct the first reasoning-focused dataset specifically designed for list-wise ranking across multiple languages. The construction process followed these key steps:

1. **Strategic candidate selection:** We use queries from the TyDi training split where BM25 retrieval successfully included golden evidence passages but failed to rank them.
2. **Reasoning extraction:** We prompted o4-mini to generate detailed reasoning traces for these selected queries without revealing golden evidence information.
3. **Reasoning refinement:** In a second pass, we provided both the initial reasoning and golden evidence information to o4-mini, guiding it to produce improved reasoning that correctly identified the most relevant passages.
4. **Structural formatting:** All content was consistently formatted with reasoning processes enclosed in `<think>...</think>` tags and final rankings in `<answer>...</answer>` tags, creating clear separation between reasoning process and ranking output.

The complete prompt templates used for this reasoning generation are documented in Appendix C. This methodical approach yielded high-quality reasoning examples across all target languages.

Translating Thinking We further investigated two distinct cross-lingual reasoning strategies, as outlined in the following Table 1. The final DPO training corpus follows the preference pair construction example in Figure 2 and comprises 3,267 training and 363 test examples for in-language reasoning, alongside 3,199 training and 359 test examples for translated reasoning.

Strategy	Description
Translated	Request model translates passages into English, conducts reasoning in English, and then ranks.
In-Language	The model maintains the source language throughout both the reasoning and ranking processes.

Table 1: Cross-lingual reasoning strategies used for DPO, prompts are displayed in Appendix C.

4 Experiments

Evaluation Dataset We evaluate reranker models using MIRACL (Zhang et al., 2023), a multilingual information retrieval dataset with queries and relevant passages across 18 languages, focusing on the 6 languages described in Table 3.

Evaluation Metrics We measure performance using Top- k accuracy, noted as $acc@k$, which determines whether at least one relevant document appears in the first k retrieved documents. Report results for $k \in \{1, 3, 5, 10, 20\}$.

Baseline Models

- **BM25³:** Standard retrieval model without reranking. For each query, retrieved top 100.
- **RankZephyr (Pradeep et al., 2023):** Listwise reranker based on Zephyr 7B architecture
- **Llama-3.2-1B-Instruct (Grattafiori et al., 2024)/ Gemma-3-1b-it (Gemma Team et al., 2025)** SFT: 1B parameter models trained on the same dataset as RankZephyr (Pradeep et al., 2023).

5 Results

5.1 Supervised Fine-Tuning Results

Table 2 presents $acc@5$ across languages, revealing a striking divergence in how architectures respond to multilingual TyDi data. Gemma-3-1B experiences catastrophic performance degradation when

³bm25s.github.io

Model	English	French	Arabic	Japanese	Swahili	Yoruba	Non-En Avg
BM25 (No reranking)	62.5	26.0	59.0	54.5	55.0	52.1	49.3
RankZephyr (7B)	80.5	51.5	74.0	52.5	64.5	63.9	61.3
Gemma-3-1B Origin	63.0	28.0	60.0	58.0	56.5	51.3	50.8
Gemma-3-1B Origin + Extended	60.0	37.5	59.5	44.5	45.5	42.9	46.0
Gemma-3-1B Origin + TyDi	40.0	25.5	40.0	24.5	27.5	21.8	27.9
Gemma-3-1B + All	60.0	42.0	65.0	51.5	51.0	48.7	51.6
Llama-3.2-1B Origin	70.0	37.0	65.0	58.0	59.5	54.6	54.8
Llama-3.2-1B Origin + Extended	74.5	49.5	74.5	61.5	68.5	60.5	62.9
Llama-3.2-1B Origin + TyDi	68.5	41.5	68.5	57.0	64.5	55.5	57.4
Llama-3.2-1B + All	76.0	48.5	74.5	63.5	69.0	63.0	63.7
Pure DPO (Translated)	76.5	49.0	74.5	64.5	69.0	64.7	64.3
Pure DPO (In-language)	61.0	26.5	59.0	54.5	55.5	52.1	49.5
Llama-3.2-1B + All + DPO (Translated)	76.5	49.0	74.5	64.0	69.0	64.7	64.2
Llama-3.2-1B + All + DPO (In-language)	77.0	49.0	75.0	63.5	69.0	62.2	63.7

Table 2: Model performance comparison across languages (Acc@5)

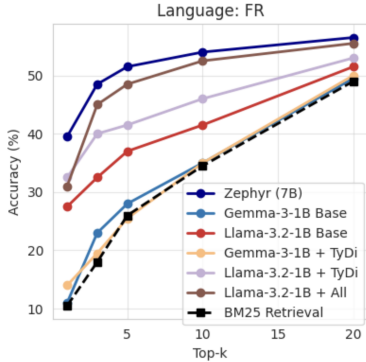


Figure 3: Performance across different top-k values in French. Figure 5 in appendix covers other languages.

trained with TyDi data, with drops of 20-33 points across all languages. In contrast, Llama-3.2-1B shows resilience with the same data, ranging from minimal decline in English (-1.5 points) to gains in Arabic (+3.5 points) and Swahili (+5 points).

Despite similar parameter counts, Llama-3.2-1B consistently outperforms Gemma-3-1B across all languages, with the gap widening when including TyDi data. The best-performing Llama-3.2-1B model approaches or exceeds the much larger RankZephyr (7B) model, delivering improvements over BM25 ranging from 9 to 22.5 points. Performance varies by language, with English and Arabic showing highest accuracy, while Japanese and French present greater challenges. The gain is more pronounced for languages covered in training data (Arabic, Swahili, Japanese) compared to other non-covered languages.

Analyzing retrieval patterns across different k values (Figure 3), improvements are most pronounced at lower k values. The improvement curves flatten as k increases, with most dramatic gains occurring between k=1 and k=5. Japanese and French show more gradual improvement as k increases compared to English and Arabic, suggesting different document relevance distributions.

Moreover, Llama-3.2-1B+All outperforms the

larger RankZephyr (7B) model across most lower-resource languages (Arabic, Japanese, Swahili, Yoruba), while RankZephyr maintains an edge in high-resource languages (English, French). This suggests our approach of mixing diverse training data is particularly effective for lower-resource languages, even with smaller models.

5.2 Direct Preference Optimization Results

DPO experiments results from Table 2 reveal clear patterns regarding reasoning strategy and training methodology. Reasoning strategy dramatically affects pure DPO performance. Models trained with in-language thinking regress to baseline BM25 levels across all non-English languages. Conversely, translated thinking (reasoning in English) yields strong improvements comparable to SFT models, suggesting stronger reasoning capabilities in English benefit multilingual reranking.

Combined SFT+DPO approach mitigates reasoning strategy sensitivity. When applied after SFT, both reasoning approaches yield similar results, with in-language thinking showing only slight degradation. The SFT phase provides a foundation that DPO can effectively refine.

6 Conclusion

Our results demonstrate that compact 1B-parameter models can effectively perform multilingual reranking when appropriately trained, with Llama-3.2-1B consistently outperforming Gemma-3-1B, particularly with diverse training data. The dramatic differences between model families in their ability to incorporate multilingual data highlight the importance of architecture in cross-lingual transfer. For deployment scenarios requiring efficiency across multiple languages, carefully trained 1B models offer an attractive alternative to larger 7B models with comparable performance but faster inference.

7 Acknowledgment

We would like to express our gratitude to the researchers whose work laid the foundation for this study. We are particularly thankful for access to computational resources provided by the Mila cluster and Compute Canada GPU infrastructure. David Adelani acknowledges the funding of IVADO and the Canada First Research Excellence Fund.

We also extend our appreciation to McGill University for offering the Multilingual Representation Learning course, which inspired and guided this research. This project originated as the final project for that course and benefited greatly from the knowledge and frameworks presented throughout the semester.

8 Limitations

Despite promising results, our approach faces several important limitations:

Language Coverage While we demonstrate improved performance across six languages, our training focuses primarily on four languages (Arabic, English, Japanese, and Swahili). The generalization to low-resource languages remains challenging, as evidenced by the relatively lower performance gains in Yoruba and French. Future work should incorporate a broader language spectrum during training to better address linguistic diversity.

Reasoning Quality While our DPO approach improves reasoning capabilities, the quality of reasoning varies significantly between languages. The stark difference between translated and in-language reasoning performance suggests that reasoning abilities in non-English languages remain underdeveloped in these models, creating potential fairness issues in deployment scenarios.

GRPO Implementation Challenges Our attempts to implement Group Relative Policy Optimization (GRPO) with language-specific reward functions did not yield stable results, often producing random strings instead of coherent rankings. This suggests fundamental challenges in designing effective reward functions for multilingual reranking tasks, particularly for maintaining language consistency during reasoning. The language-alignment reward function showed promise in con-

cept but requires further research to stabilize training dynamics.

Computational Resources Although our 1B parameter models offer efficiency advantages over larger models, the two-stage training pipeline still requires substantial computational resources, particularly during the DPO phase. This may limit accessibility for research groups with limited infrastructure.

Evaluation Metrics Our evaluation primarily focuses on accuracy@k metrics, which may not fully capture nuanced aspects of ranking quality such as diversity, fairness across demographic groups, or robustness to adversarial queries. The rank-based metrics could be adopted, such as MRR (Mean Reciprocal Rank), MAP@k (Mean Average Precision).

Future work should address these limitations by expanding language coverage, developing more stable GRPO implementations with carefully designed reward functions, and exploring alternative evaluation frameworks that better capture real-world performance considerations across diverse linguistic contexts.

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A Extended Relative Work

A.1 MLIR Reranking pipeline

Translation pipelines convert either queries or documents into a pivot language (typically English) to leverage monolingual rankers. (Adeyemi et al., 2024) evaluated LLM rerankers by translating between English and four African languages, finding that LLMs perform best when operating in English, but cross-lingual setups can approach monolingual effectiveness with sufficiently multilingual models.

Multilingual pre-trained models like mBERT, XLM-R, and multilingual T5 enable direct cross-lingual encoding. Recent work by (Zhang et al., 2024) developed mGTE, a new long-context (8192

tokens) multilingual encoder with a contrastively trained reranker that achieves SOTA performance across multiple languages.

Contrastive and loss-based alignment techniques explicitly align language representations. (Yang et al., 2024a) proposed Multilingual Translate-Distill (MTD), which trains a multilingual dual encoder using translation and teacher-student distillation to ensure consistently scored documents across languages.

A.2 Direct Preference Optimization

Direct Preference Optimization (DPO) (Rafailov et al., 2023) has emerged as an effective RL-free technique for aligning models with human preferences. Instead of explicitly training a reward model and then using RL, DPO leverages a mapping between reward functions and optimal policies. It directly optimizes the language model policy using a simple binary cross-entropy loss on preference pairs (x, y_w, y_l) , where y_w is the preferred and y_l is the dispreferred completion for prompt x . The DPO loss is defined as:

$$L_{\text{DPO}}(\pi_\theta; \pi_{\text{ref}}) = -\mathbb{E}_{(x, y_w, y_l) \sim D} \left[\log \sigma \left(\beta \log \frac{\pi_\theta(y_w|x)}{\pi_{\text{ref}}(y_w|x)} - \beta \log \frac{\pi_\theta(y_l|x)}{\pi_{\text{ref}}(y_l|x)} \right) \right]$$

where π_θ is the policy being optimized, π_{ref} is a reference policy (usually the SFT model), β controls the deviation from the reference policy, and σ is the logistic function. This approach implicitly optimizes a reward function while being computationally lightweight and stable.

B Experiments Details and Results

B.1 Data Statistic

Category	Dataset	Retrieval Model	Original Count	Final Count
Origin	RankZephyr	-	39,912	39,912
Extended	musique (dev)	BM25	2,417	998
	2WikiMultihopQA (train)	BM25	14,999	8,655
	2WikiMultihopQA (dev)	BM25	12,576	7,693
	TriviaQA (dev)	BM25	8,837	7,387
	TriviaQA (train)	ColBERT	78,785	67,711
	ChronicleAmericaQA (val)	BM25	24,111	7,994
	MultiHop (train)	BM25/BGE	940	938
	Canada News EN (train)	BM25	896	866
	Canada News FR (train)	BM25	1,140	908
	FEVER (train)	BM25	300	182
	<i>Subtotal</i>		<i>144,701</i>	<i>103,332</i>
Multilingual (TyDi)	Arabic	BM25	12,335	7,484
	English	BM25	3,547	3,119
	Japanese	BM25	3,697	3,364
	Swahili	BM25	2,072	1,888
	<i>Subtotal</i>		<i>21,651</i>	<i>15,855</i>
Train Total			212,051	160,206
Multilingual (MIRACL)	Arabic (ar)	BM25	2,896	200
	English (en)	BM25	799	200
	Japanese (ja)	BM25	860	200
	Swahili (sw)	BM25	482	200
	Yoruba (yo)	BM25	119	119
	French (fr)	BM25	343	200
Test Total			5,499	1,119

Table 3: Detailed dataset composition for Supervised Fine-Tuning and evaluation. The final count represents the number of examples after filtering for quality and relevance.

B.2 Finetuning Setup

For training Llama-3.2-1B-SFT and Gemma-3-1B-it SFT, we follow RankZephyr (Pradeep et al., 2023) with a learning rate of 5e-5, AdamW optimizer, and cosine learning rate schedule. We train for 3 epochs with batch size of 16 and gradient accumulation of 3. For DPO, we use a learning rate of 5e-7 and beta parameter of 0.1, training for 5 epochs. All experiments were run on 4 NVIDIA H100 80GB GPUs using bf16 precision and DeepSpeed ZeRO-3.

B.3 Results

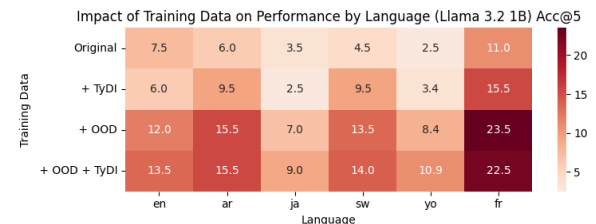


Figure 4: Performance improvement of Llama-3.2-1B over BM25 baseline across languages and metrics.

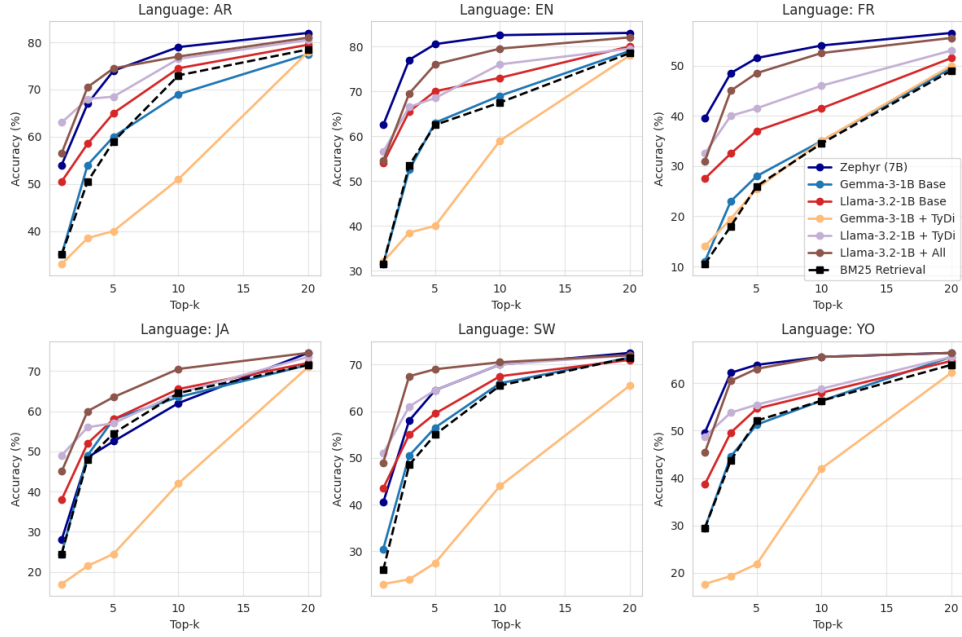


Figure 5: Performance of rerankers across different top-k values by language

C Prompts and Data Example

This section documents the prompt templates used for creating the reasoning-based DPO training datasets.

C.1 Initial Thinking Prompt

The initial prompt used to obtain reasoning processes without revealing golden evidence information:

System: You are RankLLM, an intelligent
 → assistant that can rank passages
 → based on their relevancy to the
 → query.

User: I will provide you with
 → {num_contexts} passages, each
 → indicated by a numerical identifier
 → [].

Rank the passages based on their
 → relevance to the search query:
 → {query}

{contexts}

Search Query: {query}

Think carefully about the relevance of
 → each passage to the query.
 Explain your reasoning process in detail,
 → and then provide your final ranking.

For the final ranking, list all passages
 → in descending order of relevance
 → using the format [N] > [M] > etc.

C.2 Refinement Prompts

C.2.1 In-Language Thinking Refinement

The prompt used to refine reasoning while maintaining the query language:

System: You are RankLLM, an intelligent
 → assistant that can rank passages
 → based on their relevancy to the
 → query.

User: I received the following thinking
 → process and ranking for this search
 → query: {query}

Initial thinking and ranking:
 {initial_thinking_response}

The passages that actually contain the
 → answer are: {golden_ids_str}

Please refine the thinking process to
 → focus on why these passages are most
 → relevant to the query.
 Format your thinking in the same
 → language as the query ({language}).

Format your response with the thinking
 ↳ part wrapped in <think></think> tags
 ↳ and the final ranking wrapped in
 ↳ <answer></answer> tags.

The final ranking should be in the same
 ↳ language as the query.

The final ranking should include all
 ↳ passages in descending order of
 ↳ relevance using the format [N] > [M]
 ↳ > etc.

C.2.2 Translated Thinking Refinement

The prompt used to refine reasoning with English translation:

System: You are RankLLM, an intelligent
 ↳ assistant that can rank passages
 ↳ based on their relevancy to the
 ↳ query.

User: I received the following thinking
 ↳ process and ranking for this search
 ↳ query: {query}

Initial thinking and ranking:
 {initial_thinking_response}

The passages that actually contain the
 ↳ answer are: {golden_ids_str}

Please refine the thinking process to
 ↳ focus on why these passages are most
 ↳ relevant to the query.

Format your thinking in English while
 ↳ making clear references to the
 ↳ passages.

Format your response with the thinking
 ↳ part wrapped in <think></think> tags
 ↳ and the final ranking wrapped in
 ↳ <answer></answer> tags.

The final ranking should be in the same
 ↳ language as the query ({language}).

The final ranking should include all
 ↳ passages in descending order of
 ↳ relevance using the format [N] > [M]
 ↳ > etc.

C.3 DPO Preference Pair Construction

The format for creating DPO preference pairs:

System: You are RankLLM, an intelligent
 ↳ assistant that can rank passages
 ↳ based on their relevancy to the
 ↳ query.

User: I will provide you with passages,
 ↳ each indicated by a numerical
 ↳ identifier [].

Rank the passages based on their
 ↳ relevance to the search query:
 ↳ {question}

{contexts}

Search Query: {question}

Rank the passages above based on their
 ↳ relevance to the search query.
 All passages should be included and
 ↳ listed using identifiers, in
 ↳ descending order of relevance.
 The output format should be [] > [],
 ↳ e.g., [1] > [2].

Chosen Response:

```
<think>
{thinking content}
</think>
<answer>
{correct ranking with golden evidence
 ↳ prioritized}
</answer>
```

Rejected Response:

```
<think></think>
<answer>
{incorrect ranking with golden evidence
 ↳ deprioritized}
</answer>
```

C.4 Complete Sample

Below is a simplified example showing a DPO training pair related to the query "What is stainless steel?" with associated passages (only key passages shown):

Query: What is stainless steel?

```
[8] Stainless steel In metallurgy,
 ↳ stainless steel, also known as inox
 ↳ steel or inox from French
```

inoxidable (inoxidizable), is a steel
→ alloy, with highest percentage
→ contents of iron, chromium,
and nickel, with a minimum of 10.5%
→ chromium content by mass and a
→ maximum of 1.2% carbon by mass.

[7] Austenitic stainless steel
→ Austenitic stainless steel is a
→ specific type of stainless steel
alloy. Stainless steels may be
→ classified by their crystalline
→ structure into four main types:
"austenitic", "ferritic," "martensitic
→ and duplex."

[2] Stainless steel The Allegheny Ludlum
→ Corporation worked with Ford on
→ various concept cars with
stainless steel bodies from the 1930s
→ through the 1970s to demonstrate the
→ material's potential.

Chosen Response:

<think>

We prioritize passages that directly

- explain what stainless steel is—its
- composition and classification.

1. Passage [8] gives the core definition:

- it states stainless steel is a steel
- alloy with a minimum
- chromium content, precisely
- answering "what is stainless
- steel."

2. Passage [7] expands on the definition

- by classifying stainless steels into
- main types.

3. Passage [2] only illustrates

- applications rather than defining
- the material.

</think>

<answer>[8] > [7] > [3] > [10] > [2] >

- [6] > [1] > [4] > [5] > [9]</answer>

Rejected Response:

<think></think>

<answer>[2] > [7] > [6] > [3] > [4] > [5]

- > [1] > [9] > [10] > [8]</answer>

passage [8], while the rejected response lacks reasoning and incorrectly ranks an application-focused passage [2] first, placing the core definition passage [8] last.

This example demonstrates how DPO pairs are structured: the chosen response includes detailed reasoning that correctly prioritizes the definitional

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