PROMPTREFINE: Enhancing Few-Shot Performance on Low-Resource Indic Languages with Example Selection from Related Example Banks

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Abstract

Large Language Models (LLMs) have recently demonstrated impressive few-shot learning capabilities through in-context learning (ICL). However, ICL performance is highly dependent on the choice of few-shot demonstrations, making the selection of the most optimal examples a persistent research challenge. This issue is further amplified in low-resource Indic languages, where the scarcity of ground-truth data complicates the selection process. In this work, we propose PROMPTREFINE, a novel Alternating Minimization approach for example selection that improves ICL performance on low-resource Indic languages. PROMPTRE-FINE leverages auxiliary example banks from related high-resource Indic languages and employs multi-task learning techniques to align language-specific retrievers, enabling effective cross-language retrieval. Additionally, we incorporate diversity in the selected examples to enhance generalization and reduce bias. Through comprehensive evaluations on four text generation tasks—Cross-Lingual Question Answering, Multilingual Question Answering, Machine Translation, and Cross-Lingual Summarization using state-of-the-art LLMs such as LLAMA-3.1-8B, LLAMA-2-7B, Qwen-2-7B, and Qwen-2.5-7B, we demonstrate that PROMPTREFINE significantly outperforms existing frameworks for retrieving examples.[1]

1 Introduction

Large Language Models (LLMs) have recently made remarkable progress, demonstrating human-level performance across a wide range of tasks (Adiwardana et al., 2020; Wang et al., 2019). However, despite these advancements, most LLMs, such as LLaMA-3 (Dubey et al., 2024), LLaMA-2 (Touvron et al., 2023), and Qwen (Yang et al., 2024), are predominantly pre-trained on English

texts, leading to significant performance disparities when applied to low-resource, non-English languages (Ahuja et al., 2023). The scarcity of ground-truth paired data in many low-resource languages makes text generation particularly challenging, as fine-tuning LLMs becomes infeasible in such settings. This issue is especially pronounced in lesser-known Indic languages such as Tibetan which has only around 5000 Wikipedia articles compared to 6.6M+ Wikipedia articles in English, despite having approximately 6M speakers. In this work, we focus on downstream generation tasks with low-resource Indic languages, a critical challenge for making LLMs more widely accessible.

When downstream tasks have limited labeled data, few-shot learning or in-context learning (ICL) has emerged as a powerful and practical approach for text generation (Tanwar et al., 2023; Zhang et al., 2021; Winata et al., 2021; Huang et al., 2023; Etxaniz et al., 2023). ICL operates by providing the LLM with a prompt that consists of task-specific instructions and a set of input-output examples (demonstrations) to guide the model's output generation for a specific input query. While ICL is computationally efficient (it requires no parameter updates), it faces two critical challenges when labeled data is scarce, particularly for low-resource Indic languages.

(**Relevance**) First, as in any learning task with limited data, the small size of the available example pool can result in a lack of relevant examples to guide the model effectively. In the context of ICL, this scarcity can severely degrade performance, as the quality of examples is crucial. Poor example selection can lead to performance worse than zero-shot scenarios, while optimal selection can achieve near state-of-the-art results (Liu et al., 2021). (**Diversity**) Second, existing example selection techniques, such as random selection or retrieving semantically similar examples (Zhang et al., 2021; Winata et al., 2021; Tanwar et al., 2023), often

struggle to account for diversity among the selected examples, which can further limit performance. An appropriate diverse set of selected examples in the prompt can improve generalization significantly.

Proposed Approach. In this work, we focus on an ICL approach for enhancing LLM performance in low-resource Indic languages. Specifically, our goal is to identify an optimal subset of guiding examples to be inserted into the prompt, without modifying the LLM parameters. Rather, we train retrievers to extract a near optimal set of examples (demonstrations) based on the input query. To this end, we propose a novel trainable approach PROMPTREFINE that combines examples from auxiliary example banks associated with the related task. While PROMPTREFINE is broadly applicable across different language families and even low-resource task clusters, in this study we focus on Indic languages (Singh et al., 2024), to enhance performance specifically on low-resource Indic languages through improved example selection.

Given a specific input text generation task in a low-resource Indic language, we use the following set of key ideas to enhance model performance (see Algorithm 1): 1) First, we utilize example banks from closely-related relatively high-resource [2] Indic languages to provide relevant guidance, improving LLM performance on low-resource tasks. Therefore, the first step in our algorithmic approach given an input low-resource task is to select relevant high-resource languages (see Algorithm 2) with associated example banks. 2) Second, merging these example banks is non-trivial, as each language-specific retriever is trained on a unique representation space. *To address this, we adapt data-scarce multi-task learning techniques (Thekumparampil et al., 2021) to align the individual retrievers into a shared representation space, enabling cross-language retrieval.* 3) Third, we incorporate diversity in the selected examples to improve generalization and reduce bias during generation.

To empirically validate the effectiveness of PROMPTREFINE, we evaluate its performance across four distinct text generation tasks on a subset of languages outlined in Singh et al. (2024): Cross-Lingual Question Answering (XorQA-In), Multilingual Question-Answering (XQuAD-In), Ma-

chine Translation (Flores-In), and Cross-Lingual Summarization (CrossSum-In), using recent LLMs such as LLAMA-3.1-8B (Dubey et al., 2024), LLAMA-2-7B (Touvron et al., 2023), Qwen-2-7B (Yang et al., 2024), and Qwen-2.5-7B (Team, 2024). Our results demonstrate that PROMPTRE-FINE significantly improves generation performance in all tasks compared to baseline approaches for example selection. Specifically, using LLAMA-3.1-8B as the LLM, PROMPTREFINE achieves a Token-F1 improvement of $+16.07$ and $+8.26$ over zero-shot prompting and the current state-of-the-art retriever (Ye et al., 2023), respectively, in the cross-lingual QA task. Similarly, using Qwen-2-7B, we observe an improvement in chrF1 of up to $+7.77$ on the machine translation task compared to the baseline of selecting semantically similar examples. To ensure a comprehensive evaluation, we also test PROMPTREFINE on proprietary LLMs such as GPT-3.5 and GPT-4 (OpenAI et al., 2024), where PROMPTREFINE outperforms baseline retrievers on translation task, aligning with our previous findings.

2 Related Works

In-Context Learning (ICL). First introduced in Brown (2020), ICL has emerged as a powerful approach that enables large language models (LLMs) to "learn by analogy" by providing a few input-output examples as demonstrations, without requiring any update to model parameters. In recent years, a plethora of studies have provided insights on the underlying mechanism of ICL. Saunshi et al. (2020) suggested that, by conditioning on a prompt, the task of predicting the next word becomes linearly separable, while Xie et al. (2021) observed that for ICL, the model infers a shared latent concept between the provided examples. A study pointed out that models do not rely as heavily on the provided input-output mappings as previously thought, indicating more nuanced learning dynamics in ICL (Min et al., 2022). Chen et al. (2022); Min et al. (2021); Wei et al. (2023a) showed that the in-context learning ability of LLMs can be improved through self-supervised or supervised training. A group of studies have also explored to understand the factors affecting ICL (Zhao et al., 2021; Shin et al., 2022; Wei et al., 2022a; Yoo et al., 2022; Wei et al., 2023b) and the underlying working mechanism of ICL (Olsson et al., 2022; Li et al., 2023b; Pan, 2023; Dai et al., 2022). Cahyawijaya

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[2]High resource language refers to a language in which a relatively large volume of pre-training data for training an LLM compiled from web-text is available.

et al. (2024) proposed query-alignment to improve the few-shot in-context learning performance of LLMs on low-resource languages.

Example Selection for ICL. Despite the tremendous success, the performance of ICL is sensitive to specific settings, including the prompt template (Wei et al., 2022b; Wang et al., 2022; Zhou et al., 2022; Zhang et al., 2022b), the selection (Liu et al., 2021; Rubin et al., 2021; Ye et al., 2023; Wang et al., 2024) and order of demonstration examples (Lu et al., 2021), and other factors (Liu et al., 2024). Existing literature on example selection can be broadly categorized into two major groups: (1) Unsupervised methods depending on pre-defined metrics. Liu et al. (2021) proposed selecting the closest neighbors as demonstrations, while Levy et al. (2022) observed that electing diverse demonstrations improves compositional generalization in ICL. Wu et al. (2022); Nguyen and Wong (2023); Li and Qiu (2023) explored using the output distributions of language models to select few-shot examples. (2) On the other hand, the other group of studies (Li et al., 2023a; Luo et al., 2023; Rubin et al., 2021; Ye et al., 2023) proposed fine-tuning a retriever model to select few-shot demonstrations. Recent works have also explored using reinforcement learning approaches (Zhang et al., 2022a; Scarlatos and Lan, 2023) and Chain-of-thought reasoning (Qin et al., 2023) for example selection. In this study, we propose an alternating minimization approach for selecting the optimal set of in-context examples to enhance LLM performance on low-resource Indic languages.

3 Preliminaries

3.1 In-Context Learning

In-context learning (ICL) leverages the intrinsic abilities of language models to learn and infer new tasks without the need for parameter updates. Formally, let π_{LM} be a language model with a vocabulary $\mathcal{V}$. Consider a downstream generation task with input space $\mathcal{X}$ and output space $\mathcal{Y}$. For a given test query $\mathbf{x}_{\text{test}} \in \mathcal{X}$ and a retrieved subset of K input-output pairs $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^K \in \mathcal{X} \times \mathcal{Y}$ describing the intended task, ICL generates the output $\mathbf{y}_{\text{test}} \in \mathcal{Y}$ as follows:

$$\mathbf{y}_{\text{test}} \sim \pi_{\text{LM}}(\cdot | \mathbf{x}_1, \mathbf{y}_1, \mathbf{x}_2, \mathbf{y}_2, \ldots, \mathbf{x}_K, \mathbf{y}_K, \mathbf{x}_{\text{test}})$$

Here, $\sim$ represents the sampling techniques commonly used in the literature, such as Greedy Sampling, Top-p Sampling (Holtzman et al., 2019),

Top-k Sampling (Fan et al., 2018), and Beam Search (Freitag and Al-Onaizan, 2017). Each in-context example $a_i = (x_i, y_i) \in \mathcal{X} \times \mathcal{Y}$ is drawn from a training set example bank $\mathcal{D} = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^N$ of input-output sequences.

3.2 Example Retrieval for Few-shot learning

Our main goal is to train a retriever $\mathcal{R}_\phi(\mathbf{x}_{\text{test}}, \mathcal{D})$ model parameterized by ϕ, that retrieves a set of in-context examples $\{a_i\}_{i=1}^K \subset \mathcal{D}$ given a test sample $\mathbf{x}_{\text{test}}$ where typically $K \ll N$. Usually, $\phi : (\mathcal{X} \cup \mathcal{Y})^\star \to \mathbb{R}^d$ represents[3] the embedding function that maps the text in the input space $\mathcal{X}$ into a d-dimensional vector representation. Such representations are subsequently used to measure similarity between samples. Previous works have explored various retrieval strategies, ranging from random example selection to using off-the-shelf retrieval models (Liu et al., 2021; Wu et al., 2022), as well as fine-tuning the retriever's embeddings (Ye et al., 2023; Rubin et al., 2021).

Relevance Based Fine-tuning. In this study, we leverage the framework proposed by Rubin et al. (2021) to fine-tune an efficient dense retriever $\mathcal{R}_\phi$. The core idea is to train the retriever on a labeled dataset curated from the training data itself, optimizing it to select examples that serve as effective prompts. For each sample $(\mathbf{x}, \mathbf{y}) \in \mathcal{D}$, we generate a candidate set $\mathcal{A} = \{a_i\}_{i=1}^F$, where $a_i \in \mathcal{D} \backslash (\mathbf{x}, \mathbf{y})$. The candidate set is selected using an unsupervised BM25 retriever: $\mathcal{A} = \text{BM25}((\mathbf{x}, \mathbf{y}), \mathcal{D})$ that simply retrieves K examples with closest vector embedding to $\phi(\mathbf{x})$. Next, each candidate example $\mathbf{a}_i \in \mathcal{A}$ is scored using a language model π_{Scorer} based on its relevance to the sample $(\mathbf{x}, \mathbf{y})$.

$$s(\mathbf{a}_i; (\mathbf{x}, \mathbf{y})) = \pi_{\text{Scorer}}(\mathbf{y} \mid \mathbf{a}_i, \mathbf{x}). \quad (1)$$

The best candidate example for the sample $(\mathbf{x}, \mathbf{y})$ is selected as $\widetilde{\mathbf{a}} = \arg\max_{\mathbf{a}_j} s(\mathbf{a}_j; (\mathbf{x}, \mathbf{y}))$. Finally, the retriever $\mathcal{R}_\phi$ is fine-tuned to rank the candidate examples optimally (align with ranking induced by π_{Scorer}) by minimizing the negative log-likelihood under softmax loss:

$$\min_\phi \mathcal{L}_{\text{rel}}(\mathcal{D}; \phi) = \frac{1}{N} \sum_{i=1}^N \ell(\mathbf{x}_i, \mathcal{A}_i) \quad (2)$$

$$\ell(\mathbf{x}, \mathcal{A}; \phi) = -\log \frac{e^{\text{sim}(\mathbf{x}, \widetilde{\mathbf{a}})}}{\sum_{\mathbf{a}_i \in \mathcal{A}} e^{\text{sim}(\mathbf{x}_i, \mathbf{a}_i)}} \quad (3)$$

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[3] $\mathcal{A}^\star$ denotes the smallest superset of $\mathcal{A}$ closed under set concatenation - known as Kleene operator. In this case $(\mathcal{X} \cup \mathcal{Y})^\star$ corresponds to the concatenation of strings in $\mathcal{X}$ and $\mathcal{Y}$.

where $\text{sim}(\mathbf{a}_i, \mathbf{a}_j) = \phi(\mathbf{a}_i)^\top \phi(\mathbf{a}_j)$ measures the cosine similarity between the embeddings. Note, that although a fine-tuned $\mathcal{R}_\phi$ is better aligned with the ranking induced by π_{Scorer}, it only optimizes for relevance and does not account for diversity. This often leads the finetuned retriever to choose near-identical samples thus hurting generalization.

3.3 Determinantal Point Processes

In this subsection, we introduce a recently studied framework Determinantal Point Processes (DPPs) (Ye et al., 2023) for example selection that ranks subsets of examples rather than individual ones. Introduced in Macchi (1975), DPP's are elegant probabilistic models that have been extensively used in the literature (Ye et al., 2023; Borodin and Olshanski, 2000; Benard and Macchi, 1973; Kulesza et al., 2012; Liu et al., 2022) to capture negative correlation among items.

We leverage the DPP framework to promote diversity within the set of retrieved in-context examples. Formally, a point process $\mathcal{P}$ is called a DPP if, for any random subset Y drawn according to $\mathcal{P}$, the probability that a subset S is contained within Y is given by:

$$\mathcal{P}(S \subseteq Y) \propto \det(\mathbf{Z}_S)$$

where $\mathbf{Z} \in \mathbb{R}^{n \times n}$ is a PSD similarity matrix, and $\mathbf{Z}_S$ denotes the submatrix of K corresponding to the rows and columns indexed by S. For in-context learning, given a test sample $\mathbf{x}_{\text{test}}$, the input dependent similarity of any two examples $\mathbf{a}_i, \mathbf{a}_j$ is denoted by $\mathbf{Z}_{ij}$ - formally, we model $\log \mathbf{Z}_{ij}$ as

$$\sum_{k \in \{i,j\}} \log \phi(\mathbf{a}_k)^T \phi(\mathbf{x}_{\text{test}}) + \log \phi(\mathbf{a}_i)^\top \phi(\mathbf{a}_j)$$

where $\phi(\mathbf{a}_i)^T \phi(\mathbf{x}_{\text{test}}) \in \mathbb{R}^+$ measures the relevance of $\mathbf{a}_i$ to input $\mathbf{x}_{\text{test}}$ and $\phi(\mathbf{a}_i)^T \phi(\mathbf{a}_j)$ measures the similarity between the ith and j^{th} example.

4 Proposed Framework

Problem Setup. Despite the growing focus on evaluating the multilingual capabilities of large language models (LLMs), there remains a substantial performance gap between high-resource languages and those with limited web resources (Ahuja et al., 2023; Singh et al., 2024). In this study, we aim to address this gap by enhancing the few-shot performance of low-resource Indic languages. To

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Algorithm 1 PROMPTREFINE

1: **Input:** Low-resource language $\mathcal{T}$ example bank $\mathcal{D}^\mathcal{T}$; validation set $\mathcal{D}^\mathcal{T}_{\text{val}}$; Auxiliary example bank $\mathcal{D}^{\text{aux}} = \{\mathcal{D}^{\mathcal{H}_1}, \cdots, \mathcal{D}^{\mathcal{H}_M}\}$, number of iterations $\mathcal{I}$, Accuracy Metric Acc.
2: $\alpha \leftarrow \emptyset$
3: $\rho \leftarrow$ MBERT $\triangleright$ Initialize the retriever embedding with pre-trained Multilingual BERT encoder
4: **for** iter in $\{1, \cdots, \mathcal{I}\}$ **do**
5:     $\Phi \leftarrow \emptyset$
6:     **for** each dataset $\mathcal{D}^i \in \{\mathcal{D}^\mathcal{T}, \mathcal{D}^{\mathcal{H}_1}, \cdots, \mathcal{D}^{\mathcal{H}_M}\}$ **do**
7:         $\phi_i \leftarrow \min_\rho \mathcal{L}_{\text{rel}}(\mathcal{D}^i; \rho)$
8:         $\Phi \leftarrow \Phi \cup \phi_i$
9:     **end for**
10:     $\rho = \frac{1}{|\Phi|} \sum_{\theta \in \Phi} \theta$ $\triangleright$ Merge the retriever embeddings
11:     $\alpha_{\text{iter}} \leftarrow \text{Acc}(\rho, \mathcal{D}^\mathcal{T}_{\text{val}})$ $\triangleright$ Calculate validation accuracy
12:     $\alpha \leftarrow \alpha \cup \alpha_{\text{iter}}$
13: **end for**
14: $\rho^* \leftarrow \arg\max_\rho \alpha_{\text{iter}}$
15: $\bar{\rho} \leftarrow \min \mathcal{L}_{\text{DPP}}(\mathcal{D}^\mathcal{T} \cup \mathcal{D}^{\text{aux}}; \rho^*)$
16: **return** $\bar{\rho}$

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this end, we adopt the recently released IndicGen Benchmark (Singh et al., 2024), targeting a subset of Indic languages for our analysis. Specifically, we focus on the following low-resource languages:

> **Low/Mid-Resource Languages**: Bodo, Odia, Santali, Rajasthani, Manipuri, Awadhi, Marwari, and Maithili.
>
> **Auxiliary High-Resource Languages**: Bengali, Hindi, Marathi, Gujarati, Kannada, Malayalam, Tamil, Telugu, Urdu.

Additionally, we assume the availability of data from relatively high-resource Indic languages, which we refer to as the auxiliary dataset. This assumption is justified by the fact that these languages have relatively ample web-text resources (Singh et al., 2024).

4.1 Our Approach: PROMPTREFINE

To enhance the performance of language models on low-resource languages, we introduce PROMPTREFINE, a three-step framework that: 1) identifies closely related high-resource Indic languages and

leverages associated example banks (Section 4.1.1), 2) iteratively refines retriever embeddings $\mathcal{R}_\phi$ (Section 4.1.2), and 3) incorporates diversity-based fine-tuning of retriever $\mathcal{R}_\phi$ to rank subsets of in-context examples for a given input query (Section 4.1.3). The complete approach is outlined in Algorithm 1. In what follows, we provide an in-depth overview of each component.

4.1.1 Auxiliary Dataset Selection

Despite the advent of numerous LLMs, low-resource Indic languages constitute only a negligible portion of their pre-training corpora, resulting in a suboptimal performance for generation tasks in these languages. To address this, we propose using relatively high-resource Indic languages, such as Hindi and Bengali, as auxiliary datasets. Our approach involves selecting auxiliary languages that are closely related to the target Indic low-resource language. Specifically, for each low-resource language, we compute the cosine similarity between the embeddings and those of the auxiliary languages. An auxiliary language is included if its similarity score surpasses a threshold parameter δ, as outlined in Algorithm 2 (Appendix H). The underlying motivation for this approach is that for an input query in a low-resource Indic language, relevant examples that can guide the LLM in generation might not be present in the associated example bank - therefore, by incorporating examples from the related high-resource languages, we provide the LLM additional context or rather relevant guidance that can help improve the model's performance on the input query. However, the following critical challenge is now raised: *"How can we effectively integrate the diverse information from auxiliary datasets for optimal performance?"*

4.1.2 Iterative Prompt Refinement

We denote the example bank of the low-resource target language $\mathcal{T}$ as $\mathcal{D}^\mathcal{T} = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^N$, the selected set of auxiliary languages (using Alg. 2) as $\mathcal{H} = \{\mathcal{H}_1, \cdots, \mathcal{H}_M\}$ and the auxiliary example banks as $\mathcal{D}^{\text{aux}} = \{\mathcal{D}^{\mathcal{H}_1}, \cdots, \mathcal{D}^{\mathcal{H}_M}\}$. Note that the number of high-resource auxiliary example banks M is determined by the threshold parameter δ, as defined in Section 4.1.1. Our goal is to train a single retriever $\mathcal{R}_\rho(\mathbf{x}_{\text{test}}, \mathcal{D}^{\text{aux}} \cup \mathcal{D}^\mathcal{T})$ - however the challenge is both the shared representation space for all example banks combined and the parameter weights ϕ are unknown. At the same time, the retriever must capture the specific traits of each

individual language. Balancing these requirements requires an alternating optimization procedure.

To maximize the information gain from the auxiliary example banks, we propose an Alternating Minimization (AM) framework that alternately performs the following two steps successively until convergence 1) **(Specialize)** Fine-tune relevance-based retrievers $\{\mathcal{R}_{\phi_i}\}_i$ on each of several selected languages by retraining only on the example bank associated with the corresponding language (Step 7 in Alg. 1). Intuitively, the goal of this step is to allow a particular retriever to acquire task / language-specific knowledge associated with the corresponding language. Note that each of the individual retrievers $\{\mathcal{R}_{\phi_i}\}_i$ is initialized with pre-trained multilingual BERT encoder weights at the beginning of first iteration - in subsequent iterations, all the individual retrievers are initialized with shared parameter weights ρ computed in the next step 2) **(Merge)** merges the individual retrievers $\{\mathcal{R}_{\phi_i}\}_i$ into a single retriever $\mathcal{R}_\rho$ by simple parameter averaging to obtain a *shared representation space enabling cross-language retrieval* (Step 10 in Alg. 1). Intuitively, the shared retriever $\mathcal{R}_\rho$ encapsulates the diverse knowledge learnt by each individual retriever.

In essence, our alternating minimization algorithm (Alg. 1) alternately finetunes the individual retriever on language-specific example bank and creates a merged retriever enabling a shared representation space for $\mathcal{I}$ iterations. We denote the model with the highest validation accuracy on the target language $\mathcal{T}$ after $\mathcal{I}$ iterations as ρ^* (Step 11 in Alg. 1).

4.1.3 Divsersity-induced finetuning

A major limitation of relevance-based finetuning is that the in-context examples are retrieved solely based on relevance, thereby ignoring diversity and inter-relationship among the selected examples (Ye et al., 2023). To overcome this challenge, we leverage the DPP framework to enhance diversity within the retrieved in-context examples. Specifically, we obtain the final retriever model by fine-tuning ρ^* on the merged dataset $\widetilde{\mathcal{D}} = \mathcal{D}^\mathcal{T} \cup \mathcal{D}^{\text{aux}}$. Due to the technically involved training procedure of the DPP framework via contrastive learning, we delegate the training details to the Appendix D. Note that during inference, we use the retriever model further fine-tuned in the DPP framework to retrieve both diverse and relevant samples (Ye et al., 2023). Specifically, we perform MAP inference using the

Aux. Data Used	Finetuning-Based	Methods	Bodo			Manipuri			Maithili		
			QW-2-7B	QW-2.5-7B	LM-3.1-8B	QW-2-7B	QW-2.5-7B	LM-3.1-8B	QW-2-7B	QW-2.5-7B	LM-3.1-8B
✗	✗	Zero-shot	0.68	0.21	1.20	0.68	0.44	0.97	3.41	2.72	13.05
✗	✗	Random	4.57	4.02	5.83	4.72	3.80	6.10	13.97	12.02	18.73
✗	✗	BM25	6.20	6.47	9.41	5.68	4.14	6.98	13.21	11.77	20.15
✗	✗	Top-K	5.90	6.37	5.10	5.80	4.21	6.08	13.25	12.95	18.02
✗	✗	Diverse	5.88	5.92	5.34	5.54	4.09	5.98	13.27	12.53	18.29
✗	✓	EPR	6.29	7.15	7.81	6.40	4.91	7.22	14.85	14.03	20.18
✗	✓	CEIL	7.83	7.33	8.20	6.73	6.17	9.33	16.80	15.72	21.96
✓	✓	EPR	6.61	7.99	7.98	6.34	4.58	7.18	14.27	13.70	19.71
✓	✓	CEIL	7.95	8.07	9.01	6.62	6.09	9.28	16.84	15.49	22.38
✓	✓	PROMPTREFINE (Ours)	**13.68**	**11.40**	**17.27**	**12.79**	**11.50**	**19.54**	**24.56**	**23.37**	**25.59**
		Absolute Gain (Δ)	+6.05	+3.33	+8.26	+6.17	+5.33	+10.21	+7.76	+7.65	+3.21

Table 1: **Evaluation on XorQA-In.** We report Token-F1 results for performance on Bodo, Manipuri and Maithili. The evaluation includes three LLMs: Qwen-2-7B (QW-2-7B), Qwen-2.5-7B (QW-2.5-7B), and LLAMA-3.1-8B (LM-3.1-8B).

Aux. Data Used	Finetuning-based	Methods	Santali → English			Rajasthani → English			Manipuri → English		
			LM-2-7B	LM-3.1-8B	QW-2-7B	LM-2-7B	LM-3.1-8B	QW-2-7B	LM-2-7B	LM-3.1-8B	QW-2-7B
✗	✗	Zero-shot	5.89	16.83	9.95	21.94	37.90	34.09	10.62	14.40	10.04
✗	✗	Random	8.54	16.92	10.85	22.08	37.69	37.45	11.96	16.57	11.87
✗	✗	BM25	9.77	17.55	11.60	24.35	36.62	36.92	11.67	17.81	12.18
✗	✗	Top-K	9.98	18.66	11.98	25.12	38.33	37.05	11.81	17.40	14.93
✗	✗	Diverse	8.86	18.67	11.64	24.88	39.12	38.13	12.44	18.13	13.82
✗	✓	EPR	10.35	18.59	12.09	25.99	40.09	37.97	13.90	18.99	18.79
✗	✓	CEIL	10.68	18.41	12.20	26.04	41.85	38.77	14.02	19.53	19.47
✓	✓	EPR	10.27	18.73	12.38	25.77	41.60	38.30	13.88	18.82	20.18
✓	✓	CEIL	10.63	17.90	13.01	25.72	41.93	40.04	14.15	18.97	20.23
✓	✓	PROMPTREFINE Ours)	**15.14**	**23.58**	**15.48**	**31.75**	**45.88**	**43.43**	**18.69**	**23.90**	**22.70**
		Absolute Gain (Δ)	+4.48	+4.85	+2.47	+5.71	+3.95	+3.39	+4.54	+4.37	+3.27

Table 2: **Evaluation on Flores-In.** We report chrF1 results for translation performance from three low-resource languages to English. The evaluation includes three LLMs: LLAMA-2-7B (LM-2-7B), LLAMA-3.1-8B (LM-3.1-8B), and Qwen-2-7B (QW-2-7B).

model within the DPP framework - however exact MAP inference is NP-Hard (Ko et al., 1995) since it involves an exact search over an exponentially large collection of subsets of examples. However, in our setting, we can use a greedy but computationally efficient procedure to build the subset by inserting one example at a time (Chen et al., 2018).

5 Experiments

Implementation Details. In this study, we evaluate the multilingual and cross-lingual language generation capabilities of various LLMs on low-resource Indic languages mentioned in Section 4. Our experiments involve a range of recently released open-source LLMs, including Qwen-2-7B (Yang et al., 2024), Qwen-2.5-7B (Team, 2024), LLAMA-2-7B (Touvron et al., 2023), and LLAMA-3.1-8B (Dubey et al., 2024), as well as proprietary models such as GPT-3.5 and GPT-4 (OpenAI et al., 2024). For open-source LLMs, we use the same model for scoring (π_{Scorer}) and inference (π_{LM}). For all experiments, we set the number of in-context examples as $K = 16$. Following previous literature (Ye et al., 2023; Rubin et al., 2021), we sort the in-context examples in ascending order of their similarity to the input text.

In our proposed approach, PROMPTREFINE, the retriever embeddings are initialized using a pre-trained multilingual BERT encoder[4]. For fine-tuning, we use an Adam optimizer with a batch size of 64 and a learning rate of $1e - 4$. For relevance-based training, we fine-tune the model for $\mathcal{I} = 10$ iteration with 120 epochs in each iteration. We further fine-tune for 10 epochs during DPP-based training. All experiments are run using the configurations listed in Appendix A.

Baselines. In this work, we introduce PROMPTRE-FINE, a fine-tuning-based retrieval framework designed to enhance in-context example selection for low-resource Indic languages. For a comprehensive evaluation, we compare PROMPTREFINE with fine-tuning-free retrievers such as Random, BM25 (Robertson et al., 2009), Top-K, and Diverse. Among fine-tuning-based retrievers, we benchmark against EPR (Rubin et al., 2021) and CEIL (Ye et al., 2023). We refer the reader to Appendix E for a detailed description of the baselines used in this study.

Datasets. We evaluate PROMPTREFINE on four diverse tasks, as outlined in Singh et al. (2024), to comprehensively assess its retrieval capabilities for low-resource Indic languages. These tasks include Cross-Lingual Question Answering (XorQA-In-

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[4]google-bert/bert-base-multilingual-cased

Aux. Data Used	Finetuning-Based	Methods	Rajasthani		Manipuri		Marwari		Awadhi	
			LM-3.1-8B	QW-2-7B	LM-3.1-8B	QW-2-7B	LM-3.1-8B	QW-2-7B	LM-3.1-8B	QW-2-7B
✗	✗	Zero-shot	1.10	3.06	0.15	0.36	0.16	2.09	0.19	2.16
✗	✗	Random	8.38	5.93	3.14	3.88	7.38	6.05	9.10	4.20
✗	✗	BM25	7.86	5.85	3.52	3.92	7.81	5.54	8.40	4.83
✗	✗	Top-K	11.03	6.08	4.43	4.50	8.91	5.91	9.36	6.07
✗	✗	Diverse	10.77	6.21	4.39	4.68	8.93	5.78	9.05	6.11
✗	✓	EPR	11.25	7.16	5.11	5.13	9.33	6.32	10.59	6.44
✗	✓	CEIL	11.93	7.39	5.49	5.92	10.49	6.70	11.92	7.02
✓	✓	EPR	11.22	7.09	5.08	5.59	9.11	6.25	11.36	6.58
✓	✓	CEIL	11.50	7.28	5.71	6.04	10.20	6.67	12.41	7.33
✓	✓	PROMPTREFINE (Ours)	**15.88**	**9.43**	**6.67**	**6.92**	**15.95**	**8.06**	**15.36**	**8.49**
		Absolute Gain (Δ)	+3.95	+2.04	+0.96	+0.88	+5.46	+1.36	+2.95	+1.47

Table 3: **Evaluation on CrossSum-In.** We report chrF1 results for the summarization performance of an English text into four low-resource languages. The evaluation includes two recent LLMs: LLAMA-3.1-8B (LM-3.1-8B), and Qwen-2-7B (QW-2-7B).
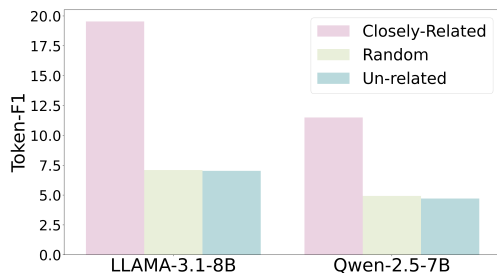

Figure 1: Token-F1 evaluation on the cross-lingual QA task in Manipuri, with retrievers trained using different auxiliary high-resource example banks: (1) Closely related language, (2) Random language, and (3) Unrelated language.

XX), Multilingual Question Answering (XQuAD-IN), Machine Translation (Flores-In-XX-En), and Cross-Lingual Summarization (CrossSum-IN). We refer the reader to Appendix F for a detailed description of the datasets used in this study. We present the prompt template used for different datasets in Table 6 (Appendix).

Evaluation Metrics. Following prior work (Singh et al., 2024), we report the Character-F1 (chrF1) metric (Popović, 2015; Gala et al., 2023) for cross-lingual summarization and translation tasks, as token-level metrics like ROUGE and BLEU are considered unreliable for low-resource languages (Bapna et al., 2022; Singh et al., 2024). For QA tasks (XQuAD-IN and XorQA-IN), we use the Token-F1 metric to maintain consistency with the existing literature (Singh et al., 2024).

5.1 Main Results

Evaluation on open-source LLMs. We present the evaluation results on state-of-art open-source models, including LLAMA-3.1-8B, LLAMA-2-7B, Qwen-2-7B, and Qwen-2.5-7B, for Cross-Lingual QA task (Table 1), Machine Translation task (Table 2), Cross-lingual Summarization task (Table 3), and Multi-lingual QA task (Table 4). Our empiri-

cal findings yield several key insights: (1) Across all diverse tasks, PROMPTREFINE consistently outperforms both finetuning-based and finetuning-free baselines, with a improvement of up to 2.09x compared to current state-of-art. Notably, for Cross-lingual QA task, for Manipuri, PROMPTREFINE improves the Token-F1 by +10.21 over CEIL (Ye et al., 2023). (2) Compared to fine-tuning free baselines such as Top-K, PROMPTREFINE provides a staggering improvement of upto 3.38x on low-resource language such as Bodo. Further, when compared to finetuning-based retrievers like EPR (Rubin et al., 2021) and CEIL, PROMPTREFINE consistently delivers superior performance across all tasks, as exemplified by a +3.21 Token-F1 improvement on Maithili. (3) Interestingly, even when auxiliary datasets are available, other finetuning-based retrievers such as EPR (Rubin et al., 2021) and CEIL (Ye et al., 2023) do not exhibit significant improvements. This finding highlights the importance of learning a better representation space to effectively integrate and leverage auxiliary data. In contrast, PROMPTREFINE successfully utilizes auxiliary data to generate a richer set of in-context examples, as reflected by its substantial performance gains across multiple tasks.

Evaluation on proprietary LLMs. To ensure a comprehensive evaluation, we also test PROMPTREFINE on proprietary LLMs such as GPT-3.5/4 (OpenAI et al., 2024). However, since we do not have access to the output logits in proprietary models, required for scoring candidate examples, we use a different open-source LLM architecture for scoring. To be specific, for this experiment, we employ LLAMA-3.1-8B as the scorer model π_{Scorer}. The results for the translation task are reported in Table 5 (Appendix). Consistent with our findings using open-source LLMs, PROMPTRE-
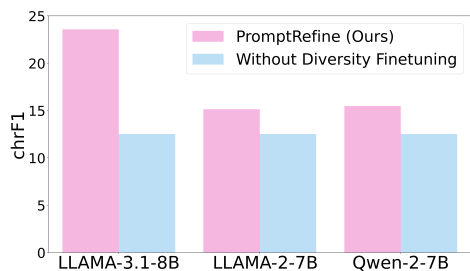
Figure 2: To highlight the importance of DPP training, we compare the quality of responses generated with and without diversity-induced fine-tuning on the task of translating from Santali to English.

FINE significantly improves generation quality, as measured by chrF1, compared to other retrieval methods.

6 Discussion

Note, ablation studies on threshold parameter δ for selecting related languages and number of ICL examples are deferred to Appendix C.

Why is choosing a closely related auxiliary example bank important? In Section 4.1.1, we discussed the approach of selecting a closely related high-resource Indic language as an auxiliary example bank for a target low-resource language. To highlight importance of selecting the right set of related languages, we present ablation studies in this section.

We evaluate three setups: (1) Our method (Alg. 2) of selecting the most closely related language as the auxiliary example bank, (2) selecting a random language, and (3) selecting the most unrelated language. We show the few-shot performance on cross-lingual QA task in Figure 1, with retrievers trained under each setup. Our findings show that: (1) As expected, using the most closely related language as the auxiliary example bank yields the best performance, as it provides relevant guidance to the LLM, and (2) Selecting a random or unrelated language results in little to no improvement, with performance remaining close to the relevance-based EPR baseline (Rubin et al., 2021) that only uses target-language specific data.

Importance of Diversity-Induced Fine-Tuning. A key factor contributing to the improved performance of PROMPTREFINE is the retrieval of a diverse set of in-context examples. Merging auxiliary example banks imply a larger overall example bank and therefore incorporating diversity during example selection becomes important to improve generalization. In this section, we empirically demonstrate the significance of diversity-induced
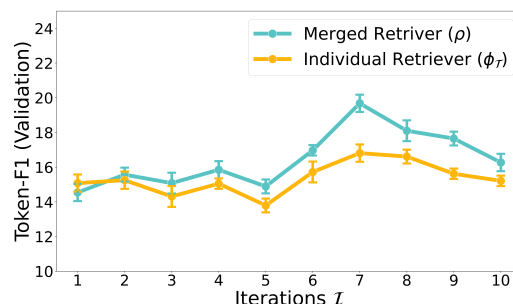

Figure 3: We plot the validation accuracy (measured by Token-F1) obtained by individual and merged retrievers over different iterations of finetuning.

fine-tuning (Section 4.1.3). Figure 2 compares the text generation quality in Santali-to-English translation task, where examples are selected using two retriever models namely our approach PROMPTRE-FINE with and with-out diversity-induced fine-tuning - in the latter, we skip line 15 in Alg. 1. Results clearly show that incorporating diversity training leads to performance improvements across different LLMs, underscoring its effectiveness.

Importance of Alternating-Minimization approach. In Section 4.1.2, we proposed an alternating minimization approach to alternately fine-tune the retriever on language-specific data and merge the parameters in order to learn a shared representation space that captures the knowledge associated with both the target language $\mathcal{T}$ and the auxiliary languages $\mathcal{H}$. In Figure 3, we plot the validation accuracy across different iterations for the merged retriever ρ and the target language retriever $\phi_{\mathcal{T}}$. The results show that merging the retriever embeddings provides a significant boost in validation accuracy over the iterations, thereby justifying the effectiveness of the parameter-averaging strategy.

7 Conlusion

The pre-training data for state-of-the-art LLMs (Dubey et al., 2024; Yang et al., 2024) predominantly comprises English text, resulting in suboptimal performance on low-resource Indic languages (Singh et al., 2024). To address this, we propose a novel Alternating Minimization approach PROMPTREFINE for example selection that improves ICL performance on low-resource Indic languages. Our approach follows a three-step framework: (1) identifying closely related high-resource Indic languages and utilizing their example banks, (2) iteratively refining retriever embeddings, and (3) employing diversity-based finetuning to rank subsets of in-context examples

for a given input query. Comprehensive testing across various tasks and LLMs demonstrates that PROMPTREFINE significantly enhances text generation quality on low-resource Indic languages.

8 Limitations

In Section 5.1, we demonstrated the effectiveness of our proposed framework across diverse tasks. However, PROMPTREFINE has the following limitations:

- To improve text generation quality in low-resource Indic languages, PROMPTREFINE depends on the availability of example banks from closely related, relatively high-resource Indic languages to provide additional context. We believe this is a reasonable assumption, as publicly available web-text resources are accessible for high-resource languages.

- As explained in Algorithm 1, our proposed approach involves three key steps: (1) identifying closely related example banks, (2) iterative refinement of retriever embeddings, and (3) diversity-based finetuning. These steps could have been arranged in several different configurations. However, we empirically tested several alternatives and found that our proposed approach consistently delivers the best performance improvements.

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A Software and Hardware

We run all experiments with Python 3.12.4, PyTorch 2.2.0, and Transformers 4.43.3. For all experimentation, we use four Nvidia RTX A6000 GPUs.

B Extended Results

In the main paper, we showed the effectiveness of PROMPTREFINE for cross-lingual QA (Table 1), machine translation (Table 2), and summarization tasks (Table 3). In Table 4, we further present results on multi-lingual QA task for Odia language. Note that Xquad-In (Singh et al., 2024) only includes medium-resource languages; therefore, we report results for only one language for this task. For a comprehensive evaluation, we also test PROMPTREFINE on proprietary LLMs such as GPT-3.5/4 (OpenAI et al., 2024). We report results in Table 5.

C Extended Discussion

Ablation Study on Threshold Parameter δ. In this section, we present an ablation study on the threshold parameter δ, which governs the selection of high-resource languages in the auxiliary dataset. A lower δ expands the inclusion to a broader set of high-resource languages, potentially introducing less relevant examples. On the other hand, a higher δ is more selective, which may restrict the diversity of examples and reduce the contextual richness. Our goal is to identify the optimal δ that balances these factors, ensuring the auxiliary dataset consists of examples from closely related high-resource languages that effectively improve LLM generation performance. Figure 4 illustrates the translation performance from three different low-resource languages to English as a function of varying δ. The results suggest that setting δ to the 95th percentile

Aux. Data Used	Finetuning-Based	Methods	Odia		
			QW-2-7B	LM-3.1-8B	QW-2.5-7B
✗	✗	Zero-shot	12.67	13.08	21.76
✗	✗	Random	25.55	33.60	34.18
✗	✗	BM25	31.10	32.46	34.89
✗	✗	Top-K	28.90	29.30	33.20
✗	✗	Diverse	28.37	31.70	33.98
✗	✓	EPR	32.36	34.91	36.51
✗	✓	CEIL	33.11	36.70	36.37
✓	✓	EPR	32.79	37.02	37.18
✓	✓	CEIL	32.40	39.88	36.28
✓	✓	PROMPTREFINE (Ours)	**35.92**	**46.87**	**43.65**
		Absolute Gain (Δ)	+2.81	+6.59	+6.47

Table 4: **Evaluation on Xquad-In.** We report Token-F1 results for QA performance from Odia to English. The evaluation includes three LLMs: Qwen-2-7B (QW-2-7B), Qwen-2.5-7B (QW-2.5-7B), and LLAMA-3.1-8B (LM-3.1-8B).

Aux. Data Used	Finetuning-Based	Methods	sat		mni	
			GPT-3.5	GPT-4	GPT-3.5	GPT-4
✗	✗	Zero-shot	15.57	15.98	22.21	27.90
✗	✗	Random	14.34	15.21	20.19	26.98
✗	✗	BM25	16.52	16.77	25.61	29.05
✗	✗	Top-K	16.63	17.12	25.80	30.21
✗	✗	Diverse	16.27	16.59	24.85	29.01
✗	✓	EPR	18.35	18.71	26.93	31.26
✗	✓	CEIL	18.62	19.13	27.31	32.09
✓	✓	EPR	18.27	18.58	26.49	30.88
✓	✓	CEIL	18.61	19.02	27.03	31.85
✓	✓	PROMPTREFINE (Ours)	**19.33**	**20.98**	**28.38**	**34.35**

Table 5: **Evaluation on Proprietary LLMs.** We report chrF1 results for translation performance from Santali (sat) and Manipuri (mni) to English on GPT-3.5/GPT-4. For this evaluation, we used LLAMA-3.1-8B as the scorer LLM.

of the cosine similarity values between target language embeddings and high-resource languages yields optimal performance.

Ablation Study on the Number of In-Context Samples K. In Figure 5, we present ablation results on the number of demonstrations, K, included in the prompt. Specifically, we evaluate the translation task from Rajasthani to English using chrF1 scores for outputs generated with varying $K = \{1, 2, 4, 8, 16\}$. Due to computational constraints, we cap the maximum number of in-context examples at 16. Our results show that setting $K = 16$ achieves the best performance.

D Details on Diversity-induced finetuning

We introduced DPP-based diversity finetuning in Section 4.1.3. In this section, we provide additional details regarding the training procedure. We obtain the final retriever by fine-tuning ρ^* on the merged dataset $\widetilde{\mathcal{D}} = \mathcal{D}^{\mathcal{T}} \cup \mathcal{D}^{aux}$. Specifically, for each sample $(\mathbf{x}_i, \mathbf{y}_i) \in \widetilde{\mathcal{D}}$, a subset of $\mathcal{E}_i$ in-context examples are retrieved from $\widetilde{\mathcal{D}}$. Out of the $\mathcal{E}_i$ subsets, a positive subset $E_i^{(+)}$ is selected using maximum a posteriori (MAP) sampling (Chen et al., 2018) from the kernel matrix $\mathbf{Z}$. The other $\mathcal{E}_i - 1$ negative subsets ($E_i^{(-)}$) are selected using non-replacement
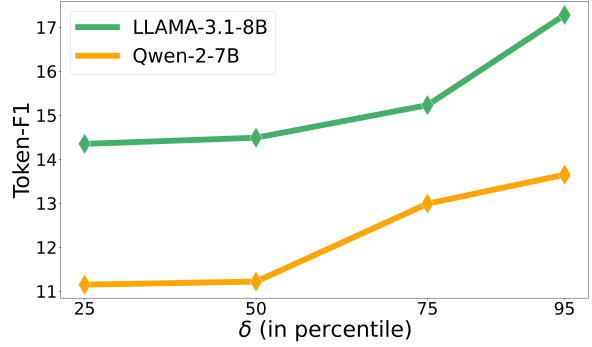

Figure 4: We vary the threshold parameter δ to evaluate its impact on model performance. Our results show that setting δ to the 95th percentile of cosine similarity values between target language embeddings and high-resource languages yields optimal performance. The evaluation task for this experiment is cross-lingual QA on Bodo.

Figure 5: We plot the chrF-1 score for different values of $K \in \{1, 2, 4, 8, 16\}$, where K represents the number of in-context examples. The task for this experiment is translation from Rajasthani to English and LLM is LLAMA-3.1-8B.

random sampling, with no repeating examples in each subset. Based on these ground-truth sets, the retriever is fine-tuned using the following loss:

$$\ell_i = \sum_{\left(E_i^{(+)}, E_i^{(-)}\right) \in \mathcal{E}_i} \max\{0, \log \det \left(\mathbf{Z}_{E_i^{(-)}}\right)$$
$$- \log \det \left(\mathbf{Z}_{E_i^{(+)}}\right)\}, \quad (4)$$

$$\mathcal{L}_{\text{DPP}} = \frac{1}{\widetilde{N}} \sum_{i=1}^{\widetilde{N}} \ell_i, \quad (5)$$

where $\widetilde{N}$ is the number of samples in $\widetilde{\mathcal{D}}$.

E Baseline Descriptions

For a thorough and fair evaluation, we compare PROMPTREFINE with the following baselines:

- Random: In-context examples are randomly selected from the training set without repetition.

- BM25: A classical sparse retrieval method, BM25 (Robertson et al., 2009), is employed to rank and select the top-scoring examples as in-context samples.
- Top-K: This baseline uses a dense retriever initialized with pre-trained multilingual BERT embeddings without any fine-tuning. The top-ranked examples are selected as in-context samples.
- Diverse: We initialize the retriever with pre-trained BERT embeddings and apply Maximum a Posteriori (MAP) during inference to retrieve a diverse subset of examples.
- EPR (Rubin et al., 2021): The multi-lingual BERT retriever is fine-tuned using the relevance loss and at the inference stage the top selected examples are selected for use as in-context samples.
- CEIL (Ye et al., 2023): The retriever is fine-tuned using the DPP loss, incorporating both diversity and relevance.

F   Dataset Description

1. Cross-Lingual Question-Answering (XorQA-In-XX): This task involves generating answers in non-English languages, given English evidence passages. Specifically, each example consists of a question in language XX, an English passage, and an answer in language XX, where the task is to generate the answer in the same language (XX) as the question.
2. Multilingual Question-Answering (XQuAD-IN): In this dataset, each example consists of a passage, question, and short answer in a source language (XX), and the task is to generate the answer in XX.
3. Machine Translation (FLORES-IN-XX-En): For this dataset, the task is to translate a sentence from a source language (XX) to English.
4. Cross-Lingual Summarization (CrossSum-IN): Given a news article in a non-English language (XX), the task is to generate a summary of the article in the same language.

G   Prompts

We present the prompts used for evaluation in Table 6

H   Algorithm

We elaborate the auxiliary dataset selection approach in Algorithm 2.

Dataset	Prompt
CrossSum-In	[Context] Summarize the article in [Target Language Name] language. Summarize the following article: [Article in English] Summary:
XorQA-In-XX	[Context] Generate an answer in [Target Language Name] language for the question based on the given passage. [Passage in English] Question: [Question in Target Language] Answer:
Flores-In	[Context] Translate the following sentence to English. Input: [Sentence in Target Language] Output:
XQuAD-In	[Context] Generate an answer for the next question in [Target Language Name] language. [Passage in Target Language] Question: [Question in Target Language] Answer:

Table 6: Prompt template used for various datasets.

Algorithm 2 Auxiliary Dataset Selection

1: **Input:** High-resource language example bank $\mathcal{D}^{\text{high}} = \{\mathcal{D}^{\mathcal{H}_1}, \cdots, \mathcal{D}^{\mathcal{H}_V}\}$; low-resource target language examples $\mathcal{D}^{\mathcal{T}} = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{N}$; pre-trained multi-lingual BERT encoder ϕ; Threshold δ.

2: $e_{\mathcal{T}} \leftarrow \frac{1}{N} \sum_{i=1}^{N} \phi((\mathbf{x}_i, \mathbf{y}_i))$ ▷ Compute average of BERT embedding for low-resource samples

3: $\text{sim} \leftarrow \emptyset$

4: **for** each $\mathcal{D}^h \in \mathcal{D}^{\text{high}}$ **do**

5:      $e_h \leftarrow \frac{1}{N_h} \sum_{j=1}^{N_h} \phi((\mathbf{x}_{jh}, \mathbf{y}_{jh}))$ ▷ Compute mean BERT embedding for each auxiliary dataset

6:      $\text{sim}_h \leftarrow \frac{e_h^{\top} e_{\mathcal{T}}}{|e_h||e_{\mathcal{T}}|}$

7:      $\text{sim} \leftarrow \text{sim} \cup \text{sim}_h$

8: **end for**

9: $\mathcal{D}^{\text{aux}} \leftarrow \{\mathcal{D}^h \in \mathcal{D}^{\text{high}} \mid \text{sim}_h \geq \text{percentile}(\text{sim}, \delta)\}$

10: **return** $\mathcal{D}^{\text{aux}}$