LLaMAX: Scaling Linguistic Horizons of LLM by Enhancing Translation Capabilities Beyond 100 Languages

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Abstract

Large Language Models (LLMs) demonstrate remarkable translation capabilities in high-resource language tasks, yet their performance in low-resource languages is hindered by insufficient multilingual data during pre-training. To address this, we conduct extensive multilingual continual pre-training on the LLaMA series models, enabling translation support across more than 100 languages. Through a comprehensive analysis of training strategies, such as vocabulary expansion and data augmentation, we develop LLaMAX. Remarkably, without sacrificing its generalization ability, LLaMAX achieves significantly higher translation performance compared to existing open-source LLMs (by more than 10 spBLEU points) and performs on-par with specialized translation model (M2M-100-12B) on the Flores-101 benchmark. Extensive experiments indicate that LLaMAX can serve as a robust multilingual foundation model. The code [1] and the models [2] are publicly available.

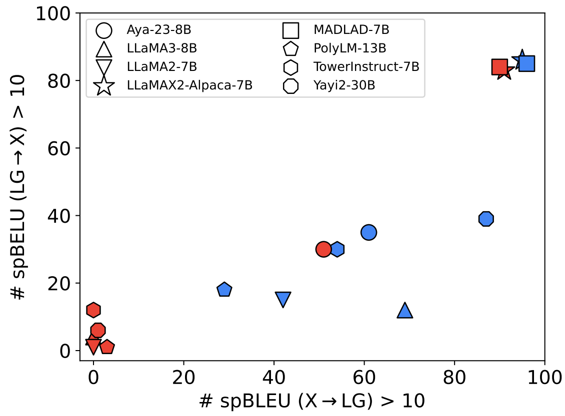

Figure 1: We assess translations in both directions, X→LG and LG→X, across various models using Flores-101 test, with X representing all 101 languages included in Flores-101. The results are visualized in a figure where different markers represent various models, a red marker indicates that the language (LG) is Arabic, while a blue marker indicates English. We count the number of translation directions that achieve a spBLEU score higher than 10. The findings indicate that modest LLMs demonstrate strong support for English-centric translation, but underperform in Arabic-centric translation.

1 Introduction

Large Language Models (LLMs; Brown et al., 2020; Zhang et al., 2022; Chowdhery et al., 2022; OpenAI, 2023; Touvron et al., 2023a,b) exhibit excellence performance in translation tasks involving high-resource languages (Vilar et al., 2023; Zhu et al., 2024b), yet their effectiveness in low-resource translation is suboptimal (Hendy et al., 2023; Bang et al., 2023; Zhu et al., 2024b). Figure 1 illustrates the number of translation directions with performance exceeding 10 spBLEU (Goyal et al., 2022) score on Flores-101 (Goyal et al., 2022). It is evident the majority of models are clustered around the origin point for Arabic-centric translations, demonstrating a significant disparity when compared to their English-centric performance.

This discrepancy is primarily due to the lack of pre-training data for these languages (Wei et al., 2023; Yuan et al., 2024b; Alves et al., 2024). Many researchers are actively working to address this issue. Guo et al. (2024) enhance the LLMs' ability by translating low-resource languages after learning textbooks. Zhu et al. (2024b) find cross-lingual examples that can provide better task guidance for low-resource translation. In addition to the efforts focus on the fine-tuning stage, some studies have attempted to train a multilingual LLM from scratch (Wei et al., 2023), or to train a language-specific LLM (Faysse et al., 2024; Alves et al., 2024; Cui et al., 2024). However, the languages covered by these works are not extensive (Wei et al., 2023; Alves et al., 2024; Luo et al., 2023), and the translation performance is still unsatisfactory (Wei

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[1]https://github.com/CONE-MT/LLaMAX/.
[2]https://huggingface.co/LLaMAX/.

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et al., 2023; Alves et al., 2024; Luo et al., 2023).

To tackle this discrepancy, we conduct a massive multilingual continual pre-training for non-English languages. Firstly, we present a comprehensive analysis of critical technical designs, including vocabulary extension (Section 2.1) and data augmentation (Section 2.2). These analyses establish the groundwork for the training procedure, directly influencing the efficacy and, ultimately, the performance of the LLMs. Subsequently, we apply those strategies in continual pre-training using both parallel and monolingual data to enhance the translation performance of LLMs across the 102 languages covered by Flores-101, particularly for low-resource languages.

A primary challenge in expanding language support lies in determining the appropriate vocabulary (Cui et al., 2024; Fujii et al., 2024). After assessing the impact of adding language-specific tokens from various angles: tokenization granularity, embedding quality, and the model's inner distribution, we find that introducing a small number of new tokens significantly degrades existing LLM performance, while a larger new token set increases training complexity and data requirements. Surprisingly, adhering to the original vocabulary of LLMs emerges as the most cost-effective strategy for extending LLMs to 102 languages.

Another great challenge in extending language support is the scarcity of data for low-resource languages (Chang et al., 2023; Guo et al., 2024). To alleviate the scarcity of training data, we delve into dictionary-based data augmentation (Pan et al., 2021; Lu et al., 2023) and conduct a comprehensive analysis of various augmentation strategies. This analysis takes into consideration different dictionaries and data sources (monolingual or parallel data). We find that the optimal approach for data augmentation involves using parallel data, with the choice of dictionary correlated to the number of target language entities it covers.

Finally, we leverage the above discussed techniques to perform large-scale, multilingual continual pre-training on LLaMA series models (Touvron et al., 2023b; AI@Meta, 2024), resulting in LLaMAX series models (LLaMAX2 and LLaMAX3). The LLaMAX2, trained over 60 days using 24 A100 GPUs, significantly enhances translation capabilities and achieves comparable performance (evaluated on Flores-101) to the specialized translation model M2M-100-12B (Fan et al., 2021). Specifically, our method demonstrates an average improvement of more than 10 spBLEU compared to baseline models in low-resource-centric translation, as shown in Table 3. Furthermore, when extending our evaluation to Flores-200 (Team et al., 2022), it shows significant performance enhancements even for languages not included in the training set. All these translation performance improvements do not compromise general task performance. Interestingly, enhancing translation capabilities also establishes a robust multilingual base model foundation. When comparing results of supervised fine-tuning using task-specific English data on the X-CSQA (Lin et al., 2021a), XNLI (Conneau et al., 2018), and MGSM (Shi et al., 2023) tasks, we observe an average improvement of 5 points over LLaMA2. Our main contributions can be summarized as follows:

- A series of open-sourced LLaMAX models enhance the translation performance across more than 100 languages.
- Comprehensive analysis of the key techniques in multilingual continual pre-training, including vocabulary extension and data augmentation.
- Extensive experiments on key technique design, comprehensive translation benchmark evaluation across various models, general task testing, and supervised fine-tuning on task-specific data demonstrate the superiority of LLaMAX.

2 Key Technique Design

Existing Pipeline. Exploring adapting pre-trained LLMs to new languages without starting from scratch seems to have a concise pipeline, resulting in ChineseLLaMA2 (Cui et al., 2024), Swallow (Fujii et al., 2024), and so on. This pipeline comprises three crucial steps: 1) vocabulary expansion: extending the vocabulary of LLMs by adding new tokens specific to that language and initializing these new tokens as the average of embeddings from the existing tokens (Dobler and de Melo, 2023). 2) continual pre-training: continual pre-training LLM on a large corpus of text data from the target language. 3) instruction tuning: aligning the model with specific tasks or instructions, enhancing its performance. Instead of simply following the pipeline, we analyze primarily two key challenges related to the extension of language support: determining an appropriate vocabulary (in Section 2.1) and improving the effectiveness of data augmentation (in Section 2.2). For a more

# New Token	Romanian (ro)						Bengali (bn)					
	fertility	cosine	R@1	shift distance	# shift token	spBLEU	fertility	cosine	R@1	shift distance	# shift token	spBLEU
0	2.25	0.39	0.37	0.4708	112	**32.50**	8.62	0.17	0.01	0.4689	112	**20.12**
100	2.19	0.36	0.34	0.4720	112	28.75	4.96	0.14	0.02	0.4680	113	14.02
800	2.02	0.35	0.36	0.4682	113	27.78	3.21	0.13	0.02	0.4706	113	10.18
1600	1.93	0.34	0.34	0.4690	113	26.40	2.78	0.13	0.02	0.4695	113	1.82
6,400	1.74	0.31	0.31	0.4694	113	22.66	2.15	0.12	0.02	0.4712	113	1.96
12,800	1.63	0.29	0.29	0.0205	1	21.95	1.95	0.12	0.02	-	0	1.84
25,600	1.53	0.27	0.28	-	0	19.72	1.80	0.12	0.02	-	0	2.58
51,200	1.45	0.26	0.25	0.0203	1	17.79	1.70	0.12	0.03	-	0	1.14

Table 1: Building upon LLaMA2, we add varying numbers of languages-specific new tokens, fully fine-tune LLaMA2, and test the translation performance of en→ro (bn) using Flores-101 test. Furthermore, we assess the effect of new tokens using several metrics: fertility, the cosine similarity with English sentence embeddings, the performance in the English language retrieval translation task (R@1), and the distribution shift of the original embedding vector. Our experiments demonstrate that the inclusion of new words significantly complicates the learning process, underscoring that the integration of new words is a complex task.

detailed analysis, refer to the discussions on the selection of multi-hop translation in the lexicon (see Appendix E) and the format of parallel data during continual pre-training (see Appendix F).

2.1 Existing Vocabulary is Adequate.

Setting. We conduct a series of analytical experiments on the LLaMA2 vocabulary. Our initial focus is on examining the correlation between fertility and the quality of token representation. Here, fertility refers to the ratio of the length of the token sequence produced by the LLaMA2 tokenizer to the length of the input sentence when split by spaces (Chinese and Japanese is split by character). Furthermore, we carry out experiments using 10,000 en→ro and en→bn bilingual sentence pairs from Lego-MT dataset. For new tokens, the BBPE algorithm is executed on language-specific data from MADLAD-400 to produce a vocabulary of 100,000 tokens. Within this vocabulary, language-specific tokens are arranged based on their frequency in the corpus. Subsequently, we identify the top-k tokens (where k is determined by the corresponding "#New Token" in Table 1) that are absent in the original LLaMA vocabulary and incorporate them as new tokens into the LLaMA vocabulary. In each experiment, we introduce a varying number of language-specific new tokens and evaluate each model on the Flores-101.

Research Question 1: Why is adding new tokens considered a straightforward method for extending language support? We assess the quality of representation by en→X translation task. This task identifies the translated result that best aligns with the corresponding English sentence within an extensive target dataset, and evaluates with Recall at top 1, denoted as R@1 (Kabir and Carpuat, 2021). A higher R@1 value signifies a more robust quality of the representation. Concurrently, we present the cosine similarity of representations generated by LLaMA2 for identical sentences in English and other languages. On experiments across 102 languages, more details in Appendix C, there exists a strong correlation between fertility and the quality of representation, evidenced by a Spearman correlation coefficient of approximately **-0.88** for each assessed quality metric.

Research Question 2: Does adding new tokens to reduce fertility yield prompt performance improvements? Extending vocabulary is a common method to reduce fertility. However, while adding new tokens indeed reduces fertility, it does not necessarily enhance its ability to capture and generalize linguistic patterns across multiple languages. As shown in Table 1, the more new tokens added, the worse the translation performance.

Research Question 3: What is the impact of adding new tokens on model performance? As demonstrated in Table 1, even the addition of a small number (100) of new language-specific tokens can have a significant impact on the multilingual performance of LLMs. In addition, we conduct a further analysis on the original tokens (32k) embedding distribution and the token number before and after adding new tokens by KS-Lottery (Yuan et al., 2024a). For more details on KS-Lottery, refer to Appendix D. As the experimental result of "shift distance" and "# shift token" in Tabel 1, fine-tuning the entire model with limited new tokens follows a similar pattern to that with the original vocabulary. However, an excessive number of new tokens can shift the model's training focus. This holds true regardless of whether the

Setting	spBLEU MUSE	spBLEU PanLex	spBLEU Δ	# entity MUSE	# entity PanLex	# entity Δ	# entity ratio	similarity MUSE	similarity PanLex	similarity Δ
en→ta	3.74	3.45	-0.29	139,134	91,652	-47,482	0.66	0.08	0.04	-0.04
en→th	5.45	6.14	0.69	21,567	297,573	276,006	13.80	0.20	0.06	-0.14
en→fr	44.03	43.85	-0.18	139,134	568,428	429,294	4.09	0.31	0.35	0.04
en→zh	14.65	16.64	1.99	139134	1,333,762	1,194,628	9.59	0.14	0.09	-0.05
en→es	26.98	27.36	0.38	142,780	433,468	290,688	3.04	0.28	0.32	0.04

Table 2: Evaluate a specific data augmentation technique with different dictionaries. We measure translation performance (spBLEU), the number of target language entities in the dictionary (# entity), and average cosine similarity of entities (similarity), revealing a strong correlation between performance and "# entity".

language (ro) is well-supported by the model or not (bn). The influence of these additional tokens is substantial, indicating that the process of enhancing the multilingual capabilities of LLMs is not as straightforward as simply expanding the vocabulary and training with more multilingual data.

Finding: The original vocabulary suffices to present the multilingualism of LLMs. The LLaMA tokenizer, which utilizes the Byte-level Byte Pair Encoding (BBPE; Wang et al., 2019) algorithm, is the foundation for multilingual language processing tasks. Its universal compatibility across all languages, in conjunction with the absence of the requirement for an "unknown" token, optimizes vocabulary sharing (Yuan et al., 2024b) and improves its robustness. It allows the model to understand/generate responses in various languages using the same vocabulary. Meanwhile, studies have shown that LLMs trained on unbalanced English-centric datasets, often use English as an internal pivot language. This helps LLMs to map the inputs closer to English in internal space before generating the output (Zhu et al., 2024a; Huang et al., 2024b; Yoon et al., 2024). Maintaining the original vocabulary helps to preserve this behavior, which also benefits for improving the multilingual capability.

2.2 Data Augmentation

Setting. Given a parallel dataset subset ($\mathcal{D}_{\mathrm{P}}$) from $\mathcal{D}^{A}_{\mathrm{para}}$ that contains translations in all directions for 6 languages (en,fr,es,zh,ta,th) and a monolingual subset ($\mathcal{D}_{\mathrm{M}}$) from $\mathcal{D}^{A}_{\mathrm{mono}}$ for the same 6 languages. We then perform non-repetitive sampling 12,500 sentence pairs from $\mathcal{D}_{\mathrm{P}}$ in each direction to generate two subsets of parallel corpus data $\mathcal{D}_{\mathrm{P}_1}$ and $\mathcal{D}_{\mathrm{P}_2}$, respectively. Consequently, we preserve $\mathcal{D}_{\mathrm{P}_1}$ and evaluate the effect of augmentation on parallel data $\mathcal{D}_{\mathrm{P}_2}$ or monolingual data $\mathcal{D}_{\mathrm{M}}$, resulting in two new dataset, $\mathcal{D}'_{\mathrm{P}_2}$ and $\mathcal{D}'_{\mathrm{M}}$, post-augmentation. To assess both the in-domain and out-of-domain capabilities of the model, we perform inference on it using 10 languages (en, fr, es, pt, de, zh, ta, th, is, zu), utilizing the Flores-101.

Finding: The choice of dictionary is related to the number of entities in the dictionary. As shown in Table 2, there is no clear dictionary preference is observed for en/ta/th/zh-centric translation, with optimal performance randomly distributed across the two dictionaries. Furthermore, we conduct an in-depth analysis of the MUSE and PanLex dictionary for translation from en to another 5 languages. We compare the end-to-end translation performance (spBLEU), the number of target language entities in the dictionary (# entity), and the similarity of entities embedding (simple average with entity token embeddings) extracted from the trained model. And find a clear correlation between the translation performance and #entity.

3 Training Data Construction

To build powerful LLMs that support translation across a hundred languages, it is crucial to collect and construct a sufficient amount of data.

3.1 Components of Training Data

During the continual pertaining stage, the collected training data covering 102 languages (refer to A, which are all languages supported by Flores-101), mainly consists of two parts: monolingual ($\mathcal{D}^{A}_{\mathrm{mono}}$) and parallel ($\mathcal{D}^{A}_{\mathrm{para}}$) data. For languages with limited data availability, we generated a pseudo-parallel dataset ($\mathcal{D}_{\mathrm{aug}}$) with multilingual dictionaries: MUSE (Lample et al., 2018) and PanLex (Wang et al., 2022). The whole continual pretraining utilizes over 64 billion tokens. More details on supported languages, dataset description, and data statistics can be found in the Appendix A.

Monolingual Data ($\mathcal{D}^{A}_{\mathrm{mono}}$). Our monolingual training data includes 94 languages supported by

Algorithm 1: Illustration of the Training Data Construction Process During a Single Training Epoch

Input: A: all language list. $\mathcal{D}^A_{\text{mono}}$: monolingual data for all languages. $\mathcal{D}_{\text{En}}$: an English monolingual data. $\mathcal{D}^A_{\text{para}}$: a parallel data for all translation directions. Notably, $\mathcal{D}^A_{\text{mono}} \bigcap \mathcal{D}_{\text{En}} = \varnothing$. $\boldsymbol{x}$: a single data point. $g(\boldsymbol{x};\boldsymbol{\varphi})$: A translation model with parameter $\boldsymbol{\varphi}$. In a parallel sentence pair, s represents the language of the source sentence, and t represents the language of the target sentence. $f(\boldsymbol{x};\boldsymbol{\theta})$: a large language model with parameter $\boldsymbol{\theta}$. $h(\boldsymbol{x}, z)$: augmentation function h enhances input sentence $\boldsymbol{x}$ using the dictionary z.

Output: $\mathcal{D}_{\text{train}}$: a training dataset for current training epoch.

```
D_train = {}
for s ∈ A do
    D^s_mono ⊂ D^A_mono // Extract a s-specific monolingual subset
    for t ∈ A do
        D_para ← D^{s→t}_para ∪ D^{t→s}_para
        D^s_para ⊂ D_para // Extract the s-centric parallel subset
        if |D^s_para| < 25,000 then
            // The quantity of 25,000 determined by the machine's memory capacity
            D^s_En ⊂ D_En, s.t. |D^s_En| = 25,000 − |D^s_para| // Extract an English subset for s language
            D^{s→t}_En ← g(x; φ) or D^{t→s}_En ← g(x; φ), where x ∈ D^s_En
            D^{s→t}_aug ← h(x, z), where x ∈ D^{s→t}_En, or D^{t→s}_aug ← h(x, z), where x ∈ D^{t→s}_En
            D^s_aug ← D^{s→t}_aug ∪ D^{t→s}_aug
    end
    D_train ← D_train ∪ D^s_mono ∪ D^s_para ∪ D^s_aug
end
```

Flores-101 from MC4 (Xue et al., 2021) and MADLAD (Kudugunta et al., 2024), totaling 40,000,000 sentences. To ensure efficient handling and processing of the data, we use a strategy in which each piece of monolingual data is split into multiple entries, with a block size of 512.

Parallel Data ($\mathcal{D}^A_{\text{para}}$). Our parallel data from Lego-MT (Yuan et al., 2023) encompasses 102 languages, forming a total $4,737$ language pairs and $9,474$ translation directions. For each translation direction, denoted as source language (s) to target language (t), we concatenate each translation pair, merely using a space as a delimiter, to form a single entry for training data. For each language pair, the probability of occurrence for each translation direction, for example, $s \rightarrow t$ and $t \rightarrow s$ is set as 50%. During the training stage, the gradient is computed for the entire data entry, rather than only for the target sentence. For language pairs that have fewer than 25,000 (bound by machine resources) sentence pairs, we replicate the original data thrice (Muennighoff et al., 2023).

Data Generated Through Augmentation ($\mathcal{D}_{\text{aug}}$). The way which is followed by Pan et al. (2021), to obtain code-switch data consists of two steps: 1) build multilingual lexicons; 2) construct pseudo-parallel data. We show the data augmentation process in Figure 2.

Step 1: Building multilingual lexicons. The existing multilingual dictionaries, MUSE and PanLex, encompass multiple bilingual dictionaries, such as

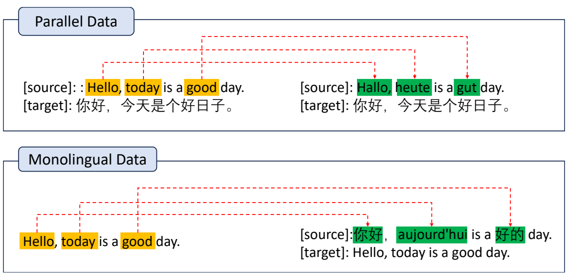

Figure 2: A case illustrating the detailed process of constructing pseudo-parallel data using multilingual dictionary from monolingual or parallel data sources.

en-fr, en-de, en-zh bilingual dictionaries. A dictionary comprises numerous entries, each being a word or a term defined, usage, and provided with other relevant information. We iterate through each entry in the bilingual dictionary, reformat all entries, and create entries in the format of *{entity}_{language}*. For instance, the English word "hello" as translation in three bilingual dictionaries (en-fr, en-de, en-zh), leading us to construct a multilingual lexicons entry as *hello_en, Bonjour_fr, Hallo_de, 你好_zh*.

Step 2: Constructing pseudo-parallel data. The foundational data for construction can be based on either parallel or monolingual data, as shown in Figure 2. For each sentence, we convert it to lowercase and subsequently divide it into multiple words using spaces (for Chinese sentences, the Jieba tokenizer is utilized). In parallel data processing, words in a source sentence are randomly replaced

System	Size	en-X		zh-X		de-X		ne-X		ar-X		az-X		ceb-X	
		COMET	BLEU	COMET	BLEU	COMET	BLEU	COMET	BLEU	COMET	BLEU	COMET	BLEU	COMET	BLEU
Encoder-Decoder Models															
M2M-100* (Fan et al., 2021)	418M	63.76	17.26	61.41	10.13	61.62	14.10	46.98	4.03	59.97	11.52	45.75	4.17	44.23	6.13
M2M-100* (Fan et al., 2021)	1.2B	70.00	21.54	67.29	13.13	67.62	17.73	56.04	7.14	62.62	12.57	52.39	6.06	52.79	9.46
M2M-100* (Fan et al., 2021)	12B	74.19	24.74	71.56	14.91	72.07	20.34	62.19	9.68	68.91	16.36	54.78	6.24	60.09	12.48
Lego-MT* (Yuan et al., 2023)	1.2B	69.49	24.96	68.23	16.28	69.20	21.42	68.37	16.98	65.57	18.38	65.69	13.51	58.21	16.83
NLLB-200 (Team et al., 2022)	1.3B	81.69	31.77	78.05	19.61	79.49	25.99	81.63	23.65	78.66	24.32	78.46	19.18	76.50	23.71
MADLAD-400 (Kudugunta et al., 2024)	7B	77.79	29.19	74.07	18.23	74.73	23.15	72.74	17.74	74.53	22.14	61.29	9.92	64.44	15.29
Aya-101 (Üstün et al., 2024)	13B	77.26	24.30	75.29	15.50	76.17	20.86	77.78	18.65	74.82	18.44	75.36	15.46	71.90	18.76
LLM based Decoder-Only Models															
LLaMA2 (Touvron et al., 2023b)	7B	43.95	4.21	44.62	0.91	45.26	2.14	38.22	0.39	39.43	0.54	47.43	0.68	33.50	1.49
LLaMA2 (Touvron et al., 2023b)	13B	31.37	0.24	34.91	0.25	31.22	0.10	35.32	0.21	32.34	0.11	36.03	0.17	30.84	0.17
LLaMA3 (AI@Meta, 2024)	8B	45.04	3.84	45.14	3.50	42.11	3.27	44.15	2.65	39.36	2.36	43.00	1.86	36.06	2.43
LLaMA2-Alpaca (Taori et al., 2023)	7B	52.83	9.44	51.29	3.80	51.47	6.82	46.59	1.31	46.76	2.84	48.63	1.36	41.02	2.69
LLaMA2-Alpaca (Taori et al., 2023)	13B	57.16	11.85	53.93	6.25	54.70	9.42	51.47	3.11	50.73	5.23	50.68	2.74	47.86	4.96
LLaMA3-Alpaca (Taori et al., 2023)	8B	67.97	17.23	64.65	10.14	64.67	13.62	62.95	7.96	63.45	11.27	60.61	6.98	55.26	8.52
PolyLM (Wei et al., 2023)	13B	45.16	5.72	52.41	1.42	47.89	3.59	38.00	0.45	45.82	1.04	38.65	0.57	29.74	0.77
Yayi2 (Luo et al., 2023)	30B	54.13	7.80	55.23	4.38	56.48	4.72	47.88	0.92	49.45	1.73	53.06	1.23	36.75	1.87
TowerInstruct (Alves et al., 2024)	7B	58.69	9.41	57.75	4.15	58.31	6.79	51.42	2.07	50.76	3.35	48.01	1.79	41.69	3.36
Aya-23 (Aryabumi et al., 2024)	8B	57.91	11.18	56.65	7.20	55.69	9.30	51.78	3.50	55.49	8.00	51.45	3.27	44.14	4.24
Qwen2-Instruct (Bai et al., 2023)	7B	59.64	9.61	59.70	6.84	57.44	7.69	58.62	4.40	57.22	6.35	54.49	3.83	49.61	3.76
ChineseLLaMA2-Alpaca (Cui et al., 2024)	7B	-	-	49.72	2.31	-	-	-	-	-	-	-	-	-	-
LLaMAX2-Alpaca	7B	**76.66**	**23.17**	**73.54**	14.17	**73.82**	**18.96**	74.64	14.49	72.00	15.82	70.91	11.34	68.67	15.53
LLaMAX3-Alpaca	8B	75.52	22.77	73.16	**14.43**	73.47	18.95	**75.13**	**15.32**	**72.29**	**16.42**	**72.06**	**12.41**	**68.88**	**15.85**

System	Size	X-en		X-zh		X-de		X-ne		X-ar		X-az		X-ceb	
		COMET	BLEU	COMET	BLEU	COMET	BLEU	COMET	BLEU	COMET	BLEU	COMET	BLEU	COMET	BLEU
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NLLB-200 (Team et al., 2022)	1.3B	84.22	38.60	76.75	15.27	79.50	25.71	73.70	21.84	79.85	21.80	80.02	15.55	69.05	24.72
MADLAD-400 (Kudugunta et al., 2024)	7B	83.05	38.14	78.49	20.48	77.50	26.79	61.94	13.93	77.84	22.25	75.41	13.85	51.33	4.24
Aya-101 (Üstün et al., 2024)	13B	80.72	31.92	78.51	22.49	77.37	15.43	69.69	17.13	77.90	16.54	78.70	13.51	67.76	21.58
LLM Based Decoder-Only Models															
LLaMA2 (Touvron et al., 2023b)	7B	55.46	11.80	43.50	0.55	43.10	3.22	34.41	0.42	39.13	0.25	43.98	0.59	41.64	1.16
LLaMA2 (Touvron et al., 2023b)	13B	38.25	0.75	37.06	0.22	31.73	0.25	30.13	0.15	33.68	0.06	33.47	0.08	37.49	0.20
LLaMA3 (AI@Meta, 2024)	8B	67.66	19.81	42.52	1.37	49.42	6.61	33.38	0.52	34.12	0.49	37.27	0.79	37.97	1.41
LLaMA2-Alpaca (Taori et al., 2023)	7B	65.85	16.44	56.53	4.46	56.76	9.01	34.96	1.03	44.10	2.18	40.67	0.63	45.69	1.73
LLaMA2-Aplaca (Taori et al., 2023)	13B	68.72	19.69	64.46	8.80	62.86	12.57	38.88	2.16	52.08	4.48	41.18	0.87	48.47	2.51
LLaMA3-Alpaca (Taori et al., 2023)	8B	77.43	26.55	73.56	13.17	71.59	16.82	46.56	3.83	66.49	10.20	58.30	4.81	52.68	4.18
PolyLM (Wei et al., 2023)	13B	50.98	7.75	42.60	1.20	43.95	3.69	33.69	0.36	42.27	1.67	40.24	0.44	39.29	0.96
Yayi2 (Luo et al., 2023)	30B	68.06	19.37	57.81	6.07	53.82	5.62	40.95	0.48	46.61	0.52	49.29	0.71	45.50	1.71
TowerInstruct (Alves et al., 2024)	7B	65.37	18.87	64.26	10.37	60.73	12.81	38.80	0.62	44.72	0.39	47.17	0.71	47.15	2.24
Aya-23 (Aryabumi et al., 2024)	8B	67.53	20.57	66.11	11.20	63.09	14.09	44.33	2.69	63.59	11.84	46.97	1.19	45.17	2.29
Qwen2-Instruct (Bai et al., 2023)	7B	73.25	19.04	72.52	13.52	64.61	11.33	41.41	2.27	64.94	8.50	47.96	1.66	55.45	3.00
ChineseLLaMA2-Alpaca (Cui et al., 2024)	7B	-	-	55.06	6.15	-	-	-	-	-	-	-	-	-	-
LLaMAX2-Alpaca	7B	80.55	30.63	75.52	13.53	74.47	19.26	**67.36**	**15.47**	75.40	15.32	**72.03**	**10.27**	**65.05**	**16.11**
LLaMAX3-Alpaca	8B	**81.28**	**31.85**	**78.34**	**16.46**	**76.23**	**20.64**	65.83	14.16	**75.84**	**15.45**	70.61	9.32	63.35	12.66

Table 3: Comparison with different architecture, including **encoder-decoder** and **decoder-only** models, on Flores-101 dataset, where X refers to any language in 101 languages. * refers to that model comparisons are restricted to 85 languages, denoted as |X| = 85. We make this choice because the M2M-100 baselines cover only 86 languages, as reported in the work by Flores-101 (Goyal et al., 2022; Yuan et al., 2023). This table compares our instruction-aligned LLaMAX2 model (LLaMAX2-Alpaca) with the instruction-aligned LLaMA2 model (LLaMA2-Alpaca) to demonstrate the benefits of our multilingual continual pre-training. Additionally, we compare LLaMAX with other open-source multilingual-focus LLMs to highlight the impressive multilingual capabilities.

System	Size	TED (en-X)		TED (X-en)		TICO (en-X)		WMT23 (en-X)		WMT23 (X-en)	
		COMET	BLEU	COMET	BLEU	COMET	BLEU	COMET	BLEU	COMET	BLEU
LLaMA2 (Touvron et al., 2023b)	7B	52.15	3.34	61.54	8.66	39.63	3.45	51.55	2.96	65.68	14.87
LLaMA2 (Touvron et al., 2023b)	13B	34.66	0.17	40.87	0.49	31.65	0.42	33.74	0.43	41.18	0.85
LLaMA3 (AI@Meta, 2024)	8B	44.72	2.09	53.56	6.04	40.02	4.82	47.44	2.61	55.18	7.84
LLaMA2-Alpaca (Taori et al., 2023)	7B	62.04	9.15	68.62	12.67	44.73	8.60	73.17	17.23	75.82	24.97
LLaMA2-Alpaca (Taori et al., 2023)	13B	65.62	11.40	70.74	14.54	48.64	10.79	77.93	21.60	77.90	28.67
LLaMA3-Alpaca (Taori et al., 2023)	8B	73.20	14.13	75.03	16.83	56.73	14.49	80.05	24.11	79.22	29.76
PolyLM (Wei et al., 2023)	13B	50.18	5.53	55.16	7.28	40.36	7.17	62.67	10.62	69.15	19.09
Yayi2 (Luo et al., 2023)	30B	61.53	8.54	70.92	14.09	47.02	7.91	65.69	10.76	75.60	20.47
TowerInstruct (Alves et al., 2024)	7B	64.83	8.22	70.91	15.29	50.48	10.14	74.03	18.42	80.08	30.03
Qwen2-Instruct (Bai et al., 2023)	7B	66.68	8.84	71.83	13.37	55.16	11.47	75.11	18.86	77.48	25.61
Aya-23 (Aryabumi et al., 2024)	8B	68.06	10.69	72.87	16.44	52.44	12.98	**83.29**	**27.15**	**82.00**	**31.21**
LLaMAX2-Alpaca	7B	**75.58**	**16.12**	76.18	17.81	**68.33**	19.79	80.17	23.91	79.55	30.30
LLaMAX3-Alpaca	8B	74.95	15.15	**76.99**	**18.47**	67.71	**20.06**	79.96	24.49	79.88	30.34

Table 4: Benchmarking results on WMT23, TED and TICO dataset. X denotes various languages across different translation benchmarks; detailed information is available in Appendix A. Evaluation results across these benchmarks further validate the strong multilingual translation capabilities of LLaMAX.

	Knowledge			Commonsense Reasoning		Math Reasoning		Code		Avg.
	MMLU	BBH	NQ	HellaSwag	Winogrande	GSM8K	Math	HumanEval	MBPP	
LLaMA2-Alpaca	44.22	37.95	24.32	31.12	61.09	14.03	3.82	14.63	27.63	28.76
LLaMAX2-Alpaca	44.60	38.25	23.21	33.75	61.48	12.21	3.74	12.20	25.29	28.30

Table 5: Evaluation results, assessed by OpenCompass (Contributors, 2023), on monolingual general benchmarks.

with translation from a different language using the multilingual dictionary created in Step 1. During the training, the loss is computed solely on the target sentence. In monolingual data processing, each word is individually replaced with a randomly chosen word from the multilingual dictionary. If no suitable replacement word in another language is found, the original word remains unchanged. Consequently, the modified sentence and the original sentence can form pseudo-parallel data. During the training, the loss is computed solely on both the source and the target sentence.

3.2 Training Algorithm.

Given an LLM $f(\boldsymbol{x};\boldsymbol{\theta})$ on a collected training data $\{\boldsymbol{x}^{(i)}\}_{i=1}^{n}$, where $\boldsymbol{\theta}$ is the pre-trained parameters, our objective is to obtain an LLM through continual pre-training, denoted as $f(\boldsymbol{x};\boldsymbol{\theta}')$. Here, $\boldsymbol{\theta}'$ indicates the updated parameters. The target of $f(\boldsymbol{x};\boldsymbol{\theta}')$ is to preserve the general capabilities of the model in high-resource languages while simultaneously enhancing the translation performance across all translation directions among 102 languages. The process of constructing training data is outlined in Algorithm 1. We gather monolingual data for each of the languages and parallel data for every translation direction. In particular, there is no augmentation for translations involving high-resource languages. Instead, we solely augment the translation data that is insufficient by utilizing a trained translation model, Lego-MT model. Then we train the $f(\boldsymbol{x};\boldsymbol{\theta})$, the loss function is:

$$\arg\max_{\boldsymbol{\theta}} \sum_{i=1}^{n}\sum_{t=1}^{T_i} \log f(x_t^{(i)}|\boldsymbol{x}_{<t}^{(i)};\boldsymbol{\theta}) \qquad (1)$$

where T is the total decoding time step.

After continual pre-training, we perform instruction tuning on **LLaMAX** using Alpaca (Taori et al., 2023), a dataset comprising 52,000 English instruction examples. This process enhances the model's capability to comprehend and follow instructions without introducing additional multilingual information, resulting in **LLaMAX-Alpaca**. We are currently using Alpaca to enhance the model's capacity for instruction following. In the future, we will release a more robust instruction model fine-tuned with a multilingual instruction dataset.

4 Benchmarking Results

In this section, we present multilingual benchmarking results to comprehensively demonstrate the potential of LLaMAX2. We evaluate translation quality with spBLEU (Goyal et al., 2022) and COMET-22 (Rei et al., 2020) for both LLMs and translation models. See Appendix B for training details on LLaMAX2 and description of baseline models.

We significantly enhances the multilingual translation capabilities of the base LLaMA2 model through massive multilingual continual pre-training. The benefits of our continual pre-training is enhancing the base LLM's multilingual translation capabilities. Evaluation results on Flores-101 benchmark are shown in Table 3. By comparing our multilingual-enhanced model with the base LLaMA2 model in instruction-tuned versions (LLaMAX2-Alpaca vs. LLaMA2-Alpaca), we consistently observe a significant performance improvement on both English-centric and non-English-centric translation. In addition to Flores-101, we also make evaluation on a range of diverse translation benchmarks (Table 4). The performance enhancement brought by our multilingual continual pre-training is consistent across these benchmarks.

LLaMAX outperforms other open-source decoder-only LLMs on multilingual translation by a large margin. Next, we compare LLaMAX2-Alpaca model with other open-source decoder-only LLMs built for multilingual purposes (Table 3, Table 4). Compared to other from-scratch trained LLMs, such as PolyLM, Yayi2, LLaMAX2 consistently shows better performance across various multilingual translation benchmarks, indicating that the LLaMA2 base model provides a strong foundation for language extension. Furthermore, when compared to other LLaMA-based continual pre-trained models, such as TowerInstruct, LLaMAX2 also achieves superior performance, demonstrating the effectiveness of our optimized continual pre-training pipeline.

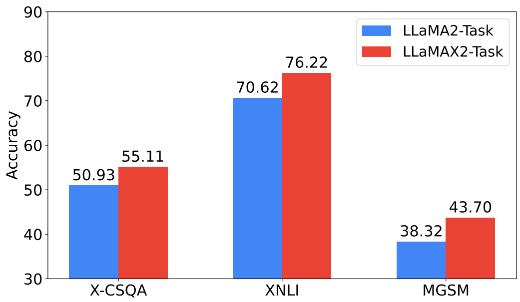

Figure 3: Comparison results between instruction-tuning our multilingual enhanced model and the base model with specialized instruction data. We take X-CSQA, XNLI, MGSM as three examples tasks.

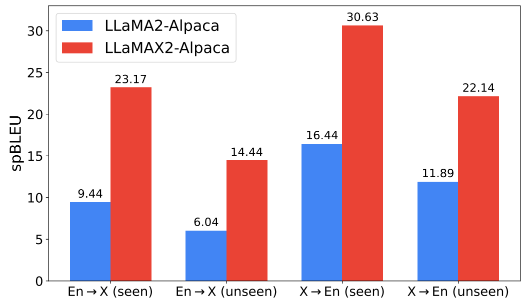

Figure 4: Comparison results between LLaMAX2-Alpaca and LLaMA2-Alpaca on Flores-200. Some non-English languages are not covered in Flores-200, but LLaMAX2 also boosts its translation performance.

LLaMAX benefits unseen long-tail low-resource languages as well. A significant challenge in multilingual enhancement is that the substantial cost of collecting scarce multilingual resources makes it prohibitive to cover massive languages. While our multilingual pre-training corpus already covers 102 languages, we acknowledge that there remains a large group of long-tail, low-resource languages that are not well covered. To assess the generalization capability of LLaMAX2, we evaluate it on Flores-200 dataset and observe its performance on these unseen languages (Figure 4). We find that for languages not encountered during training, LLaMAX2 still achieves significant improvements, demonstrating the generalization capability of our massive continual pre-training.

LLaMAX is closing the performance gap between open-source LLM translator and specialized encoder-decoder translation systems. While LLaMAX2 has achieved the state-of-the-art translation performance among open-source decoder-only LLMs, the next critical question is whether we can close the gap between LLMs and specialized encoder-decoder translation systems. Table 3 provides a comprehensive comparison, reveals LLaMAX2 has reached the level of the M2M-100-12B model. Future work will be needed to optimize the language extension framework to match the performance of advanced translation systems.

LLaMAX provides a better starting point for specialized instruction-tuning on English task data. In the end, we demonstrate the usage of our continual pre-trained model (LLaMAX2) on tasks beyond translation. While in previous experiments we use basic Alpaca instruction data to teach LLM to follow translation instructions, we now show that our released checkpoint can be enpowered to handle more multilingual tasks beyond translation. Figure 3 presents three example tasks where we use specialized instruction data to unlock LLaMAX2's abilities on specific tasks, such as math reasoning and common sense reasoning. We find that the instruction-tuned LLaMAX2 model outperforms its LLaMA2 model counterpart in non-English performance across all three tasks, demonstrating that provides a better starting point for instruction-tuning with task-specific data.

LLaMAX circumvents catastrophic forgetting issue. A common concern with continual pre-training on additional multilingual corpus is that the process might disturb the parametric knowledge and working pattern of the original model, a phenomenon known as catastrophic forgetting (Goodfellow et al., 2013). Furthermore, we compare LLaMAX2 with LLaMA2 on popular English benchmarks that measure a diverse set of core capabilities of LLMs. Experiment results in Table 5 show that the two models achieve very similar performance on these benchmarks (More details about these benchmarks are in Appendix A.), demonstrating that our continual pre-training does not compromise the general capability of the base model.

Beyond the English-centric translation is more efficient and effective. We further investigate the necessity and feasibility of multilingual augmentation for an English-centric LLM. We can effectively transform a translation task (src→trg) from the source language (src) to the target language (trg) into src→en and en→trg, which allows us to leverage the power of English as a central language, facilitating seamless communication and comprehension across various language

Direct	spBLEU				COMET			
	LLaMA3-Alpaca		LLaMAX2-Alpaca		LLaMA3-Alpaca		LLaMAX2-Alpaca	
	src→trg	src→en→trg	src→trg	src→en→trg	src→trg	src→en→trg	src→trg	src→en→trg
zh→X	10.14	11.34	14.17	**15.54**	64.65	66.61	73.54	**74.74**
X→zh	13.17	**15.37**	13.53	15.11	73.56	75.66	75.52	**77.21**
de→X	13.62	14.24	18.96	**19.38**	64.67	65.79	73.82	**74.36**
X→de	16.82	18.08	19.26	**20.71**	71.59	73.11	74.47	**76.04**
ar→X	11.27	12.60	15.82	**17.10**	63.45	65.33	72.00	**73.17**
X→ar	10.20	10.88	15.32	**16.00**	66.49	69.54	75.40	**76.32**
ne→X	7.96	10.29	14.49	**16.16**	62.95	67.87	74.64	**76.86**
X→ne	3.83	7.08	15.47	**16.86**	46.56	58.89	67.36	**69.47**
az→X	6.98	9.52	11.34	**13.54**	60.61	65.16	70.91	**73.60**
X→az	4.81	6.96	10.27	**11.44**	58.30	67.52	72.03	**75.60**
ceb→X	8.52	10.69	15.53	**16.98**	55.26	60.71	68.67	**70.76**
X→ceb	4.18	7.17	16.11	**18.94**	52.68	59.55	65.05	**66.52**
Avg.	9.29	11.19	15.02	**16.48**	61.73	66.31	71.95	**73.72**

Table 6: We can convert a translation task from the source language (src) to the target language (trg), represented as src→trg, to src→en→trg. The experimental results indicate that the performance of English as a powerful pivot falls short compared to LLaMAX2-Alpaca (LLaMA3 pivot translation vs. LLaMAX2-Alpaca). Furthermore, conducting similar pivot translation experiments on LLaMAX2-Alpaca can further improve translation performance.

pairs. We refer to this experimental setup as a pivot translation experiment. As shown in Table 6, the experimental results demonstrate that the pivot translation experiments effectively leverage the power of English to enhance translation performance (compared src→en→trg to src→trg on the same model), although it still falls short of the results obtained from large-scale multilingual continual pre-trained models (LLaMA3-Alpaca src→en→trg vs. LLaMAX2-Alpaca src→trg). Interestingly, conducting pivot translation experiments based on LLaMAX2-Alpaca reveals the potential for significant improvements in translation performance (LLaMAX2-Alpaca src→en→trg vs. LLaMAX2-Alpaca src→trg).

5 Related Work

Multilingual Large Language Models. Large Language Model (LLMs; OpenAI, 2023; Zhang et al., 2022; Brown et al., 2020; Chowdhery et al., 2022; Touvron et al., 2023a,b) trained with English-centric data can also solve various non-English tasks (Hendrycks et al., 2021a,b; Srivastava et al., 2022; Kwiatkowski et al., 2019; Hendrycks et al., 2021c), but the performance between non-English and English is significantly large (Yuan et al., 2024b). Efforts to develop more multilingual LLMs in two different ways: retraining LLMs with diverse multilingual data from scratch (Wei et al., 2023); or continuous training of pre-trained models using language-specific data with the option to expand the vocabulary (Zhao et al., 2024a; Cui et al., 2024; Faysse et al., 2024; Alves et al., 2024). Instead of training from scratch, continual pre-training aims at updating pre-trained models with new data, making the process more efficient and cost-effective (Gupta et al., 2023; Alves et al., 2024; Xie et al., 2023).

Multilinguality in LLMs. Recent research has shed light on the multilingual capabilities of LLMs. A comprehensive survey by Huang et al. (2024a) discusses various aspects of multilingualism in LLMs, including training and inference methods, model security, multi-domain with languages culture, and emphasizes the need for language-fai technology. Yuan et al. (2024b) analysis multilingualism of LLMs from the vocabulary sharing aspect. Zhao et al. (2024b) delve into the architecture of LLMs to find how LLMs handle multilingualism. Recently, Li et al. (2024) quantify the multilingual performance of LLMs. These studies provide valuable insights into the multilingual capabilities of LLMs, and the key technical design of continual pre-training for LLaMAX.

6 Conclusion

In this work, we enhance the series models of LLaMA translation performance for 102 languages through continual pre-training, creating LLaMAX. We compare LLaMAX 's translation capabilities with other decoder-only LLMs and encoder-decoder models across multiple benchmarks. LLaMAX is also assessed on general tasks and fine-tuned with task-specific instructions. Our results indicate that LLaMAX improves translation quality while maintaining general capabilities and can serve as a powerful foundation model for downstream multilingual applications.

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Limitations

This work focuses on the discussion of some key technologies, such as the use of vocabulary lists and the determination of data augmentation schemes. However, it does not delve into further processing of the quality of open-source data. We acknowledge a gap in the literature regarding the thorough evaluation of open-source data quality, suggesting an opportunity for future research to improve data preprocessing methods for better model training outcomes.

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Outline

- Section A: The comprehensive details of the training data, including monolingual and parallel data, and the evaluation benchmark (Table 7).
- Section B: The detailed information of different models, including open-source Large Language Models (Section B.1) and well-trained translation models (Section B.2).
- Section C: Analysis the correlation between embedding quality of LLaMA2 and fertility using Flores-101 test (Figure 5).
- Section D: A detailed introduction to the KS-Lottery method.
- Section E: Selection about multi-hop translation (Table 9 and Table 10).
- Section F: The selection of the appropriate format for parallel data during training (Table 11).
- Section G: The comparison of translation performance across all seven languages between Lego-MT and GPT-4 (Figure 6).
- Section H: Comparison results between LLaMAX2-Alpaca with language-specific enhanced LLMs (Table 13).
- Section I: We present comprehensive instructions utilized for all LLMs (Table 14).

A Data Information

In this section, we will introduce the sources of our training data (Section A.1), the evaluation benchmarks (Section A.2). For translation tasks, we apply beam search to each model with beam size=4.

A.1 Training Dataset

The dataset was compiled from three distinct open-source datasets, with details on supported languages presented in Table 7 and continual pre-training data statistics in Table 7 and Table 8.

MC4 (Xue et al., 2021) is a multilingual variant of the C4 dataset, comprising natural text in 101 languages sourced from the Common Crawl web scrape. It was introduced to support the training of massively multilingual pre-trained text-to-text transformers like mT5.

MADLAD-400 (Kudugunta et al., 2024) is a manually audited, general domain monolingual dataset based on CommonCrawl, encompassing 419 languages and designed for document-level analysis. It is notable for its extensive language coverage and the rigorous auditing process involved in its creation.

Lego-MT (Yuan et al., 2023) is a benchmark for massively multilingual machine translation, featuring a detachable model built upon an efficient training recipe. It includes a comprehensive translation benchmark with data from OPUS, covering 433 languages and 1.3 billion parallel data points.

A.2 Evaluation Benchmark

Flores-101 (Goyal et al., 2022) is a benchmark for machine translation evaluation, comprising a multi-way dataset derived from English Wikipedia and produced by professional translators.

Flores-200 (Team et al., 2022) is an extension of Flores-101 dataset and also serves as a benchmark for machine translation. This dataset contains parallel sentences for 200 languages, with each language identified by its ISO 639-3 code ((e.g. eng)) and an additional code (e.g., "eng_Latn",) that describes the script.

WMT-23 (Kocmi and Federmann, 2023) is also a comprehensive translation evaluation benchmark, proposed in 2023. We incorporate this dataset into

Family	ISO	Language	# Mono.	# Para.	# Direct.	Family	ISO	Language	# Mono.	# Para.	# Direct.
Afro-Asiatic	ha	Hausa	420,964	3,147,704	96	Indo-European	ne	Nepali	702,334	8,907,527	97
	om	Oromo	18,895	191,319	96		or	Odia	100,530	812,235	97
	so	Somali	697,864	3,804,551	97		pa	Punjabi	513,987	3,737,780	97
	am	Amharic	269,171	4,031,552	97		sd	Sindhi	472,217	821,996	95
	ar	Arabic	716,063	9,940,756	97		ur	Urdu	711,354	4,137,619	97
	he	Hebrew	300,000	3,928,938	96		fa	Persian	721,307	4,111,536	97
	mt	Maltese	671,716	1,518,533	94		ku	Kurdish	517,239	3,597,863	97
Austroasiatic	km	Khmer	687,690	4,044,652	97		ps	Pashto	588,340	3,717,480	97
	vi	Vietnamese	760,472	4,112,089	97		tg	Tajik	700,237	4,131,709	97
Austronesian	jv	Javanese	505,619	2,799,761	97		ast	Asturian	0	1,535,714	96
	id	Indonesian	707,962	4,243,235	97		ca	Catalan	724,597	4,145,004	97
	ms	Malay	711,895	4,121,713	97		es	Spanish	706,307	4,258,477	98
	mi	Maori	180,678	3,437702	97		fr	French	787,316	4,290,003	99
	ceb	Cebuano	418,058	2,217,926	91		gl	Galician	726,512	3,131,730	96
	tl	Tagalog	0	3,927,576	97		it	Italian	846,107	4,233,108	96
Dravidian	te	Telugu	708,459	4,219,702	97		oc	Occitan	36,379	1,752,951	95
	kn	Kannada	712,832	3,592,636	97		pt	Portuguese	795,818	4,258,604	97
	ml	Malayalam	715,387	4,516,012	97		ro	Romanian	702,002	4,219,414	97
	ta	Tamil	711,863	4,444,734	97	Japonic	ja	Japanese	726,455	4,207,728	97
Indo-European	hy	Armenian	712,835	3,677,780	97	Kartvelian	ka	Georgian	703,515	4,182,651	97
	lt	Lithuanian	718,382	3,946,735	96	Koreanic	ko	Korean	711,406	4,234,653	97
	lv	Latvian	700,889	4,011,628	97	Kra–Dai	lo	Lao	357,758	2,642,799	97
	be	Belarusian	708,288	4,169,719	95		th	Thai	707,719	4,437,476	97
	bg	Bulgarian	711,500	4,131,053	97	Mongolic	mn	Mongolian	701,304	3,894,353	97
	bs	Bosnian	300,000	2,953,912	97	Niger–Congo	wo	Wolof	871	802,521	97
	cs	Czech	711,179	4,135,944	97		ln	Lingala	3,325	159,684	96
	hr	Croatian	300,000	4,106,335	97		ns	Northern Sotho	0	96,288	88
	mk	Macedonian	702,035	4,009,787	97		lg	Luganda	13,030	216,135	95
	pl	Polish	792,829	4,200,001	98		ny	Nyanja	226,940	3,104,349	92
	ru	Russian	853,407	4,204,365	97		sn	Shona	386,588	3,140,063	97
	sk	Slovak	715,540	4,100,272	98		sw	Swahili	700,422	3,775,394	97
	sl	Slovenian	731,613	4,073,213	97		umb	Umbundu	0	54	2
	sr	Serbian	711,535	4,033,130	97		xh	Xhosa	122,720	3,955,426	97
	uk	Ukrainian	714,181	4,070,250	97		yo	Yoruba	98,281	3,364,040	96
	cy	Welsh	703,507	3,777,953	97		zu	Zulu	470,403	2,899,738	97
	ga	Irish	693,460	2,814,912	96		ig	Igbo	147,319	3,314,731	96
	is	Icelandic	704,159	4,088,886	97		kam	Kamba	0	8	1
	sv	Swedish	726,893	4,213,939	97		ff	Fulani	26	313,870	97
	da	Danish	721,543	4,194,587	97	Nilo-Saharan	luo	Dholuo	0	91	6
	no	Norwegian	721,715	4,045,571	97	Portuguese	kea	Kabuverdianu	0	0	0
	af	Afrikaans	703,546	4,143,358	98	Sino-Tibetan	zh	Chinese	726,112	14,215,583	96
	de	German	881,553	10,273,597	97		zhtrad	Chinese	0	3,747,297	96
	en	English	846,712	19,548,583	100		my	Burmese	579,160	3,887,841	97
	lb	Luxembourgish	574,166	1,035,619	94	Turkic	uz	Uzbek	723,096	2,344,375	95
	nl	Dutch	769,778	4,199,773	96		kk	Kazakh	701,849	3,836,259	97
	el	Greek	707,751	4,081,607	97		ky	Kyrgyz	704,438	3,725,583	97
	bn	Bengali	707,099	4,560,978	97		az	Azerbaijani	712,947	8,080,151	97
	as	Assamese	33,825	1,656,861	97		tr	Turkish	727,711	4,169,259	97
	gu	Gujarati	704,619	3,761,401	97	Uralic	et	Estonian	706,720	4,056,200	97
	hi	Hindi	715,691	4,186,127	97		fi	Finnish	719,416	40,76,885	97
	mr	Marathi	702,382	4,295,708	97		hu	Hungarian	731,479	4,154,132	97

Table 7: The detailed information of the collected monolingual and parallel datasets includes the translation directions for each supported language. Specifically, the "# Para." represents the count of language-centric sentence pairs, while "# Mono." denotes the number of individual monolingual sentences.

our evaluation to mitigate the risk of data leakage in LLMs. Based on benchmark, we evaluate the English-centric translation task performance, including de→en, en→cs, en→de, en→he, en→ja, en→ru, en→uk, en→zh, he→en, ja→en, ru→en, uk→en, zh→en.

TICO (Anastasopoulos et al., 2020) dataset represents a joint translation effort targeting COVID-19 materials, developed in collaboration with academic, industry stakeholders, and Translators without Borders. It comprises translation memories, a glossary of translated COVID-19 terms, and functions as a benchmark for translation-related evaluations. The all evaluated translation is en→{am, bn, din, fa, fuv, hi, km, ku, ln, ms, ne, om, ps, ru, so, ta, ti_ER, tl, zh, ar, ckb, es_LA, fr, ha, id, kr, lg, mr, my, nus, prs, pt_BR, rw, sw, ti, ti_ET, ur, zu}.

TED (Cettolo et al., 2012) is a massively multilingual dataset derived from TED Talk transcripts, covering 60 languages with parallel arrays of language and text. It is designed for natural language processing tasks and filters out missing or incomplete translations. We also evaluate the English-centric translation performance. The translation direction covers all 60 languages, including en↔{af, am, ar, arq, art-x-bork, as, ast, az, be, bg, bi, bn, bo,

ISO	# Para.	# Mono.	ISO	# Para.	# Mono.	ISO	# Para.	# Mono.	ISO	# Para.	# Mono.
af	201,367,199	360,215,552	hi	593,592,809	366,433,792	mn	332,967,182	359,067,648	tg	347,063,556	358,521,344
am	903,470,803	137,815,552	hr	212,708,153	153,600,000	mr	609,131,394	359,619,584	th	597,728,017	362,352,128
ar	1,054,714,212	366,624,256	hu	232,631,392	374,517,248	ms	234,113,298	364,490,240	tl	244,687,985	0
as	313,146,729	17,318,400	hy	579,250,350	364,971,520	mt	102,804,684	343,918,592	tr	272,252,613	372,588,032
ast	70,949,987	0	id	232,953,602	362,476,544	my	1,002,285,410	296,529,920	uk	218,572,425	365,660,672
az	654,492,231	365,028,864	ig	242,306,836	75,427,328	ne	1,237,255,500	359,595,008	umb	3,170	0
be	306,891,318	362,643,456	is	251,875,378	360,529,408	nl	193,189,558	394,126,336	ur	557,337,279	364,213,248
bg	229,686,547	364,288,000	it	195,146,279	433,206,784	no	190,141,837	369,518,080	uz	148,867,813	370,225,152
bn	755,297,957	362,034,688	ja	292,857,869	371,944,960	ns	6,056,515	0	vi	372,555,263	389,361,664
bs	155,671,162	153,600,000	jv	150,347,166	258,876,928	ny	194,642,682	116,193,280	wo	45,422,689	445,952
ca	196,058,689	370,993,664	ka	627,397,650	360,199,680	oc	91,504,042	18,626,048	xh	242,467,614	62,832,640
ceb	135,958,864	214,045,696	kam	477	0	om	13,239,275	9,674,240	yo	282,242,956	50,319,872
cs	218,791,438	364,123,648	kea	0	0	or	289,074,437	51,471,360	zh	878,523,029	371,769,344
cy	247,455,922	360,195,584	kk	299,995,454	359,346,688	pa	1,088,815,314	263,161,344	zhtrad	252,942,548	0
da	201,340,176	369,430,016	km	1,266,785,006	352,097,280	pl	223,440,053	405,928,448	zu	189,932,839	240,846,336
de	456,147,707	451,355,136	kn	1,198,503,370	364,969,984	ps	482,900,652	301,230,080			
el	629,383,799	362,368,512	ko	415,419,459	364,239,872	pt	189,507,878	407,458,816			
en	523,902,024	433,516,544	ku	494,346,376	264,826,368	ro	224,472,825	359,425,024			
es	193,760,704	361,629,184	ky	284,261,983	360,672,256	ru	213,581,742	436,944,384			
et	223,902,240	361,840,640	lb	58,408,912	293,972,992	sd	107,023,879	241,775,104			
fa	505,307,774	369,309,184	lg	12,860,033	6,671,360	sk	232,485,422	366,356,480			
ff	16,917,593	13,312	ln	8,942,304	1,702,400	sl	211,807,076	374,585,856			
fi	242,982,346	368,340,992	lo	932,379,487	183,172,096	sn	196,567,944	197,933,056			
fr	198,627,139	403,105,792	lt	231,673,345	367,811,584	so	255,665,827	357,306,368			
ga	190,006,560	355,051,520	luo	4,996	0	sr	217,789,020	364,305,920			
gl	145,312,272	371,974,144	lv	261,558,146	358,855,168	sv	190,891,437	372,169,216			
gu	1,157,006,948	360,764,928	mi	234,795,047	92,507,136	sw	218,972,852	358,616,064			
ha	185,399,766	215,533,568	mk	230,161,774	359,441,920	ta	805,830,274	364,473,856			
he	401,537,464	153,600,000	ml	773,141,254	366,278,144	te	1,387,859,988	362,731,008			

Table 8: The detailed information about the tokens used in the continual pre-training stage. The "# Para." shows the total tokens in the parallel dataset, and "# Mono." represents the total tokens in the monolingual dataset.

bs, ca, ceb, cnh, cs, da, de, el, eo, es, et, eu, fa, fi, fil, fr, fr-ca, ga, gl, gu, ha, he, hi, hr, ht, hu, hup, hy, id, ig, inh, is, it, ja, ka, kk, km, kn, ko, ku, ky, la, lb, lo, lt, ltg, lv, mg, mk, ml, mn, mr, ms, mt, my, nb, ne, nl, nn, oc, pa, pl, ps, pt, pt-br, ro, ru, rup, sh, si, sk, sl, so, sq, sr, srp, sv, sw, szl, ta, te, tg, th, tl, tlh, tr, tt, ug, uk, ur, uz, vi, zh, zh-cn, zh-tw}

X-CSQA (Lin et al., 2021a) is a multilingual extension of the Commonsense Question Answering (CSQA) dataset, designed for commonsense reasoning research. It facilitates the evaluation and improvement of multilingual language models in commonsense reasoning tasks.

XStoryCloze (Lin et al., 2021b) is a benchmark dataset that comprises the professionally translated English StoryCloze dataset (Spring 2016 version) into 10 non-English languages. It is designed to evaluate the zero- and few-shot learning capabilities of multilingual language models.

XCOPA (Ponti et al., 2020) is a benchmark dataset that assesses machine learning models' ability to transfer commonsense reasoning across languages. It is an extension of the English COPA dataset and includes 11 languages from diverse language families and geographical regions.

XWinograd (Muennighoff et al., 2022; Tikhonov and Ryabinin, 2021) s a benchmark dataset that consists of a multilingual collection of Winograd Schemas, designed for the evaluation of cross-lingual commonsense reasoning capabilities covering six languages.

XNLI (Conneau et al., 2018) is a cross-lingual extension of the SNLI (Bowman et al., 2015)/MultiNLI (Williams et al., 2018), consisting of a subset of English examples translated into 14 different languages. It is used for evaluating textual entailment and classification tasks, where the goal is to determine if one sentence implies, contradicts, or is neutral to another sentence

MGSM (Shi et al., 2023) a dataset of grade-school math problems, each translated into 10 languages by human annotators. It is derived from the GSM8K (Cobbe et al., 2021) dataset and is designed to support question answering on basic mathematical problems that require multi-step reasoning.

MMLU (Hendrycks et al., 2021a,b) is a benchmark for evaluating language models' capabilities in language comprehension and reasoning across diverse domains. It consists of about 16,000 multiple-choice questions spanning 57 academic

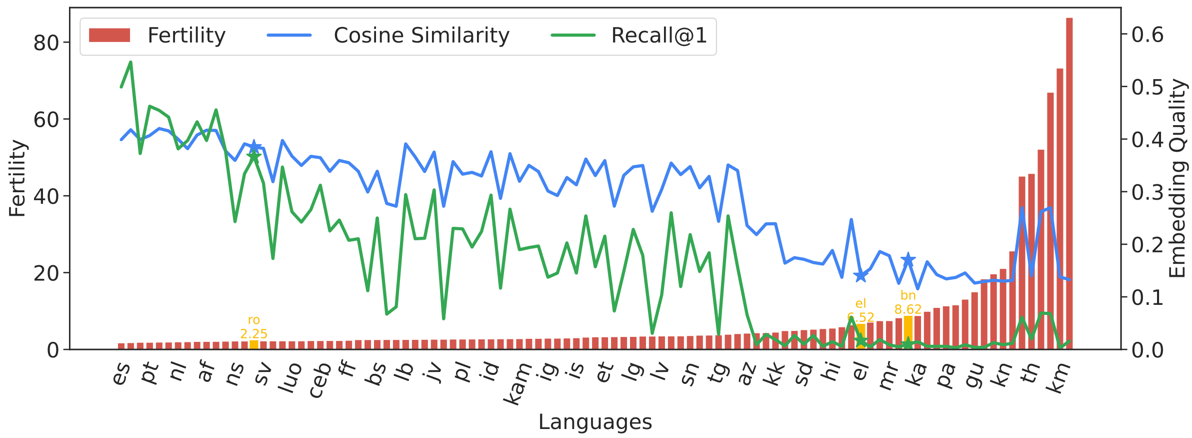

Figure 5: Correlation between embedding quality and fertility. The embedding quality of LLaMA2 is measured by cosine similarity and Recall@1 on Flores-101 test. Fertility refers to the ratio of the length of a sentence after tokenization compared to its length before tokenization. A high fertility may result in a poor quality of embedding.

subjects, designed to measure knowledge acquired during pretraining in zero-shot and few-shot settings.

BBH (**Srivastava et al., 2022**) is a subset of the BIG-Bench, focusing on 23 challenging tasks that current language models struggle to perform, where they do not outperform the average human-rater. It serves as a rigorous evaluation suite to test the limits of language models' capabilities.

HellaSwag (**Zellers et al., 2019**) s a dataset designed to evaluate advanced natural language understanding and common sense reasoning, which introduces more complexity and diversity, challenging AI models to predict the ending of incomplete narratives.

WinoG (**Sakaguchi et al., 2021**) is a large-scale dataset containing 44k problems inspired by the Winograd Schema Challenge, designed to improve the scale and hardness of coreference resolution tasks. It presents fill-in-the-blank questions with binary options, testing the model's ability to understand nuanced human language.

NQ (**Kwiatkowski et al., 2019**) is a dataset for question answering research, containing over 300,000 examples each consisting of a real user query and a corresponding Wikipedia page. It is designed to train and evaluate automatic question answering systems by emulating how people search for information.

HumanEval (**Chen et al., 2021**) is designed to evaluate the code generation capabilities of large language models, featuring 164 hand-crafted programming challenges that include function signatures, docstrings, bodies, and unit tests. On average, each problem is accompanied by 7.7 tests to assess functional correctness.

MBPP (**Austin et al., 2021**) comprises approximately 1,000 crowd-sourced Python programming problems, aimed at entry-level programmers and covering programming fundamentals and standard library functionality. Each problem includes a task description, code solution, and three automated test cases.

GSM8K (**Cobbe et al., 2021**) consists of 8.5K high-quality, linguistically diverse grade school math word problems created by human problem writers. It is designed to support question answering on basic mathematical problems that require multi-step reasoning.

Math (**Hendrycks et al., 2021c**) is a collection of 12,500 intricate problems derived from competition mathematics. Every problem within the Math dataset includes a comprehensive solution with step-by-step guidance, which serves as a resource for training models to produce detailed answer justifications and explanations.

B Model Information

Model details about the baseline models for comparison, including decode-only large language models (LLMs) in Section B.1 as well as translation models in Section B.2 with an encoder-decoder structure.

Setting	Aug	en-centric en→X	en-centric X→en	ta-centric ta→X	ta-centric X→ta	th-centric th→X	th-centric X→th	zh-centric zh→X	zh-centric X→zh
LLaMA2	✗	18.31	23.61	0.99	0.49	4.83	1.15	10.02	7.35
$\mathcal{D}_{\mathrm{P}_1}$	✗	19.06	25.98	3.20	0.91	7.66	3.13	11.32	7.83
$\mathcal{D}_{\mathrm{P}_1}$+$\mathcal{D}_{\mathrm{P}_2}$	✗	19.46	26.40	4.17	1.76	7.28	3.02	11.65	8.82
$\mathcal{D}_{\mathrm{P}_1}$+$\mathcal{D}_{\mathrm{M}}$	✗	19.22	25.91	3.51	1.34	7.64	2.83	11.56	7.99
$\mathcal{D}_{\mathrm{P}_1}$+$\mathcal{D}_{\mathrm{P}_2}$+$\mathcal{D}_{\mathrm{M}}$	✗	19.36	26.47	4.35	1.82	7.78	3.49	11.44	9.14
$\mathcal{D}_{\mathrm{P}_1}$+$\mathcal{D}'_{\mathrm{P}_2}$	✓	19.47	26.65	4.54	1.83	7.66	3.13	11.89	9.17
$\mathcal{D}_{\mathrm{P}_1}$+$\mathcal{D}'_{\mathrm{M}}$	✓	18.59	25.98	3.61	1.36	6.72	2.35	10.81	6.45
$\mathcal{D}_{\mathrm{P}_1}$+$\mathcal{D}'_{\mathrm{P}_2}$+$\mathcal{D}_{\mathrm{M}}$	✓	**19.70**	**26.71**	4.68	1.82	**8.21**	**3.65**	**12.05**	**9.28**
$\mathcal{D}_{\mathrm{P}_1}$+$\mathcal{D}_{\mathrm{P}_2}$+$\mathcal{D}'_{\mathrm{M}}$	✓	19.17	26.58	4.57	**1.95**	7.12	3.12	11.52	7.73
$\mathcal{D}_{\mathrm{P}_1}$+$\mathcal{D}'_{\mathrm{P}_2}$+$\mathcal{D}'_{\mathrm{M}}$	✓	18.80	26.56	**4.78**	1.79	7.31	3.18	11.35	7.28

Setting	Dictionary	en-centric en→x	en-centric x→en	ta-centric ta→x	ta-centric x→ta	th-centric th→x	th-centric x→th	zh-centric zh→x	zh-centric x→zh
$\mathcal{D}_{\mathrm{P}_1}$+$\mathcal{D}'_{\mathrm{P}_2}$+$\mathcal{D}'_{\mathrm{M}}$	MUSE: 1-hop	18.80	26.56	4.78	1.79	7.31	3.18	11.35	7.28
$\mathcal{D}_{\mathrm{P}_1}$+$\mathcal{D}'_{\mathrm{P}_2}$+$\mathcal{D}'_{\mathrm{M}}$	MUSE: 2-hop	18.70	26.50	4.47	1.83	7.08	3.26	10.74	6.68
$\mathcal{D}_{\mathrm{P}_1}$+$\mathcal{D}'_{\mathrm{P}_2}$+$\mathcal{D}'_{\mathrm{M}}$	PanLex: 1-hop	19.33	26.54	4.40	1.83	7.57	3.31	10.86	8.08

Table 9: A comprehensive analysis of data augmentation sources reveals that using a dictionary to augment parallel data alone improves translation performance. Each cell in the table refers to the average spBLEU score. “Aug” is a boolean representing whether a dictionary is used for augmentation. Meanwhile, we select a specific data augmentation technique and evaluate various dictionary configurations, including 1-hop and 2-hop, as well as different dictionaries.

1-hop translation Direction	1-hop translation Example	2-hop translation Direction	2-hop translation Example
en→fr fr→de	dog → chien chien → Hund	en→fr→de	dog → chien → Hund

Table 10: Case of 1-hop and 2-hop translations.

B.1 Large Language Models

LLaMA2 (Touvron et al., 2023b) is a decoder-only language model that predicts the next token based on the input sequence of ordered tokens, with a collection of pre-trained and fine-tuned models ranging from 7 billion to 70 billion parameters. The LLaMA2 7B model serves as our foundational model. Unless otherwise specified, any reference to LLaMA or LLaMA2 is the LLaMA2 7B model. The model leverages a Byte-level Byte Pair Encoding (BBPE; Wang et al., 2019) tokenizer, an efficient subword tokenizer that tokenizes at the byte level, allowing it to handle any language and be robust to noise in the data. The BBPE tokenizer is particularly useful for languages with large vocabularies and many rare words.

LLaMAX2 follows the model architecture of LLaMA2 without vocabulary extension. We utilize 24 A100 80GB GPUs and extended the pre-training on the amassed data for over 60 days. We set per device training batch size to 32, the learning rate to 2e-5, and the epoch number to 1.0.

PolyLM (Wei et al., 2023) is an open-source multilingual Large Language Model (LLM) trained on 640 billion tokens, available in two model sizes: 1.7B and 13B. It boasts proficiency in 15 major non-English languages, employing advanced training techniques to enhance its language processing capabilities.

Yayi2 (Luo et al., 2023) is a multilingual open-source Large Language Model pre-trained from scratch on a corpus containing 2.65 trillion tokens. It is aligned with human values through supervised fine-tuning and reinforce ment learning from human feedback.

TowerInstruct (Alves et al., 2024) is a 7B parameter language model fine-tuned on translation-related tasks, supporting multiple languages including English, Portuguese, Spanish, French, and others. It is designed for tasks such as machine translation, automatic post-editing, and paraphrase generation. In our paper, we evaluate the instruction-tuned model TowerInstruct-7B-v0.2.

Aya-23 (Aryabumi et al., 2024) is an open weights research release of an instruction fine-tuned decoder-only model with advanced multilingual capabilities, serving 23 languages. It pairs a performant pre-trained Command family of models with the Aya Collection for robust language processing tasks.

Setting	Translation Tasks		General Tasks			Multilingual Tasks		
	ceb→x	x→ceb	QNLI	QQP	MRPC	XStoryCloze	XCOPA	XWinograd
splited-parallel + mono	3.36	2.74	49.46	36.82	68.38	59.20	56.82	73.72
connected-parallel + mono	4.45	3.68	49.46	36.82	68.38	59.10	56.80	74.07
Setting	**ceb→ca**	**ceb→de**	**ceb→en**	**ceb→es**	**ceb→fr**	**ceb→it**	**ceb→pt**	**ceb→ru**
splited-parallel + mono	10.32	8.94	23.19	13.30	15.96	10.01	12.66	8.05
connected-parallel + mono	10.97	11.37	27.06	14.91	18.04	12.03	15.55	10.26
Setting	**ca→ceb**	**de→ceb**	**en→ceb**	**es→ceb**	**fr→ceb**	**it→ceb**	**pt→ceb**	**ru→ceb**
splited-parallel + mono	5.90	4.91	7.44	5.14	6.02	5.54	6.12	4.24
connected-parallel + mono	7.62	6.92	9.88	6.41	7.39	6.91	7.62	6.54

Table 11: Design for the utilization of parallel data, we take ceb-centric data as an example, apply two distict approaches, and discover that treating parallel data as two independent monolingual datasets harms to translation performance.

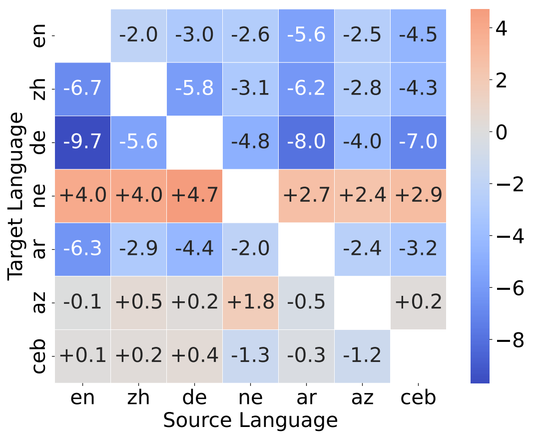

Figure 6: The spBLEU gap between LLaMAX2 and GPT-4. Positive scores mean the result of LLaMAX2 is better than GPT-4. Empirical evidence demonstrates that while LLaMAX2 trails GPT-4 in high-resource translation scenarios, it outperforms in low-resource translation contexts.

ChineseLLaMA2-Alpaca (Cui et al., 2024) is founded on LLaMA2 and enhanced with an extensive Chinese vocabulary that concentrates on Chinese languages. This is a fine-tuned version of ChineseLLaMA2 using Alpaca (Taori et al., 2023) data.

LLaMA2-SFT (Taori et al., 2023) is a fine-tuned version of LLaMA2 model, leveraging a set of 52,000 diverse English instructions in Alpaca (Taori et al., 2023) to enhance the instruction-following capabilities of the model.

Qwen2-7B-Instruct (Bai et al., 2023) is part of the Qwen2 series, which is a instruction-tuned language models. It demonstrates competitiveness against proprietary models across multilingual benchmarks.

Swallow (Fujii et al., 2024) is a large language model which enhances Japanese capability based on LLaMA2. It achieves this by extending the vocabulary with Japanese characters and conducting continued pre-training on a Japanese corpus, resulting in superior performance compared to other LLMs in both English and Japanese tasks. In our paper, we evaluate the instruction-tuned model Swallow-7B-Instruct-v0.1.

B.2 Translation Models

M2M-100 (Fan et al., 2021) encompasses multilingual machine translation models designed to translate between any pair of 100 languages directly, without the need for English as an intermediary. The M2M-100 series includes models of varying sizes, specifically 418M, 1.2B, and 12B parameters. These models are part of a groundbreaking approach in the field of machine translation, aiming to enhance direct translation efficiency across a wide array of languages.

Lego-MT (Yuan et al., 2023) is a novel approach to massively multilingual machine translation, featuring detachable models with individual branches for each language or group of languages. This design supports plug-and-play training and inference, enhancing flexibility and efficiency in language processing tasks.

MADLAD-400 (Kudugunta et al., 2024) is a multilingual machine translation model that leverages the T5 architecture and has been trained on a vast corpus of 250 billion tokens, covering over 450 languages.

Aya-101 (Aryabumi et al., 2024) is an open-source, massively multilingual generative language model that operates on the mT5 (Xue et al., 2021)

X	LLaMA2-Alpaca R_{zh}	LLaMA2-Alpaca R_{X}	ChineseLLaMA2-Alpaca R_{zh}	ChineseLLaMA2-Alpaca R_{X}	LLaMAX2-Alpaca R_{zh}	LLaMAX2-Alpaca R_{X}
af	0.20	28.36	31.32	0.10	0.30	79.84
am	1.09	40.12	67.29	21.15	0.00	89.23
ar	2.17	81.23	72.92	24.70	0.00	99.80
as	8.40	0.59	84.39	0.30	0.00	76.78
ast	0.30	0.20	18.77	0.10	0.00	33.20
az	0.20	18.87	39.23	4.25	0.00	96.44
be	0.10	49.11	2.96	2.87	0.00	99.70
bg	2.37	44.66	29.74	30.24	0.30	98.62
bn	3.95	44.96	78.75	17.79	0.10	99.60
bs	0.40	2.17	8.10	1.98	0.10	4.25
ca	0.30	90.12	5.14	79.84	0.00	98.91
ceb	0.20	21.94	6.72	16.01	0.00	95.55
cs	0.20	54.55	24.90	38.14	0.30	94.76
cy	0.30	19.66	20.55	44.66	0.00	98.81
da	0.30	49.01	22.73	39.72	0.49	91.80
de	0.79	70.55	10.97	75.69	0.30	96.94
el	0.69	21.25	52.67	28.26	0.00	100.00
en	0.00	100.00	0.30	99.70	0.00	100.00
es	0.10	96.94	4.74	93.08	0.00	99.51
et	2.27	8.50	75.49	2.96	0.10	96.34
fa	0.40	45.95	34.49	57.61	0.00	98.12
ff	0.49	0.00	73.81	0.00	0.59	0.00
fi	3.95	55.43	65.22	17.59	0.30	97.13
fr	0.10	94.17	3.46	92.98	0.00	98.72
ga	0.20	19.37	8.70	6.82	0.00	93.08
gl	0.20	0.89	26.19	0.10	0.20	83.99
gu	0.59	36.96	45.65	29.74	0.00	99.60
ha	0.79	0.00	67.98	0.00	0.10	0.00
he	1.68	58.70	65.51	31.03	0.00	100
hi	0.79	50.79	55.83	23.81	0.00	98.91
hr	0.49	41.60	20.95	20.36	0.10	69.66
hu	0.40	64.33	27.47	38.74	0.10	97.13
hy	4.74	47.13	79.15	12.15	0.00	99.60
id	0.49	81.92	16.21	60.38	0.00	95.85
ig	0.20	0.00	51.48	0.00	0.10	0.00
is	0.40	35.08	40.02	28.46	0.20	92.98
it	0.49	79.55	3.36	77.57	0.10	98.42
ja	48.02	16.70	28.36	70.95	6.62	92.00
jv	0.20	0.00	13.83	0.00	0.00	64.62
ka	3.56	31.72	70.06	4.74	0.00	99.80
kam	0.99	0.00	65.51	0.00	1.58	0.00
kea	0.59	0.00	35.47	0.00	0.40	0.00
kk	0.99	45.95	37.06	29.45	0.00	98.32
km	1.58	29.25	58.89	28.26	0.00	100.00
kn	3.16	38.24	75.59	14.72	0.00	100.00
ko	3.85	71.94	75.69	23.52	0.00	98.02
ku	0.10	14.13	31.72	0.00	0.40	75.20
ky	1.19	25.99	48.62	4.35	0.00	99.11
lb	0.10	24.21	30.73	0.40	0.59	89.53
lg	10.57	0.00	79.35	0.00	6.13	0.00

X	LLaMA2-Alpaca R_{zh}	LLaMA2-Alpaca R_{X}	ChineseLLaMA2-Alpaca R_{zh}	ChineseLLaMA2-Alpaca R_{X}	LLaMAX2-Alpaca R_{zh}	LLaMAX2-Alpaca R_{X}
ln	0.30	0.00	66.40	0.00	0.00	0.00
lo	1.38	32.71	89.03	0.10	0.00	58.30
lt	1.09	14.13	50.69	24.31	0.20	96.34
luo	5.83	0.00	87.65	0.00	1.38	0.00
lv	0.30	15.51	52.67	15.42	0.20	97.73
mi	0.49	0.00	59.58	0.00	0.00	0.00
mk	0.40	17.19	7.31	21.94	0.00	99.31
ml	8.20	12.15	79.55	7.51	0.49	51.88
mn	1.58	17.49	85.67	1.48	0.00	99.51
mr	0.40	19.86	31.42	1.58	0.00	99.01
ms	0.59	5.93	20.36	3.95	0.00	43.18
mt	0.20	63.44	29.15	25.00	0.00	97.13
my	1.78	47.33	38.74	29.74	0.00	99.90
ne	0.49	35.77	71.64	3.06	0.00	98.72
nl	0.30	65.81	4.55	65.22	0.10	94.76
no	0.99	32.21	22.53	28.06	0.20	88.74
ns	0.20	0.00	38.74	0.00	0.10	0.00
ny	0.59	0.00	60.08	0.00	0.20	0.00
oc	0.10	0.79	20.55	0.30	0.40	59.39
om	0.20	0.00	38.04	0.00	0.20	0.00
or	1.28	37.35	62.65	1.78	0.00	99.80
pa	1.28	49.41	39.62	5.43	0.00	100.00
pl	0.20	64.33	12.55	58.50	0.00	98.42
ps	0.99	20.16	39.03	0.49	0.00	97.83
pt	0.30	84.39	5.34	79.84	0.10	98.42
ro	0.10	19.57	26.98	42.39	0.20	87.15
ru	0.69	79.74	46.64	37.06	0.10	99.01
sd	0.89	7.41	41.70	0.20	0.00	95.16
sk	0.40	20.26	25.40	3.56	0.10	97.23
sl	1.19	37.25	49.60	16.21	0.69	91.90
sn	0.49	0.00	34.58	0.00	0.10	0.00
so	0.30	8.70	58.70	0.20	0.10	57.71
sr	0.59	12.45	17.89	18.87	0.20	48.02
sv	0.10	47.33	46.94	25.00	0.10	96.94
sw	0.20	39.23	36.86	22.73	0.00	94.66
ta	1.48	24.41	55.24	34.09	0.00	98.62
te	1.38	38.93	69.47	28.56	0.00	99.60
tg	1.28	2.77	44.86	7.61	0.20	97.04
th	1.28	58.60	71.25	28.56	0.00	100.00
tl	0.20	66.7	32.91	45.75	0.00	98.91
tr	0.89	37.94	48.02	31.42	0.00	95.65
uk	0.49	71.54	10.38	28.06	0.49	98.62
umb	0.59	0.00	54.94	0.00	0.30	0.00
ur	1.68	19.86	75.49	14.82	0.10	96.54
uz	0.20	30.24	58.99	2.77	0.10	89.92
vi	0.10	92.69	13.44	81.13	0.00	99.70
wo	0.30	0.00	56.62	0.00	0.49	0.00
xh	0.20	0.00	40.51	0.00	0.10	0.00
yo	0.10	3.56	57.91	0.40	0.10	15.81
zhtrad	98.12	0.00	98.42	0.00	99.51	0.00
zu	0.20	0.00	45.55	0.00	0.10	0.00

Table 12: Using langdetect (Joulin et al., 2016), we individually identify the language of the translation output in zh→X (where X represents any of the 101 languages included in Flores-101) for the LLaMA2-Alpaca, ChineseLLaMA2-Alpaca, and LLaMAX2-Alpaca models on the Flores-101 devtest. R_{zh} refers to the proportion of sentences in the zh→X translation output where the top predicted language is Chinese. R_{X}, on the other hand, denotes the proportion where the top prediction corresponds to the target translated language.

architecture, covering 101 languages and designed to bridge the performance gap in non-dominant languages. It incorporates a 13B parameter base and has undergone instruction-finetuning to achieve high performance across its extensive language range.

C The correlation between fertility and representation quality.

We conduct experiments on Flores-101. Fertility is defined as the ratio of the L_s to the L_T, where L_s is the number of words for space-separated languages and characters for others and L_T is the number of tokens after applying LLaMA2 tokenizer. The quality estimation of LLaMA on Flores-101 test. Cosine similarity focuses on the similarity in the expressions of LLaMA across sentence representation of the same sentence in English and other languages. Recall@1 is often used in the context of information retrieval, which measures the quality of representation. The experimental results, as shown in Figure 5, indicate fertility has a high correlation with the representation quality.

D Introduction to KS-Lottery.

KS-Lottery is a technique designed to identify a small, highly effective subset of parameters within LLMs for multilingual capability transfer. The core concept of this method involves utilizing the Kolmogorov-Smirnov Test to examine the distribu-

X	LLaMA2-Alpaca R_{ja}	LLaMA2-Alpaca R_{X}	Swallow R_{ja}	Swallow R_{X}	LLaMAX2-Alpaca R_{ja}	LLaMAX2-Alpaca R_{X}
af	0.20	35.28	72.23	0.00	0.59	75.69
am	0.20	61.96	77.67	0.10	0.69	90.91
ar	0.69	93.97	64.72	13.93	0.00	99.90
as	3.66	1.38	74.01	0.00	0.10	73.22
ast	0.20	1.48	71.44	0.00	0.20	34.19
az	0.20	26.58	69.57	5.53	0.30	97.43
be	0.40	60.18	72.92	0.00	0.20	99.11
bg	1.09	60.28	77.67	0.30	0.89	98.02
bn	1.78	64.62	75.69	1.78	0.00	99.90
bs	0.69	1.38	73.52	0.00	1.98	3.16
ca	0.40	89.92	65.02	11.07	0.49	98.12
ceb	0.10	33.30	44.57	3.56	0.00	95.06
cs	1.19	61.46	72.13	5.24	1.68	93.38
cy	0.20	30.83	66.90	2.47	0.20	98.52
da	0.79	57.51	70.06	4.64	0.59	91.80
de	1.28	83.40	57.41	29.25	1.28	94.17
el	1.09	42.00	75.20	7.41	0.00	100.00
en	0.00	100.00	67.29	32.41	0.00	100.00
es	0.40	97.04	57.81	20.26	0.10	99.21
et	0.69	14.03	68.48	8.70	4.35	89.13
fa	0.30	83.89	75.79	4.35	0.00	98.42
ff	0.69	0.00	73.12	0.00	11.96	0.00
fi	3.36	74.11	66.01	17.39	2.37	96.25
fr	0.49	97.04	52.47	34.29	0.00	99.70
ga	0.20	26.98	64.23	2.96	0.00	94.07
gl	0.10	1.58	63.34	3.56	0.20	83.30
gu	0.30	67.59	77.47	0.99	1.48	96.64
ha	0.59	0.00	70.06	0.00	0.99	0.00
he	1.78	76.19	63.34	16.60	0.00	100.00
hi	0.69	70.75	67.98	7.91	0.00	99.90
hr	0.89	54.55	69.37	1.28	1.19	66.60
hu	0.40	69.96	71.44	10.67	0.30	93.87
hy	0.69	77.08	79.55	1.09	0.00	99.90
id	0.20	84.98	70.65	7.61	0.00	97.04
ig	0.10	0.00	74.80	0.00	0.20	0.00
is	0.30	55.34	58.20	19.76	0.20	95.06
it	0.59	85.47	55.24	24.11	0.00	97.63
jv	1.38	0.10	66.90	0.00	0.89	67.79
ka	1.28	63.14	65.91	16.01	0.00	100.00
kam	0.30	0.00	73.22	0.00	3.56	0.00
kea	0.20	0.00	71.25	0.00	0.99	0.00
kk	0.10	55.93	76.48	0.49	0.10	99.21
km	0.40	53.66	80.34	0.69	0.00	99.90
kn	3.06	49.60	78.56	1.09	0.10	99.90
ko	1.58	94.17	60.57	21.84	0.10	99.51
ku	0.20	28.06	60.28	0.49	2.77	72.73
ky	0.40	40.71	75.79	0.00	0.10	99.41
lb	0.69	31.23	66.11	0.00	2.27	87.75
lg	1.38	0.00	74.11	0.00	12.65	0.00
ln	0.30	0.00	71.84	0.00	0.79	0.00

X	LLaMA2-Alpaca R_{ja}	LLaMA2-Alpaca R_{X}	Swallow R_{ja}	Swallow R_{X}	LLaMAX2-Alpaca R_{ja}	LLaMAX2-Alpaca R_{X}
lo	0.30	37.85	75.89	0.10	0.00	54.55
lt	4.74	32.41	70.85	4.55	3.66	94.76
luo	0.49	0.00	71.25	0.00	0.89	0.00
lv	1.09	39.92	66.80	5.53	1.68	95.36
mi	0.20	0.00	61.46	0.00	0.20	0.00
mk	0.30	17.98	78.46	0.00	0.49	98.81
ml	1.28	36.17	74.41	1.68	0.49	70.75
mn	0.59	35.18	75.59	1.48	0.00	99.31
mr	0.59	35.87	76.88	0.00	0.10	99.01
ms	0.10	5.53	61.86	0.20	0.00	39.92
mt	0.40	60.08	68.38	3.16	0.69	94.07
my	1.68	56.03	78.85	1.48	0.10	99.90
ne	0.20	50.00	70.45	0.00	0.00	99.01
nl	0.40	76.78	61.36	22.33	0.20	92.09
no	1.38	44.47	69.57	3.16	0.69	86.66
ns	1.58	0.00	62.55	0.00	1.38	0.00
ny	0.49	0.00	72.53	0.00	0.79	0.00
oc	0.20	1.09	68.97	0.00	0.59	58.10
om	0.30	0.00	72.53	0.00	2.57	0.00
or	0.69	61.86	79.45	0.00	1.09	98.52
pa	0.40	77.67	72.04	1.78	0.79	98.91
pl	0.79	73.32	71.54	8.40	0.49	98.02
ps	0.20	43.28	75.40	0.00	0.00	98.22
pt	1.09	90.71	63.14	8.20	0.20	98.22
ro	0.30	45.95	68.97	4.25	0.30	89.53
ru	0.30	83.10	71.44	12.45	0.20	99.41
sd	0.89	2.47	74.31	0.00	0.00	92.59
sk	0.49	27.27	65.42	7.81	0.59	94.57
sl	0.79	58.79	61.66	3.56	1.38	91.11
sn	0.40	0.00	68.18	0.00	1.58	0.00
so	0.10	7.71	74.31	0.20	0.99	59.19
sr	1.48	15.22	75.49	1.48	1.98	44.07
sv	2.57	49.90	66.01	13.34	1.68	95.16
sw	0.20	48.32	67.49	0.99	0.59	94.76
ta	0.30	53.46	74.31	1.98	0.00	99.80
te	0.20	73.12	75.79	2.47	0.00	99.80
tg	0.69	6.23	74.01	0.00	0.40	97.33
th	0.00	84.39	70.75	12.15	0.00	100.00
tl	0.20	73.62	62.94	6.72	0.10	99.31
tr	0.79	42.39	67.69	11.86	0.40	95.26
uk	0.59	89.53	74.31	3.36	0.49	98.12
umb	0.69	0.00	68.68	0.00	1.38	0.00
ur	1.19	25.49	76.19	2.77	0.30	97.92
uz	0.40	32.71	74.51	0.20	1.78	86.36
vi	0.00	95.85	56.42	13.24	0.10	99.70
wo	1.09	0.00	73.32	0.00	2.96	0.00
xh	0.20	0.00	70.55	0.00	0.59	0.00
yo	0.10	3.95	67.00	0.00	0.10	13.93
zh	23.22	70.16	37.15	35.67	5.93	93.08
zhtrad	32.41	0.00	43.87	0.00	7.31	0.00
zu	0.10	0.00	67.39	0.00	1.38	0.00

Table 13: We utilize langdetect to identify the translation outputs from ja→X of LLaMA2-Alpaca, Swallow and LLaMAX2-Alpaca models on Flores-101 benchmark. R_{ja} represents the ratio of sentence in the translation predicted result where the top predicted language is Japanese. Conversely, R_{X} refers to the proportion where the top predicted language aligns with the target translated language.

tion shift of parameters before and after fine-tuning. This approach helps in pinpointing the "winning tickets" or the most impactful parameters that contribute significantly to the model's performance in multilingual tasks.

E 1-hop translation in data augmentation is enough.

Given a parallel dataset subset ($\mathcal{D}_{\text{P}}$) from $\mathcal{D}^{A}_{\text{para}}$ that contains translations in all directions for 6 languages (en,fr,es,zh,ta,th) and a monolingual subset ($\mathcal{D}_{\text{M}}$) from $\mathcal{D}^{A}_{\text{mono}}$ for the same 6 languages. We then perform non-repetitive sampling 12,500 sentence pairs from $\mathcal{D}_{\text{P}}$ in each direction to generate two subsets of parallel corpus data $\mathcal{D}_{\text{P}_1}$ and $\mathcal{D}_{\text{P}_2}$, respectively. Consequently, we preserve $\mathcal{D}_{\text{P}_1}$ and evaluate the effect of augmentation on parallel data $\mathcal{D}_{\text{P}_2}$ or monolingual data $\mathcal{D}_{\text{M}}$, resulting in two new dataset, $\mathcal{D}'_{\text{P}_2}$ and $\mathcal{D}'_{\text{M}}$, post-augmentation. To assess both the in-domain and out-of-domain capabilities of the model, we perform inference on it using 10 languages (en, fr, es, pt, de, zh, ta, th, is,

<table>
<tr><th>Model</th><th>Templates</th></tr>
<tr><td>LLaMAX-
Alpaca</td><td>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:
Translate the following sentences from English to Chinese Simpl
Input:
"We now have 4-month-old mice that are non-diabetic that used to be diabetic," he added.
Response:他补充道：“我们现在有 4 个月大没有糖尿病的老鼠，但它们曾经得过该病。”</td></tr>
<tr><td>LLaMA
Series Models</td><td>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:
Translate the following sentences from English to Chinese Simpl
Input:
"We now have 4-month-old mice that are non-diabetic that used to be diabetic," he added.
Response:他补充道：“我们现在有 4 个月大没有糖尿病的老鼠，但它们曾经得过该病。”</td></tr>
<tr><td>yayi2</td><td>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:
Translate the following sentences from English to Chinese Simpl
Input:
"We now have 4-month-old mice that are non-diabetic that used to be diabetic," he added.
Response:他补充道：“我们现在有 4 个月大没有糖尿病的老鼠，但它们曾经得过该病。”</td></tr>
<tr><td>polylm</td><td>"We now have 4-month-old mice that are non-diabetic that used to be diabetic," he added.
Translate this sentence English to Chinese Simpl. 他补充道：“我们现在有 4 个月大没有糖尿病的老鼠，但它们曾经得过该病。”</td></tr>
<tr><td>TowerInstruct</td><td><|im_start|>user
Translate the following text from English into Chinese.
English: "We now have 4-month-old mice that are non-diabetic that used to be diabetic," he added.
Chinese:<|im_end|>
<|im_start|>assistant
他补充道：“我们现在有 4 个月大没有糖尿病的老鼠，但它们曾经得过该病。”</td></tr>
<tr><td>aya23</td><td><BOS_TOKEN><|START_OF_TURN_TOKEN|><|USER_TOKEN|>Translate the following sentences from English to Chinese: "We now have 4-month-old mice that are non-diabetic that used to be diabetic," he added.<|END_OF_TURN_TOKEN|><|START_OF_TURN_TOKEN|><|CHATBOT_TOKEN|>他补充道：“我们现在有 4 个月大没有糖尿病的老鼠，但它们曾经得过该病。”<|END_OF_TURN_TOKEN|></td></tr>
<tr><td>Qwen2 instruct</td><td>system
You are a helpful assistant.
user
Translate the following sentences from English to Chinese Simpl: "We now have 4-month-old mice that are non-diabetic that used to be diabetic," he added.
assistant
他补充道：“我们现在有 4 个月大没有糖尿病的老鼠，但它们曾经得过该病。”</td></tr>
<tr><td>ChineseAlpaca-2</td><td>[INST] «SYS»
You are a helpful assistant. 你是一个乐于助人的助手。
«/SYS»
Translate the following sentences from English to Chinese Simpl: "We now have 4-month-old mice that are non-diabetic that used to be diabetic," he added. [/INST] 他补充道：“我们现在有 4 个月大没有糖尿病的老鼠，但它们曾经得过该病。”</td></tr>
<tr><td>Swallow</td><td>[INST] «SYS»
あなたはで秀な日本人のアシスタントです。 «/SYS»
Translate the following sentences from Japanese to Chinese Simpl: 「我々がっている生後4か月のマウスはかつて糖尿病でしたが在は糖尿病ではない、」と彼は付け加えました。 [/INST] 「他补充道：“我们现在有 4 个月大没有糖尿病的老鼠，但它们曾经得过该病。”」</td></tr>
<tr><td>Madlad</td><td>'<2zh> "We now have 4-month-old mice that are non-diabetic that used to be diabetic," he added.' 他补充道：“我们现在有 4 个月大没有糖尿病的老鼠，但它们曾经得过该病。”</td></tr>
</table>

Table 14: Examples of instruction templates utilized for all evaluated LLMs, with the translation result, 他补充道：“我们现在有 4 个月大没有糖尿病的老鼠，但它们曾经得过该病。”, using the reference instead of the model's output.

zu), utilizing the Flores-101.

We use two different multilingual dictionaries MUSE provided by Lample et al. (2018) [3], and PanLex (Wang et al., 2022). In the context of a multilingual dictionary, we can use “1-hop” and “2-hop” to characterize the translation relationship among different languages, an example shown in Table 9.

We use the MUSE dictionary to perform data augmentation on both parallel $\mathcal{D}_{\mathrm{P}_2}$ and monolingual $\mathcal{D}_{\mathrm{M}}$ data, utilizing 1-hop and 2-hop translations. As shown in Table 9, using different hop translation for augmentation does not significantly impact the final translation performance. Multi-hop translation sometimes can even result in poorer performance.

[3] https://github.com/facebookresearch/MUSE.

F Design of parallel format

The Usage of Parallel Data. Parallel data can be utilized in two distinct ways: split-parallel or connected-parallel. **Split-Parallel**: Consider the source language data and target language data involved in parallel data as two distinct monolingual datasets, which are randomly shuffled throughout the entire training set. **Connected-Parallel**: In the training process, we treat each pair of source and target language sentences from the parallel dataset as a single data point by concatenating them.

Based on different forms of parallel data, supervised fine-tuning (SFT) is conducted separately on ceb-centric using both parallel and monolingual datasets. As indicated in Table 11, we observed that the form of parallel data primarily impacts translation performance, with no significant difference in

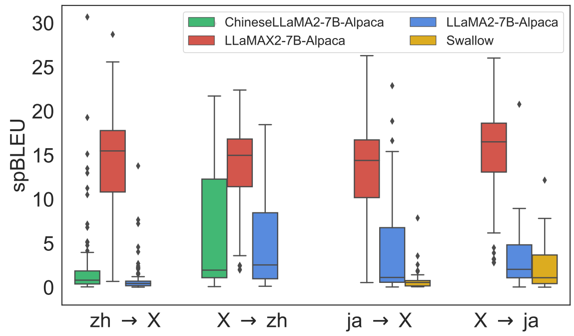

Figure 7: Significant improvements in language-specific-centric translation are observed with LLaMAX2-Alpaca compared to LLaMA2-7B-Alpaca, ChineseLLaMA2-7B-Alpaca, and Swallow, as demonstrated in the translation performance analysis on all translation directions in the Flores-101 dataset.

general tasks and cross-lingual general tasks; however, the disparity in translation is pronounced. We specifically highlighted some high-resource translation directions and found that such gaps are quite significant.

G Comparison Results Between Our Model and GPT-4

In Figure 6, we compare the performance gap between our model and GPT-4. Considering the API cost of evaluating GPT-4, we only evaluate the mutual translation performance among seven languages (en, zh, de, ne, ar, az, ceb). Experiment results show that while our model lags behind in high-resource translation directions, it achieves on-par or even superior performance in low-resource translation.

H Comparsion between LLaMAX2-Alpaca and language-specific LLMs.

The comparison between LLaMAX2-Alpaca, ChineseLLaMA2-Alpaca, and Swallow (a Japanese-specific LLM) explores the difference between the traditional pipeline for enhancing specific language capabilities based on existing pre-trained models and our proposed recipe. As shown in Figure 7, we evaluate language-specific LLMs to translate from the enhanced language to any of the 101 languages on Flores-101 and find that their performance is not significantly different from the original LLaMA2 model, but there exists a notable performance gap compared to LLaMAX2-Alpaca. As we described in Section 2.1, excessively adding new language-specific tokens can shift the focus of training the LLM.

In addition, we conduct a deeper analysis of translation output to identify the factors contributing to the limited improvement in translation performance. The experimental results in Table 12 indicate that the language-specific LLM obtained through the traditional pipeline tends to output specific languages, while LLaMAX2 can accurately produce the answer with the corresponding language.

We perform further comparisons between LLaMAX2-Alpaca and Japanese-specific LLMs-Swallow. After using LLaMAX2-Alpaca and Swallow to generate translations from Japanese (ja) to any language in Flores-101, we apply langdetect to determine the language of each translation result and calculate the proportion of Japanese and target translated language respectively. The experimental result, as shown in Table 13, indicates that the Japanese-specific LLM tends to output Japanese, whereas LLaMAX2-Alpaca performs more accurately in producing the target language.

I Prompt Templates

We offer a comprehensive collection of prompt instruction templates, as illustrated in Table 14, which are utilized for all evaluated LLMs. These templates are meticulously designed based on existing LLMs, playing a crucial role in obtaining accurate model results and ensuring fairness in comparisons. Our goal in providing these templates is to promote transparency and make it easier to reproduce our findings.