Are Small Language Models the Silver Bullet to Low-Resource Languages Machine Translation?

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Abstract

Small language models (SLMs) offer computationally efficient alternatives to large language models, yet their translation quality for low-resource languages (LRLs) remains severely limited. This work presents the first large-scale evaluation of SLMs across 200 languages, revealing systematic underperformance in LRLs and identifying key sources of linguistic disparity. We show that knowledge distillation from strong teacher models using predominantly monolingual LRL data substantially boosts SLM translation quality—often enabling 2B–3B models to match or surpass systems up to 70B parameters. Our study highlights three core findings: (1) a comprehensive benchmark exposing the limitations of SLMs on 200 languages; (2) evidence that LRL-focused distillation improves translation without inducing catastrophic forgetting, with full-parameter fine-tuning and decoder-only teachers outperforming LoRA and encoder–decoder approaches; and (3) consistent cross-lingual gains demonstrating the scalability and robustness of the method. These results establish an effective, low-cost pathway for improving LRL translation and provide practical guidance for deploying SLMs in truly low-resource settings. [1].

1 Introduction

Persistent LRL underperformance Low-resource languages (LRLs) continue to face substantial challenges due to the scarcity of linguistic resources, rooted in socioeconomic, geographical, and political constraints, which limits their representation in both academic and industrial contexts (Nigatu et al., 2024); despite advances in multilingual transfer learning and pretraining approaches (Conneau et al., 2020; Artetxe and Schwenk, 2019), exemplified by No Language Left Behind (NLLB; (Costa-jussa et al., 2022)), translation quality for LRLs still lags behind that of high-resource languages (HRLs), particularly in sensitive domains such as finance and government, where privacy and offline deployment are crucial (Zhong et al., 2024). Transformer-based models (Zhao et al., 2023), whether encoder-decoder with attention (Bahdanau et al., 2015; Vaswani et al., 2017; Naveed et al., 2024) or decoder-only frameworks like GPT (Gao et al., 2022; Hendy et al., 2023), have driven progress through techniques such as back-translation (Sennrich et al., 2016), unsupervised training (Lample et al., 2018), and multilingual initiatives like OPUSMT (Tiedemann and Thottingal, 2020), yet decoder-only models often underperform for LRLs due to English-centric data distributions (Brown et al., 2020; Hasan et al., 2024), leading to inaccuracies and hallucinations (Benkirane et al., 2024), although some evidence suggests they may outperform encoder-decoder methods in certain contexts (Gao et al., 2022; Silva et al., 2024). In general, language models exhibit consistent degradation on LRLs relative to HRLs (Robinson et al., 2023), caused by unbalanced training distributions (Lankford et al., 2021), tokenization biases, and limited exposure to linguistic diversity (Shen et al., 2024), underscoring the need for targeted data augmentation, domain-specific adaptation, and specialized fine-tuning to narrow the performance gap (Elsner et al., 2024; Li et al., 2025b).

Costly, slow gigantism Furthermore, because translation is a highly common and high-frequency use case across both industry and individual users, inference with very large models (e.g., ChatGPT-scale systems) is often impractical for academic or industrial deployment due to cost and latency constraints; however, for Small Language Models (SLMs), encountering LRL inputs substantially increases hallucination rates, rendering them not only unreliable for translation but also broadly un-

[1] Tuned models are openly available https://anonymous.4open.science/r/mt_luxembourgish-408D

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suitable for other applications that contain LRL content. Drawing inspiration from recent work on grammars versus parallel data (Aycock et al., 2025), which investigates grammar learning in the context of extremely low-resource translation, the authors conclude that nearly all models' understanding of low-resource languages stems primarily from parallel corpora rather than from grammatical descriptions or related sources. In this paper, the following research questions are formulated to empirically validate and begin to address SLMs in LRLs: **(RQ1)** How effectively can decoder-only language models address low-resource machine translation, and what performance gaps emerge across different model scales and languages? **(RQ2)** To what degree does distillation from monolingual low-resource data translate into measurable improvements in smaller large language models (LLMs) translation quality? **(RQ3)** How do varying supervised fine-tuning (SFT) configurations affect translation quality in low-resource languages, and do these configurations compromise broader model capabilities or instead yield consistent improvements across diverse LRLs?

2 LRLs' deficiencies

2.1 Situation of Language Support

Recent investigations have revealed that although LLMs are increasingly advertised as multilingual, their effective support in languages is often limited to a subset of HRLs. Moreover, systematic evaluations of language-specific performance remain scarce (for example (Lai et al., 2024; Marchisio et al., 2024; Lifewire, 2024; Ahuja et al., 2024)). Table 1 summarizes several models included in our experiments, their approximate parameter sizes, and the estimated number of languages they reportedly support. These figures are derived from official model documentation, benchmarking reports, and recent academic studies.

Despite these encouraging multilingual claims, the existing literature reveals that rigorous language-specific performance evaluations, especially for low-resource languages, are insufficient. Most current research focuses on high-resource benchmarks, leaving open critical questions about fairness and the accessibility of LLMs for diverse linguistic communities.

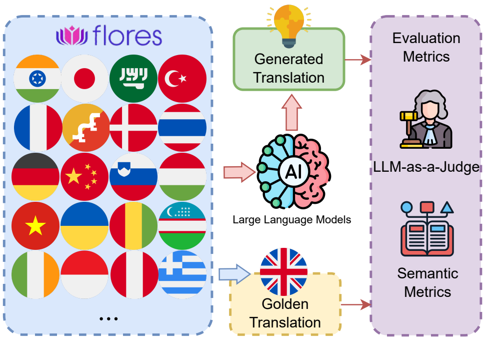


Figure 1: Evaluation pipeline

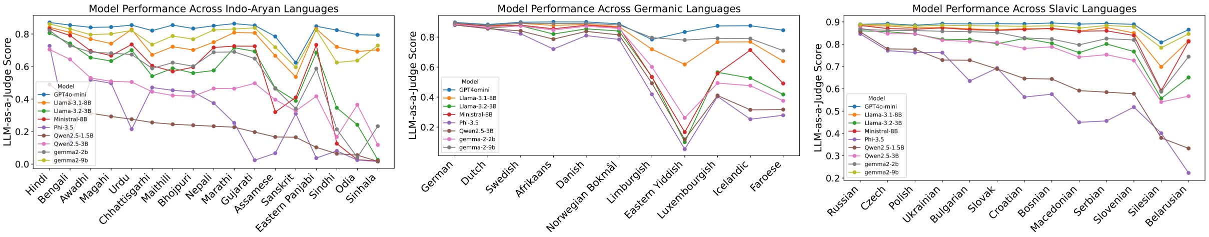
Model	Size	Languages	Date
GPT-4o-mini	—	∼25	Jul. 2024
Llama-3.1-8B-it	8B/3B	∼30	Jul. 2024
Llama-3.2-3B-it	3B	∼20	Sept. 2024
Mistral-8B-Instruct-2410	8B	∼25	Oct. 2024
Phi-3-mini-4k-instruct	4B	∼20	Apr. 2024
Phi-3.5-mini-instruct	4B	∼20	Aug. 2024
Qwen2.5 Instruct	1.5B/3B	∼25	Sept. 2024
Gemma2 Instruct	2B/9B	∼20	Jul. 2024

Table 1: Multilingual Support of LLMs

2.2 Evaluating LRLs translation Ability

We use the **FLORES-200** benchmark to systematically assess the performance of LLMs in multilingual machine translation tasks (Costa-jussa et al., 2022; Goyal et al., 2021a; Guzmán et al., 2019). FLORES-200 offers rigorously curated human-validated translation datasets across 200 languages that span diverse linguistic families and writing systems, making it highly effective for evaluating translation quality in high-resource and low-resource linguistic contexts. Our experiments leverage the full FLORES-200 dataset to comprehensively evaluate translation quality across as many languages as possible, emphasizing translations from various source languages into English.

In addition to traditional metrics, we evaluated translation quality using the **LLM**-**A**s-**A**-**J**udge (LLMaaJ) scores (Niklaus et al., 2025), which uses a large LLM to score translations from 0 to 1 based on semantic equivalence and naturalness. A score of 1.0 denotes a perfect translation and 0.0 a totally incorrect one. In practice, we consider a score ≥ 0.8 as indicative of a good translation. Research has shown that LLMaaJ tolerates synonyms, paraphrases, and cross-linguistic structural variations, enabling it to better assess translation quality when there are multiple valid phrasings or when grammatical and typological differences (e.g., omitted



(a) Indo-Aryan

(b) Germanic

(c) Slavic

Figure 2: LLMaaJ scores of SLMs on Indo-Aryan/Germanic/Slavic to-English translation

pronouns) are acceptable(Zheng et al., 2023; Piergentili et al., 2025).

Regarding the LLMs investigated, as shown in Figure 1, we systematically traversed prominent proprietary APIs and open source models (refer to Table 1), presenting results using LLMaaJ metrics with quantitative semantic evaluations. Detailed LLMaaJ and BLEU scores for all source-to-English translations are provided in the Appendix Table 8 and the Appendix Table 9, and an imprecise map reveals the geographic distribution provided in the Appendix Figure 8.

2.3 Models performance in FLORES-200

We present the performance distribution in Figure 3, which visualizes more precisely the performance gap of languages across our evaluation set by linguistic family and script, thereby addressing RQ1, and complement this with the regional distribution shown in Figure 7 for finer-grained regional insights. Each bar length is calculated based on the average score, explicitly excluding the GPT4o-mini model's score to identify which LRLs are included in our experiments and how they are situated in the broader typological space.

Each bar in Figure 3 represents one language, grouped by its primary family, with bar length corresponding to the average LLMaaJ score. The figure reveals that LRLs are not evenly distributed across families: many under-resourced African, Austronesian, and Indigenous American languages cluster toward the lower end of the performance spectrum, while certain Indo-European LRLs (e.g., Luxembourgish, Maltese) perform moderately better, likely due to greater data availability or proximity to high-resource relatives.

The circular layout also highlights structural gaps in the evaluation set. Languages absent from FLORES-200—such as many North American Indigenous languages—do not appear here, not because models perform well on them, but because no evaluation data exist. This is particularly relevant for languages with small speaker populations or those concentrated in politically marginalized communities, which remain invisible in current multilingual benchmarks.

Consistent with previous work (Nekoto et al., 2020; Joshi et al., 2020), the lowest scores are observed for many Niger–Congo, Austronesian, and smaller Afro-Asiatic languages, reflecting the severe data scarcity. In contrast, LRLs in Eastern Europe and South/Southeast Asia—such as Macedonian or Sinhala—achieve slightly higher average scores, possibly benefiting from historical ties to better-supported high-resource languages. However, the overall pattern remains unchanged: LRLs across all families systematically lag behind high-resource languages, underscoring the need for targeted data collection, typologically diverse benchmarks, and bias mitigation strategies to ensure equitable progress in multilingual NLP.

2.4 Gap between Dwarf(Smaller) and Giant LLMs

Small Language Models are consistently bad in LRLs Across the Indo-Aryan, Germanic, and Slavic branches in Figure 2 (panels (a)–(c)), we observe a consistent pattern: smaller LLMs suffer a substantially larger performance drop on LRLs than on high-resource ones, while larger LLMs degrade far less. Concretely, LRLs such as Sinhala (Indo-Aryan), Luxembourgish (Germanic), and Silesian (Slavic) exhibit steep declines in smaller models but remain comparatively competitive in larger models, as visualized in Figure 2. This disparity indicates a systematic bias in current systems—particularly pronounced in smaller models—toward high-resource languages.

Solving requires training but lacks exploration Addressing this gap calls for better LRL data curation, knowledge distillation from larger LLMs, inclusive evaluation suites, and bias-

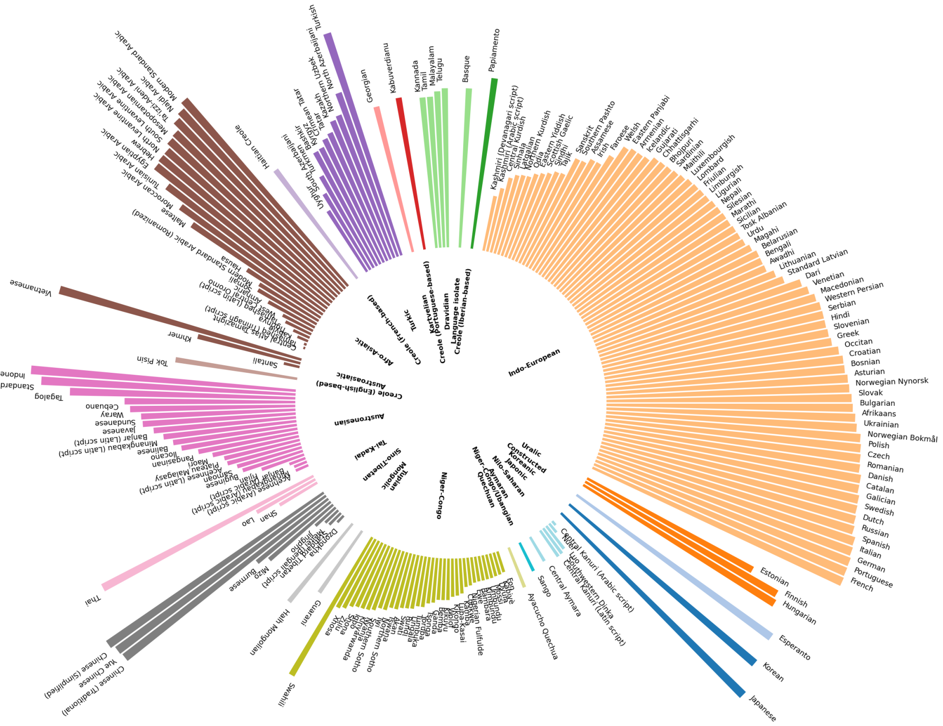


Figure 3: This circle plot illustrates the "Low-Resource" linguistic performance gap across language families. A complementary view of the geographical distribution of linguistic results is presented in Figure 8, which provides a clearer reference for cross-linguistic comparison.

mitigation strategies to ensure NLP benefits all language communities. According to the Universal Approximation Theorem (Hornik, 1991), if neural translation is viewed as a linear mapping between semantic spaces, small networks struggle to capture complex patterns and are more vulnerable to interference from HRL data. Thus, fine-tuning on high-quality paired data becomes especially crucial for smaller models, yet there remains a lack of comprehensive research on LRLs in SLMs.

3 Fine-tuning on LRLs – Taking Luxembourgish as a Key Example

3.1 Background and language selection

As highlighted in the previous section, several low-resource languages, such as Luxembourgish and Assamese (Figure 2), show a substantial translation quality gap among between large and small models. In this article, Luxembourgish serves as a representative case. Although officially recognized, it lacks sufficient high-quality corpora resources, leading to poor performance in SLMs. Its blend of Germanic roots and French influence adds complexity to NLP tasks. While larger LLMs handle Germanic languages reasonably well, they struggle with LRLs like Luxembourgish. Previous efforts to address this include LuxemBERT (Lothritz et al., 2022), LuxT5 (Plum et al., 2024), and LetzTranslate (Song et al., 2023), a low-resource translation system based on OPUS-MT.

To examine generalizability, we additionally include Ukrainian, Assamese and Khasi (an endangered language), both exhibiting similar linguistic and resource profiles, as supplementary tasks to broaden the scope of the analysis. Furthermore, generating LRL from English is more challenging for LLMs than in the reverse direction of previous research (Howcroft and Gkatzia, 2022). Regarding translation performance, LLMs exhibit a certain degree of fluent translation from LRL to English, but not vice versa (Gao et al., 2020). This asymmetry is also reflected to some extent in the hallucination issues observed when generating Luxembourgish, more details can be found in the appendix E.2.

3.2 Distillations and Soft-Target Quality

In our scenario, having only a Luxembourgish corpus without English translations rules out conventional parallel-corpus training approaches, accurately reflecting the typical data situation and model generation of LRLs. To bridge the gap between comprehension and generation in this low-resource scenario, we propose a distillation-based approach. Using a teacher model that demonstrates a robust understanding of Luxembourgish, we can distill its knowledge into a student model using the available

LRL single-side corpus. This process is expected to enhance the generation capabilities of the student model, enabling it to produce high-quality Luxembourgish output despite the limited data, and thus address the core challenge of low-resource language translation. According to further human labeling of our GPT-4o distillation dataset in Luxembourgish to English translation, **92%** of our samples were marked as fully correct.

3.3 Data Collection and Augmentations

For the training data set, we constructed a Luxembourg data set using multiple sources, including the LuxemBERT corpus, example sentences in the Luxembourg Online Dictionary (LOD) dataset[2], and additional news articles collected from previous research published data on RTL Ltzebuerg[3], following the LuxemBERT work.

Previous research has demonstrated that integrating dictionary entries can effectively enrich low-resource translation systems by providing explicit lexical alignments and clarifying semantic nuances. For example, Ghazvininejad's work improved translation fidelity in settings where parallel data is scarce (Ghazvininejad et al., 2023). Inspired by these findings, we also explore how the addition group of datasets with dictionary checks using LOD can complement our distillation approach as shown in Figure 4. Details of using the dictionary usage in the Appendix C.

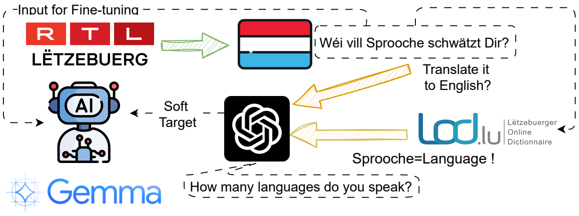


Figure 4: Pipeline of data augmentation

4 Experiments

4.1 Models and Datasets

Models The latest open-source models are used as benchmark models, and their instruction-tuned versions are utilized to leverage their general capabilities in generating dialogues and answering questions. Based on the current leaderboard for Luxembourgish proficiency in LLMs (Lothritz and Cabot, 2025), combined with the experimental results for the Germanic language group in Section 2, we select the top two base tiny models, which are Llama-3.2-3B-Instruct from Meta and Gemma-2-2b-it from Google.

Input Prompts The design of the training input templates is considered crucial. In order to prevent the model from losing its general communication and generalization abilities after instruction tuning, it is necessary for prompts to be designed in alignment with chat templates that can be understood by the model. Based on this, basic prompt testing is conducted to identify the most suitable prompt for the model. Chat-based models have been observed to be prone to losing their communication capabilities after SFT, leading to the generation of endless content and a significant increase in the likelihood of hallucinations. Therefore, in the design of the questions, the corresponding starting prompts are set at the beginning of the model responses, such as "Here is the translation: ". Through this linguistic guidance, the probability of hallucination is reduced and the model is also able to learn when to stop.

Distilled from LRL side For the training data set, the LRL monolingual corpus is used primarily as the base material, from which the LRL-to-English mapping capability is distilled from larger models. As described in Section 3.3, publicly available press datasets and dictionary example sentences are utilized as the monolingual corpus, and distillation is performed using various teacher models. Finally, the correct word-to-word mapping capability is reinforced through the lemma search to verify the dictionary content. We classify fake targets distilled into four categories: fake targets obtained by distilling facebook/nllb-200-3.3B (**D**istill-**N**LLB, DN), the fake targets obtained by distilling meta-llama/Llama-3.3-70B-Instruct. (**D**istill-**L**lama, DL), the fake targets obtained by distilling GPT-4o-mini (**D**istill-**G**PT4O, DG), and the fake targets obtained after performing dictionary checking (**D**istill-**G**PT-**D**ict-**C**hecking, DGDC). Each category contains 621,033 data samples used for model training, all having the same LRL side texts, while the corresponding fake targets are generated by different teacher models. For the validation set, the latest 300 press data entries (**Val 300**) from 2024 are used as monolingual corpus data, and the corresponding LRL entities are identified for the English mappings, thus preventing biases that may arise from the model having been trained on the

[2] https://data.public.lu/en/datasets/letzebuerger-online-dictionnaire-lod-linguistesch-daten/

[3] https://www.rtl.lu/

validation dataset. And we also do a manual check for English translations. Furthermore, we utilize the FLORES-200 benchmark as an additional validation test set.

4.2 Metrics

We evaluate translation quality using three common MT metrics (Lo et al., 2023): spBLEU, ChrF++, and the Jaccard index. spBLEU provides standardized subword-level BLEU scores using SentencePiece tokenization, enabling consistent comparison across languages. ChrF++ (Popović, 2015) combines character- and word-level n-grams and correlates well with human judgments. The Jaccard index (da F. Costa, 2021) offers a simple set-based similarity measure that is easy to interpret. For LLM-as-a-Judge evaluations, we use `google/gemma-3-27b-it` as the scoring model throughout.

4.3 Results

4.3.1 Can Small Language Models Learn?

The results in Table 2 clearly demonstrate that fine-tuning in both translation directions is highly effective. For example, the baseline EN→LB models exhibit spBLEU scores around 30, but after fine-tuning, these scores increase to nearly 38–40 values approaching our threshold for high-quality translations (spBLEU $>$ 40). In contrast, LB→EN translations consistently score above 40, yet generating fluent Luxembourgish in the EN→LB direction remains a significant challenge. Furthermore, our experiments indicate that even a 3B model, when effectively distilled, can rival or even surpass larger models in low-resource language translation tasks. Our results indicate that GPT-4o-based distillation methods, in particular, produce substantial improvements in translation quality, confirming that parallel corpora generated by LLM represent a viable and promising strategy for supporting LRL translation tasks. In order to validate the model translation performance, we also extracted a portion of the data and asked Luxembourgers who are at least bilingual in Luxembourgish and English to label it as ground truth for data quality validation. The spBLEU score achieved with this labeled data was 51.08 on our fine-tuned Gemma-2-2b-it, showing a comparable score calculated using GPT-generated data as ground truth. Regarding the LLMaaJ score of the model, we obtained performance evaluation results and trends that are largely consistent with those of the spBLEU parameter, further cross-validating the feasibility of LLMaaJ. However, since LLMs are black-box models with limited interpretability, the scores produced by LLMaaJ can only serve as a reference and do not guarantee accuracy or validity.

Moreover, it is worth noting that DN underperforms DG by approximately 5–15 percentage points overall, and, interestingly, the **"sudden stop"** phenomenon observed in Nllb-200-3.3B (Section § E.4) is faithfully inherited by the student model, which directly explains the comparatively lower post-fine-tuning performance; accordingly, selecting a teacher of the same decoder-only family during fine-tuning helps avoid this issue. **To address RQ2**, fine-tuning with data distillation yields highly significant gains: for both evaluated models, improvements are reflected in spBLEU scores that surpass those of certain expert translation systems. Furthermore, the enhancement in the EN→LB direction exceeds that of the reverse direction, further strengthening the model's Luxembourgish generation ability. Therefore, data distillation can substantially improve translation capacity for low-resource languages, enabling even smaller models to achieve promising results.

Table 4: Impact of LoRA Rank on spBLEU During Fine-Tuning, Evaluated Across Three Rank Values

EN-LB	Rank (LoRA)	Val 300 spBLEU	FLORES 200 spBLEU
Llama-3.2-3B-Instruct	**Base Model**	6.46	4.80
	32	12.95	9.46
	64	13.05	9.23
	128	13.32	9.27
Gemma-2-2b-it	**Base Model**	5.82	4.61
	32	13.07	8.88
	64	13.17	9.12
	128	13.31	9.21

4.3.2 Unlocking LRLs within SLMs?

Can we do LoRA? We also carried out experiments using the same data to assess how the LoRA rank parameter influences training performance in translation tasks involving Luxembourgish and English. Specifically, we evaluated the ranks 32, 64 and 128 in our models. The results, presented in Table 4 and 6, indicate that variations in the LoRA rank parameter have a minimal influence on the overall translation performance, with differences typically within 1 to 2 spBLEU points. More importantly, models fine-tuned using LoRA consistently underperformed compared to their fully fine-tuned counterparts, achieving notably lower performance in Table 2. Moreover, after LoRA-based SFT, we

MT Direction	Models	Methods	Val 300				FLORES-200			
			spBLEU	ChrF++	Jaccard	LLMaaJ	spBLEU	ChrF++	Jaccard	LLMaaJ
EN-LB	Nllb-200-3.3B	BM	19.97	37.03	0.27	0.75	31.14	49.62	0.35	0.85
	Llama-3.3-70B-Instruct		24.35	46.58	0.27	0.87	22.55	43.08	0.26	0.83
	Llama-3.2-3B-Instruct	**BM**	6.46	26.78	0.12	0.36	4.80	22.10	0.09	0.36
		DN	37.98	55.41	0.37	0.82	14.61	38.04	0.19	0.51
		DL	40.71	57.37	0.40	0.79	20.93	41.51	0.22	0.52
		DG	42.01	57.89	0.41	0.88	22.80	42.26	0.25	0.70
		DGDC	42.16	57.87	0.42	0.89	23.40	42.90	0.26	**0.83**
	Gemma-2-2b-it	**BM**	5.82	22.71	0.10	0.50	4.61	20.78	0.07	0.51
		DN	41.77	57.71	0.42	0.89	20.41	41.21	0.25	0.78
		DL	43.78	59.02	0.44	0.87	23.03	**42.95**	**0.28**	0.79
		DG	**44.58**	**59.73**	**0.45**	0.87	23.47	42.72	**0.28**	0.76
		DGDC	44.12	59.10	**0.45**	**0.90**	**23.50**	42.49	**0.28**	0.82
LB-EN	Nllb-200-3.3B	**BM**	40.51	56.81	0.48	0.81	**48.45**	**65.03**	**0.56**	0.85
	Llama-3.3-70B-Instruct		54.14	74.24	0.57	0.89	33.96	58.02	0.41	**0.86**
	Llama-3.2-3B-Instruct	**BM**	26.31	45.98	0.33	0.58	17.62	36.79	0.26	0.46
		DN	42.78	59.33	0.48	0.82	29.37	53.88	0.38	0.79
		DL	54.64	70.98	0.57	0.82	31.72	56.50	0.41	0.79
		DG	59.88	74.97	0.63	**0.90**	32.78	57.69	0.42	0.81
		DGDC	57.88	73.46	0.60	0.89	32.56	57.60	0.41	0.85
	Gemma-2-2b-it	**BM**	27.11	47.44	0.34	0.60	14.99	37.77	0.26	0.45
		DN	41.58	57.63	0.49	0.83	42.46	60.55	0.51	0.83
		DL	58.95	72.15	0.62	0.83	41.47	60.33	0.50	0.82
		DG	**65.44**	**76.96**	**0.68**	0.86	42.67	61.30	0.51	**0.86**
		DGDC	62.75	75.13	0.65	0.89	42.73	61.25	0.51	0.85

Table 2: This table presents the performance results obtained from training on datasets generated using different distillation models and methods. We report experimental results on two datasets, VAL 300 and FLORES 200. Additionally, we evaluated the performance of Nllb-200-3.3B and Llama-3.3-70B-Instruct on the same datasets, which strongly validate the effectiveness of our training approach. BM refers to the Base Model without any SFT. LLMaaJ refers to LLM-as-a-Judge, which gives a score from 0.0 to 1.0 with a granularity of 0.1.

MT Direction	Model	BOOLQ	CB	COPA	MULTIRC	RECORD	RTE	WIC	WSC	AVG
BM(Base Model)	Llama-3.2-3B-Instruct	0.62	0.55	0.71	0.52	0.41	0.64	0.51	0.28	0.53
	Gemma-2-2b-it	0.73	0.55	0.86	0.81	0.56	0.82	0.49	0.56	0.67
En-LB	Llama-3.2-3B-Instruct-FT	0.64	0.39	0.60	0.52	0.39	0.60	0.48	0.11	0.47
	Gemma-2-2b-it-FT	0.71	0.52	0.89	0.75	0.41	0.72	0.51	0.49	0.62
LB-EN	Llama-3.2-3B-Instruct-FT	0.64	0.30	0.69	0.51	0.46	0.62	0.52	0.24	0.50
	Gemma-2-2b-it-FT	0.69	0.25	0.90	0.76	0.45	0.73	0.51	0.43	0.59

Table 3: Variations in overall performance on the SuperGLUE benchmark before and after distillation training, evaluating whether fine-tuning on LRLs induces catastrophic forgetting. The model names appended with the suffix "-FT" denote the models after applying the proposed distillation fine-tuning method.

also observed an increased tendency toward hallucination. Due to the consistently lower performance and negligible differences observed among the varying LoRA ranks, we do not to recommend to use LoRA fine-tuning in LRLs translation tasks. These findings suggest that, while LoRA provides computational efficiency, its limited parameter updates are insufficient to capture the nuanced linguistic features required for effective translation of LRLs and may even be harmful.

Does data size really matter? Figure 6 illustrates the strong influence of the size of the data set on the quality of the translation in both directions (English⇔Luxembourgish), more detailed data in the Appendix Table 7. Even using as little as 1% of the available data yields modest improvements over the base model, yet the most substantial gains emerge only at higher data ratios. For example, increasing the data from 25% to 100% nearly doubles spBLEU in the EN→LB direction for both Llama-3.2-3B-Instruct and Gemma-2-2b-it. Notably, Gemma-2-2b-it seems to learn faster in the lower data regimes, but shows some performance attenuation beyond the 50% threshold.

Catastrophic forgetting? Because SLMs are expected to handle diverse tasks, an important question is whether LRL-oriented fine-tuning harms their general abilities. To assess this, we com-

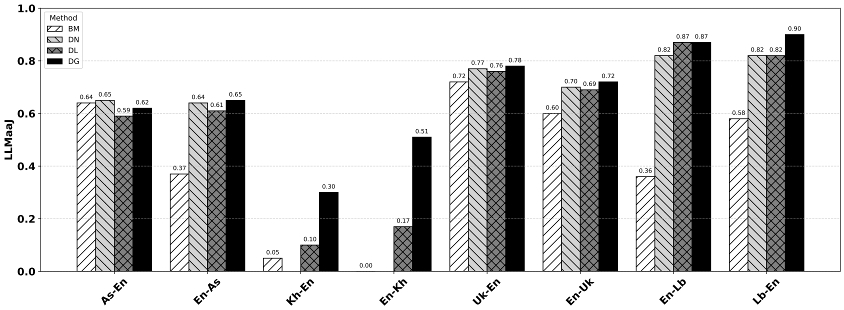


Figure 5: This figure compares the performance of four LRL pairs under the base model (Llama-3.2-3B-it) and knowledge distillation from different teacher models, evaluated using the LLMaaJ metric. “As” denotes Assamese, “Kh” denotes Khasi, and “Uk” denotes Ukrainian. Notably, the Kh—En and En-–Kh directions lack results for the DN setting (i.e., using NLLB-200-3.3B as the teacher model), as NLLB does not provide support for Khasi.

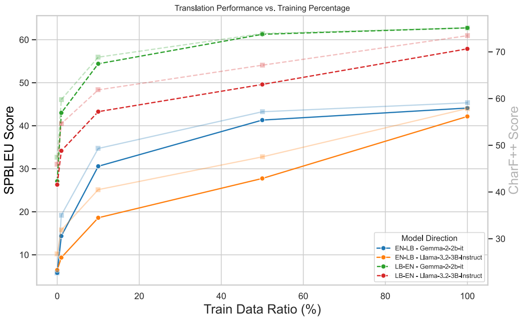


Figure 6: Performance vs. training data ratio; dashed lines show ChrF++ trends, solid lines show spBLEU; x-axis is data proportion.

pared SuperGLUE performance (Sarlin et al., 2020) before and after training. As shown in Table 3, translation-focused fine-tuning leads to only minor changes, indicating that the model retains its broader capabilities. These results suggest that distillation improves LRL translation without inducing catastrophic forgetting.

How about other LRLs? To assess generality beyond Luxembourgish, we applied the same monolingual distillation pipeline to 10,000 sentences each from Khasi, Assamese, and Ukrainian (with 1,000 validation pairs) using three teacher models: NLLB, Llama 3.3–70B, and GPT-4o-mini. We fine-tuned Llama-3.2-3B-Instruct under the same settings and evaluated it on the provided ground-truth annotations. As shown in Figure 5 and Table 10, distillation yields substantial gains in directions with low initial performance (En–As, En–Kh, En–Lb, Lb–En), while improvements are naturally smaller when the base model is already strong (e.g., As–En). Overall, these results confirm that distilled monolingual data can effectively transfer knowledge of resource-scarce languages to SLMs with minimal impact on general capabilities.

5 Conclusion

This work provides a systematic examination of small language models for low-resource language translation and shows that performance disparities across languages remain substantial. By combining monolingual corpora with knowledge distillation from high-capacity teacher models, we demonstrate that SLMs can achieve consistent and often significant improvements, in some cases surpassing much larger models. Compared to full fine-tuning, parameter-efficient approaches such as LoRA offer only limited gains, while our experiments indicate that targeted LRL training does not induce catastrophic forgetting in other capabilities. Although SLMs are not yet universally reliable for all LRL scenarios, this paper provides one of the first systematic validations of monolingual distillation for improving translation quality in LRLs.

Practical Takeaways.

1. Baseline SLM performance on LRLs is highly uneven, with large variation across language families and typologies.
2. Monolingual data combined with knowledge distillation enables small models (e.g., 3B parameters) to match or exceed models up to 70B parameters on several LRL directions.
3. LoRA-based fine-tuning is not well-suited for LRL translation; high-quality data and decoder-only teacher models provide the strongest improvements.
4. Fine-tuning on LRLs does not cause catastrophic forgetting, supporting its use in multilingual or agent-style applications involving low-resource languages.

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Limitations

Distillation for synthetic data training is not new, but comprehensive training on SLMs for low-resource languages remains underexplored. From our research, with appropriate training, small models can also learn to handle very challenging low-resource languages. However, this approach relies on powerful pretrained models for knowledge distillation, which may not always be available in extremely low-resource settings. Standard metrics such as BLEU cannot fully capture linguistic or cultural accuracy, so other evaluation metrics such as CometKiwi (Rei et al., 2022) and human evaluation are still necessary to better validate the results. Another concern is the lack of interpretability in neural translation, as it is unclear whether models truly understand LRLs, highlighting the need for more work on explainability.

Ethics Statement

All models and resources developed in this work are strictly intended for research and educational purposes according to OpenAI usage guidelines; no model weights or derivatives are used — or will be used — for any commercial application. We exclusively utilize publicly available corpora or datasets for which explicit authorization has been obtained from the original data providers. All license terms have been reviewed to ensure full compliance with copyright, attribution, and sharing requirements.

No personally identifiable information (PII) is collected during this research. All data processing, storage, and retention policies are fully aligned with the EU General Data Protection Regulation (GDPR). The dataset of LOD.lu is under the CC0 license. As most of RTL datasets are based on articles from RTL, we cannot publish them, but we make them available to researchers on request.

All code, models, and processed data artifacts will be released under an open-source, research-oriented license (e.g., CC BY-NC), accompanied by comprehensive documentation and bias-analysis methodology to promote transparency and reproducibility. We commit to ongoing ethical oversight through periodic reevaluation of datasets and model outputs, prompt updates in response to emerging concerns, and consultation with interdisciplinary advisory boards to ensure adherence to the highest ethical standards.

Reproducibility Statement

All experiments were implemented and evaluated on four NVIDIA H100 GPUs with a per-device batch size of 8 using the TRL library for training. The complete codebase, configuration files, and training/evaluation scripts are available in the anonymous repository: `https://anonymous.4open.science/r/mt_luxembourgish-408D`. Pretrained checkpoints and selected fine-tuned models are released to facilitate independent verification and reuse. The repository includes environment specifications, dependency pins, and command-line recipes that enable end-to-end reproduction of the reported results.

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Appendix

A Data Processing

Dataset selection directly impacts the reliability and generalizability of experimental results. Our criteria include having enough test samples, providing reference responses, and minimizing potential biases from overlap with pre-training data.

FLORES-200 (Costa-jussa et al., 2022) is a benchmark dataset specifically designed for low-resource and multilingual machine translation, serving as an extended version of FLORES-101 (Goyal et al., 2021b). It covers 200 languages and consists of sentences extracted from 842 web articles, with an average length of approximately 21 words. These sentences are divided into three datasets: dev, devtest, and a hidden test set. Since we require additional evaluation metrics, we use devtest as our set of tests in this study. In our paper, we primarily evaluate the translation performance of all 200 languages into English. However, in the subsequent model training, we focus solely on the Luxembourgish-English language pair for training and testing.

The VAL 300 validation set was constructed using 300 pieces of official news content from July 2024 as the source data. The corresponding ground truth in Luxembourg was generated using ChatGPT, followed by dictionary-based verification to ensure validity. Furthermore, we extracted 30 samples from the dataset and engaged Luxembourgish-English bilingual speakers to perform a quality assessment.

B Experiments settings

In our experiments, we used primarily two distinct models for supervised fine-tuning (SFT) to evaluate performance and optimization strategies. To ensure an effective training process, several hyperparameters and model configurations were meticulously selected. Specifically, the warm-up ratio was set to 0.5, facilitating a gradual increase in the learning rate during the initial training phase for improved convergence stability. The maximum gradient norm was restricted to 0.3, serving as a mechanism to prevent excessively large parameter updates and promote stable optimization dynamics. Furthermore, the input sequence length was capped at 512 tokens, ensuring that all processed data adhered to this fixed-length constraint. A weight decay of 0.01 was applied to regularize the model parameters and mitigate the risk of overfitting. It is worth noting that all of our models were trained for only one epoch. This decision was based on our observation that evaluation metrics reached their optimal performance after a single epoch, while additional epochs amplified the influence of noisy data without bringing performance gains. Moreover, we observed an increased likelihood of hallucinations and the re-emergence of uncontrolled generation, suggesting that the dialogue capability of the model after instruction fine-tuning may deteriorate due to overtraining across multiple epochs. **Therefore, we recommend employing only one epoch for translation training of LRLs on SLMs, as this constitutes a valuable training insight that warrants careful consideration.**

To ensure reproducibility across experiments, a fixed random seed of 3407 was utilized. For model architecture selection, two distinct approaches were considered: standard fine-tuning and LoRA. In cases where LoRA was employed, specific layers were targeted for adaptation, including "q_proj," "k_proj," "v_proj," "o_proj," "gate_proj," "up_proj," and "down_proj." The LoRA alpha parameter was configured to a value of 8, while the dropout rate for LoRA layers was set to 0, indicating that no dropout-based regularization was applied to these low-rank adaptation layers.

For tokenization and input preparation, a standardized procedure was adopted to ensure consistency in sequence length across the examples. The tokenizer processed each input field by truncating sequences exceeding the maximum length of 512 tokens and padding shorter sequences to this fixed length. This was achieved using the ‘padding="max_length"‘ option, thereby guaranteeing uniformity in input representation prior to model training. During the inference stage, we set the temperature parameter to 0.1 (close to 0), which has been shown to help achieve optimal machine translation performance (Li et al., 2025a). In addition, we set `max_new_tokens` to 512, enable `do_sample = True`, and set `top_p = 0.9`.

Model	**Reference**	**SFT Methods**
Llama-3.2-3B-Instruct	(Llama, 2024)	FS/ LoRA SFT
Gemma-2-2b-it	(Google, 2024)	FS/ LoRA SFT

Table 5: Various models and their SFT methods. "FS/ Lora SFT" refers to full-size and "Lora SFT" denotes Low-Rank Adaptation SFT only.

C Dictionary Processing

In our approach to enhancing translation accuracy, particularly for Luxembourgish, we developed a retrieval pipeline using Haystack 2.0. The pipeline utilizes a BM25 retriever to identify relevant dictionary entries that align closely with the input text. The retrieved dictionary entries are then incorporated directly into the prompt provided to GPT-4O, offering multiple lexical choices that help clarify ambiguous terms.

This method operates as follows: first, the BM25 retriever ranks and returns the most relevant dictionary entries based on the Luxembourgish input. These entries serve as additional context within the prompt, guiding GPT-4o toward more accurate translations. Subsequently, the original Luxembourgish sentence and the relevant dictionary context are submitted to GPT-4o for translation. By explicitly integrating these dictionary options into the prompt, GPT-4o is better equipped to resolve lexical ambiguities and correct potential translation errors, enhancing translation accuracy and coherence.

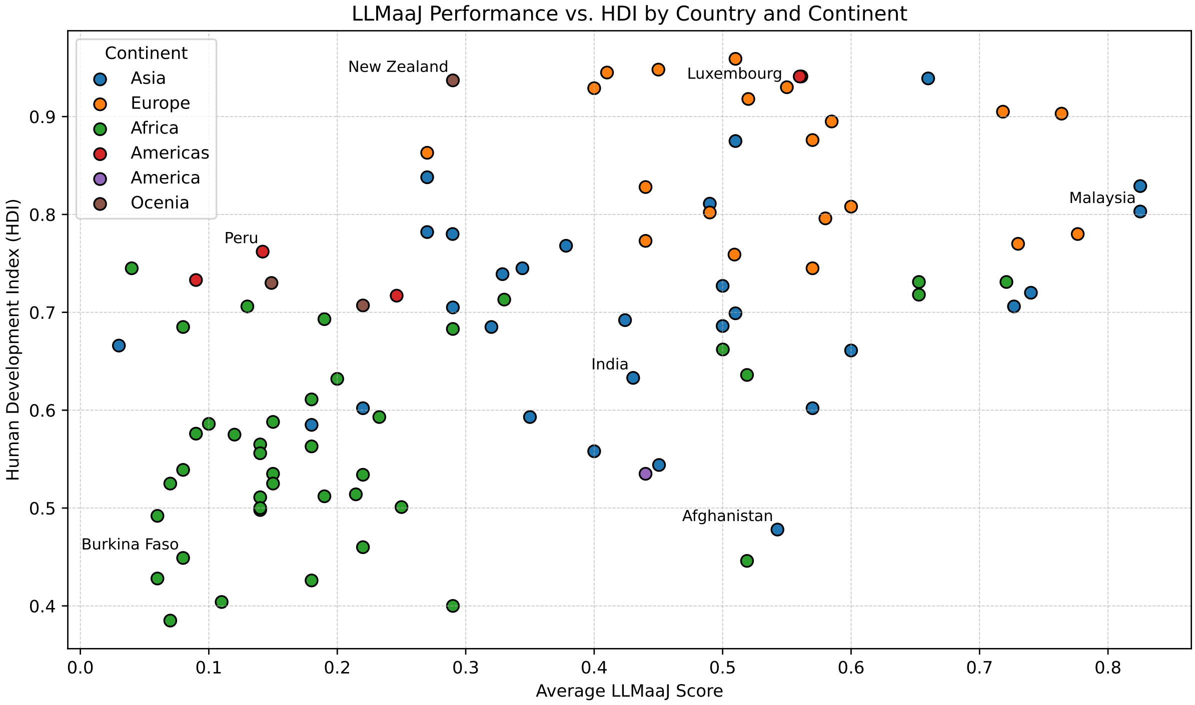

Figure 7: Scatter Plot of LLMaaJ Score and HDI Relation for LRLs

Table 6: Impact of LoRA Rank on Performance During Fine-Tuning, Evaluated Across Three Rank Values

EN-LB	Rank (LoRA)	Val 300			FLORES 200		
		spBLEU	ChrF++	Jaccard	spBLEU	ChrF++	Jaccard
Llama-3.2-3B-Instruct	**Base Model**	6.46	26.78	0.12	4.80	22.10	0.09
	r = 32	12.95	33.09	0.19	9.46	29.64	0.14
	r = 64	13.05	33.59	0.19	9.23	28.93	0.14
	r = 128	13.32	34.09	0.20	9.27	29.16	0.14
Gemma-2-2b-it	**Base Model**	5.82	22.71	0.10	4.61	20.78	0.07
	r = 32	13.07	33.36	0.21	8.88	27.93	**0.16**
	r = 64	13.17	33.35	0.21	9.12	28.06	0.16
	r = 128	13.31	**33.69**	0.21	9.21	28.20	0.16

D Dataset Size Influence

Table 7 in the appendix presents a comprehensive analysis of how dataset size influences translation performance in our low-resource Luxembourgish-English setting. We experimented with dataset sizes ranging from as small as 1% to the full dataset (100%). The results demonstrate a clear, positive correlation between the amount of data utilized during fine-tuning and the subsequent translation quality, as measured by BLEU scores.

In both translation directions (EN→LB and LB→EN), we observed that even very small datasets (e.g., 1%–5%) provide measurable improvements over baseline models, indicating that the models begin acquiring beneficial linguistic patterns early in the fine-tuning process. However, substantial performance gains occur predominantly when increasing the dataset size beyond 25%. For instance, moving from 25% to 100% dataset size nearly doubles the spBLEU scores for the EN→LB direction, clearly highlighting the significance of sufficient data availability for generating fluent, accurate translations in low-resource languages.

Interestingly, the Gemma-2-2b-it model displayed a relatively faster learning trajectory compared to the Llama-3.2-3B-Instruct model in smaller data regimes (below 50%). Nevertheless, Gemma-2-2b-it exhibited a notable attenuation in performance improvements beyond the 50% data threshold, suggesting a diminishing return effect when datasets grow larger. Conversely, the Llama-3.2-3B-Instruct model showed steadier improvements without significant attenuation up to the full dataset size, potentially indicating better scalability of linguistic capabilities with increased training data.

Table 7: Impact of Dataset Size on the Performance of Fine-Tuning

English to Luxembourgish	**Dataset Ratio**	**Val 300**			**FLORES 200**		
		spBLEU	**ChrF++**	**Jaccard**	**spBLEU**	**ChrF++**	**Jaccard**
Llama-3.2-3B-Instruct	**0%**	6.46	26.78	0.12	4.80	22.10	0.09
	1%	9.36	31.88	0.16	6.53	26.31	0.10
	10%	18.61	40.51	0.23	9.79	30.65	0.14
	50%	**27.75**	**47.52**	**0.30**	**13.39**	**34.67**	**0.17**
	100%	**42.16**	57.87	**0.42**	**23.40**	**42.90**	**0.26**
Gemma-2-2b-it	**0%**	5.82	22.71	0.10	4.61	20.78	**0.07**
	1%	14.36	35.06	0.21	9.01	27.99	**0.15**
	10%	30.58	**49.32**	0.34	15.99	36.12	0.22
	50%	41.32	**57.18**	**0.42**	22.30	**41.69**	**0.27**
	100%	44.12	59.10	**0.45**	**23.50**	42.49	**0.28**
Luxembourgish to English		**Val 300**			**FLORES 200**		
		spBLEU	**ChrF++**	**Jaccard**	**spBLEU**	**ChrF++**	**Jaccard**
Llama-3.2-3B-Instruct	**0%**	26.31	45.98	0.33	17.62	36.79	0.26
	1%	34.18	54.63	0.4	22.68	45.98	0.32
	10%	43.28	61.86	0.48	26.11	50.51	0.36
	50%	**49.60**	**67.15**	**0.53**	**29.18**	**54.35**	**0.39**
	100%	57.88	73.46	0.60	32.56	57.60	0.41
Gemma-2-2b-it	**0%**	27.11	47.44	0.34	14.99	37.77	0.26
	1%	43.00	59.80	0.47	29.25	49.15	**0.38**
	10%	54.41	68.86	0.58	36.14	55.67	0.45
	50%	61.26	**73.91**	**0.64**	41.06	**59.94**	**0.49**
	100%	62.75	75.13	0.65	**42.73**	61.25	**0.51**

E Case Study

This section mainly presents several interesting text cases encountered during the pre-trained LLM generation process, which were identified through our manual quality checks.

E.1 Uncontrollable output

A notable translation issue arises from unnecessary explanatory notes appended by the model, which negatively affects automated evaluation metrics. Consider the following example, where the original English input was:

"He added that “they should not, however, be asked to take on obligations that go beyond their development stage, responsibility and capabilities.”"

The model produced:

"Dëi gouf och gesäftlech gesëtt datt “si si och net an Obergrenzen vum ieren Entwéckelungsschatz, Responsabilität a Fähigkeeten uerecht bestallt.” (Note: Please keep in mind that Luxembourgish is a complex and nuanced language, and translations may vary depending on regional dialects and contexts. This translation is provided in standard Luxembourgish)"

The corresponding ground truth translation in Luxembourgish is:

"Hien huet bäigefüügt, datt “se awer net opgefuerdert sollte ginn, Verflichtungen ze iwwerhuelen, déi iwwer hiren Entwécklungsniveau, hir Verantwortung a Fäegkeeten erausginn.”"

The inclusion of this extraneous note, likely originating from instruction-tuned general translation settings or cautious model outputs designed for conversational contexts, significantly impacts BLEU and related metrics. Such notes introduce irrelevant lexical content and length discrepancies, lowering similarity scores and thereby inaccurately reflecting the model's genuine translation ability.

To mitigate this issue, explicit prompt engineering or fine-tuning with specific stopping criteria and clearer output formatting instructions is essential. This strategy helps ensure that model-generated translations remain concise, relevant, and aligned closely with evaluation metric expectations.

E.2 Repetition Problem

During pre-training, we frequently encountered the issue of model hallucination, characterized by repetitive generation. This problem was notably less severe in the Gemma model compared to the Llama model. The repetitive generation primarily occurred in the English-to-Luxembourgish translation direction, largely due to the model's insufficient understanding of Luxembourgish. Consequently, the model frequently confused Luxembourgish with German, exacerbating this confusion further.

Below is an example of input:

Translate the following English input text into Luxembourgish. Do not include any additional information or unrelated content. Input: The United States Strategic Command of the U.S. Department of Defense office is tracking the debris.

Below is an illustrative output that presents repetitive generation:

Here is the translation: D'United States Strategic Command vum ustrategeschen vum ustrategeschen Ufuerderungsbüro vum ustrategeschen Ufuerderungsbüro vum ustrategeschen Ufuerderungsbüro vum ustrategeschen Ufuerderungsbüro vum ustrategeschen Ufuerderungsbüro vum ustrategeschen ...

We also observed that when distillation datasets contained a small amount of hallucinated data—such as infinitely repeating Luxembourgish content (particularly prominent in Llama 3.3 70B)—the subsequently fine-tuned models strongly inherited these hallucination patterns, resulting in substantial performance degradation. Therefore, maintaining high-quality data for fine-tuning is crucial. In comparison, data distilled from ChatGPT rarely exhibited infinite repetition issues, enabling the model to learn appropriate stopping criteria during generation. Additionally, we found that incorporating certain generation prompts during training, such as "Here is the translation: ", could partially mitigate the inherited infinite generation problems originating from distilled models of Llama.

E.3 Hallucination to German

Given the English input sentence:

"At first glance, it looks slightly chaotic at the arrival, the children make a game of clapping hands with everyone who arrives, but that also contributes to the special charm of the event. The Widdebierg is not as high as one might assume from the logo, but it is still 386 meters, which is not nothing,"

Model produced the following output:

"Bei der Ankunft blickt man zunächst etwas chaotisch aus, die Kinder machen ein Spiel mit der Klatsch der Hände mit jedem, der kommt, aber das tragen auch zur besonderen Charme vun der Ävent vun der Éieren. Dëi Widdebiergëstcher Ääschten, well dass méi méi vun der Logo, mä si méi och 386 Méter, wéi déi éis gët nach Léck, wat déiweis méi och net."

In contrast the Luxembourgish ground truth is

"Op den éischte Bléck gesäit et op der Arrivée liicht chaotesch aus, d'Kanner maache sech e Spaass draus, jidderengem, deen ukënnt, an d'Hand ze klatschen, mä och dat dréit zum spezielle Charme vun der Manifestatioun bäi. De Widdebierg ass wuel net esou héich wéi een dat um Logo kéint unhuelen, mä ëmmerhi sinn et 386 Meter, dat ass net grad näischt."

This incorrect translation output primarily results from excessive usage of German vocabulary rather than proper Luxembourgish expressions. This phenomenon likely arises due to several factors:

- **Data Sparsity and Language Proximity:** Luxembourgish and German share considerable lexical and syntactic similarities. In conditions of limited Luxembourgish-specific training data, the model might unintentionally rely heavily on its knowledge of German, leading to significant linguistic interference.

- **Pretraining Corpus Bias:** The predominance of German texts over Luxembourgish in multilingual pretraining datasets likely reinforces German lexical and structural patterns, especially under resource-constrained fine-tuning conditions.

- **Limited Distinctive Training Examples:** Insufficient distinct Luxembourgish examples during fine-tuning might not effectively guide the model away from Germanic lexical choices, resulting in mixed-language outputs or incorrect lexical selections.

Addressing this issue effectively requires either extensive additional training data or targeted linguistic resources explicitly designed to emphasize lexical and grammatical distinctions between closely related languages such as Luxembourgish and German.

E.4 Sudden Stop From NLLB models distillation

We observed an intriguing phenomenon when using NLLB models: regardless of size (3.3B or the 700M distilled variant), the model would sometimes abruptly stop translating longer passages without warning, as if refusing to continue, and this occurred randomly. During subsequent training, it proved difficult to detect which outputs were complete versus incomplete translations; moreover, data curated with NLLB exhibited a severe failure to stop generation at the correct endpoint. Introducing explicit tags and an end-of-translation marker (e.g., “End of Translation”) resolved the non-stopping generation issue; however, the abrupt early-stop behavior from NLLB was fully inherited by downstream models, as shown below.

English Source Sentences

The government warns against fraudsters selling fake tickets for events such as concerts or sporting events. “Be extra cautious when purchasing tickets online” - that is the government’s warning as the Olympic Summer Games and the European Championship are about to start and the festival season is also approaching. Sellers are therefore required to provide all essential information, such as the price, category, and seating location in the hall or stadium.

Translation results for one model distilled from GPT4o-mini

D’Regierung warnt virun Bedruchsbetriber, déi falsch Tickete fir Evenementer wéi Concerten oder Sport-Evenementer verkafen. “Extra virsiichteg sinn, wann een Ticketen online kafe wëll” - dat ass d’Warnung vun der Regierung, well d’Olympesch Summerspiller an d’Europameeschterschaft untrieden an och d’Festival-Saison untrëtt. D’Vendeuren mussen deemno all wichteg Informatiounen, wéi de Präis, d’Kategorie an d’Sëtzplaz am Sall oder am Stadion, matginn.

Translation results for one model distilled from NLLB-3.3B

D’Regierung warnt virun Betrüger, déi gefälschte Ticketen fir Evenementer wéi Concerten oder Sportveranstaltungen verkafen. “Sidd extra virsiichteg beim Ticketkaaf online” - dat ass d’Warnung vun der Regierung, well d’Olympesch Summerspiller an d’Europameeschterschaft ufänken an d’Festivalsaison och no kënnt. **[......MISSING......]**

F Prompt Design for LLM

F.1 Prompt for LLM-as-a-Judge

For the prompt, we mainly adopt the previous legal translation prompt structure (Niklaus et al., 2025) but customize it simply for only the transation needs without any domain emphasis specification. In this paper, we primarily employ google/gemma-3-27b-it as the evaluation model to assess translation quality, given its strong instruction-following capabilities and competitive performance among open-weight LLMs. For efficient model inference, we adopt SGLang as the serving framework, which enables streamlined deployment and low-latency response for both evaluation and generation tasks.

Your task is to assess the accuracy, clarity, and fidelity of the model’s translation to the golden translation.

You will be provided the golden translation, and the model’s translation. Your task is to judge how correct the model’s translation is based on the golden translation, and then give a correctness score. The correctness score should be one of the below numbers: 0.0 (totally wrong), 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, or 1.0 (totally right). You should give the correctness score directly. The correctness score must strictly follow this format: "[[score]]", e.g., "The correctness score: [[0.5]].
Golden Translation: **{Golden Translation}**

Model Translation: **{Model’s Translation}**

F.2 Prompt for SFT

We primarily adopt the classical SFT approach, where the model is trained to predict the next token by minimizing the cross-entropy loss. Consequently, training data typically consist of input-output pairs, such as question-answer or instruction-response formats. The input is usually referred to as the prompt and the output as the answer. During training, the prompt and answer are concatenated and fed into the model, with the objective of guiding the model to generate the answer portion. In this work, we employ the following training template.

```
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 English input text into Luxembourgish. Do not include any additional
information or unrelated content.


### Input:
{The sentence to be translated}


### Response:
{The translated sentence}
```

G Language Ability On LLMs

G.1 Translation Performance and Human Development Disparities

In this analysis, LRLs are operationally defined as those that comprise less than 0.1% of web content (according to W3Techs statistics[4]). The average *LLMaaJ* scores were calculated exclusively for the selected LRLs that also exist in the FLORES-200 dataset. Country - LRLs pairs were identified based on a mapping that utilizes Wikipedia-derived estimates of language speaker distribution.

Figure 7 reveals a clear positive correlation between a country's human development level (HDI) and the translation quality of its low-resource languages as judged by LLMs. Each point in the scatter represents a FLORES-200 language linked to a country's HDI, and the overall trend slopes upward – higher-HDI countries tend to have languages with higher LLMaaJ translation scores. This suggests that socioeconomic factors underpin disparities in LLM translation coverage, echoing the "digital language divide" observed in AI research (Okolo and Tano, 2024). In other words, languages from more developed regions generally receive far better support in large multilingual models than those from less developed regions.

When grouping languages by development tiers, the performance gap is stark. Languages from Very High HDI countries (HDI $\geq$ 0.80) achieve an average LLMaaJ score of around 0.54, more than double the 0.22 average for languages from Low HDI countries (HDI < 0.55). Median scores likewise jump from only 0.15 in low-HDI settings to 0.53 in very-high-HDI settings. This means a typical low-resource language in a highly developed society enjoys significantly better machine translation quality than one in a low-development context. Crucially, it is not simply the number of speakers but the socioeconomic context and digital resources that dictate how well a language is served by AI. For instance, Hindi (with over 500 million speakers) has historically been treated as "low-resource" for NLP, whereas a smaller language like Dutch (with a fraction of the speakers, but backed by a high-HDI country) is well-supported. The greater availability of data and funding in high-HDI environments allows LLMs to achieve markedly better translations for those languages.

Geographic disparities are especially pronounced. Nearly all African languages in the study cluster toward the lower-left of Figure 7, indicating both low HDI and poor translation performance. In fact, none of the African languages evaluated approach the top tier of LLMaaJ scores – a finding consistent with reports that even state-of-the-art multilingual models still lag on African languages due to limited training

[4] https://w3techs.com/technologies/overview/content_language

data and quality. By contrast, European languages (from countries with generally high HDI) occupy the upper range of the plot; these languages achieve some of the highest scores (e.g. minority languages like Occitan in France reach LLMaaJ ≈ 0.76). Several Asian languages spoken in high-HDI regions likewise perform strongly – for example, Standard Malay (Malaysia/Brunei) attains average scores above 0.80 in our data. Meanwhile, many languages of low-HDI countries remain at the bottom: Dzongkha of Bhutan (medium HDI) has one of the lowest scores (LLMaaJ ≈ 0.03), and numerous Sub-Saharan African languages (e.g. Tigrinya of Eritrea) register below 0.10. These patterns suggest that languages benefiting from a robust digital infrastructure or from close linguistic ties to well-resourced tongues (as Occitan does to French) see far better outcomes, whereas languages in impoverished or isolated settings are left behind.

Overall, the strong HDI-performance correlation highlights a systemic inequality in LLM coverage. The correlation coefficient score between HDI and LLMaaJ average score is 0.566, indicating a medium-high correlation. Communities in low-development regions face a double disadvantage: they are underserved by technology on top of existing socio-economic challenges. Indeed, globally fewer than 1% of languages have sufficient data to be considered high-resource, leaving speakers of the other 99% "essentially cut off from global technological progress". This lack of access to quality translation and language tools can hinder information access, education, and opportunities, thereby exacerbating the digital divide and reinforcing global inequalities. Our findings underscore that current multilingual AI models, despite their broad reach, de facto offer far stronger support for languages of wealthy, high-HDI communities than for those of poorer regions. Addressing this gap will require concerted efforts to bring truly inclusive language coverage to the forefront, rather than merely adding more languages without improving quality for the most disadvantaged.

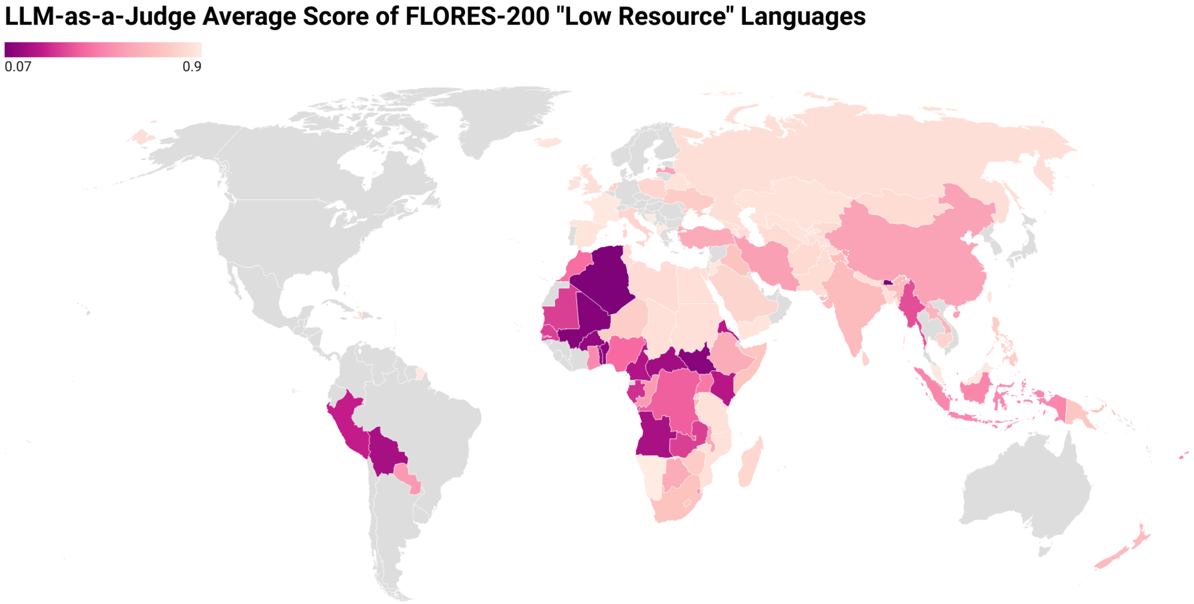
LLM-as-a-Judge Average Score of FLORES-200 "Low Resource" Languages
0.07
0.9

Figure 8: Linguistic geographical distribution results. Some countries might not be accurate because the official languages are European, especially in Africa. English major countries will only consider the minority language if in the dataset.

G.2 Result Tables

Table 8: The LLMaaJ results on the FLORES-200 dataset are derived from evaluations of 10 distinct large language models. Population estimates are based on heterogeneous sources, and the reported population are not guaranteed to be accurate. Therefore, they should be interpreted with appropriate caution.

Language Name	Language Branch	Population	GPT4o mini	Llama-3.1-8B	Llama-3.2-3B	Ministral -8B	Phi-3	Phi-3.5	Qwen2.5 -1.5B	Qwen2.5 -3B	gemma2 -2b	gemma2 -9b
Central Atlas Tamazight	Berber	3-4 million	0.017	0.008	0.006	0.008	0.007	0.014	0.006	0.01	0.011	0.014
Kabyle		5 million	0.078	0.054	0.027	0.025	0.02	0.038	0.02	0.042	0.028	0.08
Tamasheq (Latin script)		500,000	0.143	0.101	0.067	0.082	0.088	0.093	0.061	0.09	0.096	0.142
Tamasheq (Tifinagh script)		500,000	0.021	0.009	0.007	0.009	0.008	0.022	0.005	0.013	0.016	0.018
Hausa	Chadic	40 million	0.774	0.534	0.166	0.132	0.089	0.101	0.082	0.11	0.228	0.656
Somali	Cushitic	20 million	0.735	0.257	0.112	0.143	0.077	0.121	0.063	0.107	0.112	0.5
West Central Oromo		10 million	0.617	0.079	0.067	0.047	0.028	0.051	0.023	0.07	0.035	0.121
Amharic	Semitic	32 million	0.627	0.254	0.015	0.024	0.008	0.013	0.018	0.054	0.148	0.59
Hebrew		9 million	0.892	0.859	0.587	0.853	0.464	0.599	0.578	0.757	0.802	0.874
Maltese		520,000	0.892	0.793	0.551	0.428	0.237	0.261	0.202	0.311	0.627	0.855
Modern Standard Arabic		335 millions	0.881	0.858	0.792	0.847	0.573	0.799	0.771	0.832	0.814	0.863
Tigrinya		9 million	0.209	0.066	0.006	0.02	0.016	0.017	0.007	0.026	0.041	0.211
Egyptian Arabic		60 million	0.851	0.807	0.701	0.776	0.451	0.68	0.658	0.753	0.718	0.815
Mesopotamian Arabic		15 million	0.862	0.839	0.715	0.794	0.497	0.713	0.686	0.774	0.751	0.83
Moroccan Arabic		30 million	0.816	0.659	0.529	0.596	0.316	0.508	0.491	0.58	0.555	0.736
Najdi Arabic		10 million	0.861	0.868	0.772	0.826	0.542	0.775	0.751	0.817	0.788	0.842
North Levantine Arabic		20 million	0.869	0.813	0.706	0.774	0.461	0.677	0.654	0.757	0.735	0.823
South Levantine Arabic		24 million	0.875	0.824	0.714	0.788	0.485	0.715	0.673	0.767	0.743	0.831
Ta‚Äôizzi-Adeni Arabic		11 million	0.869	0.857	0.748	0.816	0.525	0.75	0.725	0.802	0.783	0.842
Tunisian Arabic		11 million	0.837	0.724	0.611	0.686	0.418	0.611	0.57	0.667	0.631	0.773
Khmer	Khmer	16 million	0.797	0.718	0.415	0.08	0.061	0.082	0.117	0.259	0.233	0.699
Santali	Munda	7.5 million	0.018	0.073	0.007	0.002	0.004	0.005	0.001	0.01	0.052	0.387
Vietnamese	Vietic	76 million	0.881	0.867	0.839	0.856	0.623	0.676	0.833	0.854	0.849	0.875
Acehnese (Arabic script)	Malayo-Polynesian	3.5 million	0.141	0.054	0.025	0.042	0.005	0.03	0.014	0.049	0.021	0.097
Acehnese (Latin script)		3.5 million	0.394	0.309	0.195	0.213	0.169	0.219	0.157	0.235	0.209	0.385
Balinese		3.3 million	0.652	0.542	0.375	0.322	0.274	0.298	0.249	0.35	0.383	0.624
Banjar (Arabic script)		4 million	0.179	0.083	0.039	0.054	0.008	0.045	0.019	0.05	0.021	0.093
Banjar (Latin script)		4 million	0.688	0.604	0.459	0.436	0.282	0.297	0.302	0.422	0.47	0.69
Buginese		4 million	0.346	0.228	0.161	0.172	0.161	0.188	0.133	0.194	0.198	0.296
Cebuano		21 million	0.877	0.743	0.496	0.538	0.379	0.38	0.287	0.414	0.614	0.819
Ilocano		8 million	0.765	0.526	0.33	0.265	0.239	0.245	0.162	0.255	0.372	0.672
Indonesian		43 million L1	0.894	0.883	0.859	0.871	0.814	0.815	0.841	0.869	0.869	0.889
Javanese		82 million	0.837	0.7	0.489	0.376	0.256	0.308	0.286	0.436	0.527	0.767
Minangkabau (Arabic script)		6.5 million	0.157	0.057	0.03	0.037	0.006	0.044	0.012	0.038	0.018	0.081
Minangkabau (Latin script)		6.5 million	0.671	0.618	0.422	0.365	0.251	0.265	0.26	0.383	0.416	0.704
Pangasinan		1.5 million	0.487	0.38	0.282	0.291	0.292	0.298	0.206	0.269	0.319	0.492
Plateau Malagasy		5 million	0.813	0.313	0.126	0.289	0.069	0.098	0.074	0.129	0.13	0.504
Standard Malay		18 million L1	0.889	0.872	0.829	0.858	0.742	0.728	0.769	0.83	0.853	0.881
Sundanese		42 million	0.854	0.687	0.464	0.414	0.286	0.325	0.324	0.45	0.47	0.748
Tagalog		28 million	0.889	0.846	0.751	0.798	0.667	0.621	0.428	0.624	0.816	0.876
Waray		3.7 million	0.856	0.679	0.447	0.552	0.386	0.408	0.297	0.403	0.553	0.79
Fijian		330,000	0.501	0.146	0.072	0.094	0.084	0.108	0.057	0.097	0.103	0.226
Maori		185,000 (L2)	0.689	0.412	0.176	0.295	0.166	0.192	0.102	0.2	0.183	0.471
Samoan		500,000	0.728	0.313	0.117	0.118	0.09	0.121	0.076	0.121	0.126	0.4
Central Aymara	Aymara	2 million	0.168	0.085	0.074	0.083	0.072	0.092	0.061	0.093	0.087	0.126
Esperanto	Constructed	2 million (est.)	0.89	0.869	0.798	0.865	0.714	0.707	0.574	0.708	0.807	0.878
Tok Pisin	(English-based)	4 million	0.739	0.529	0.279	0.356	0.299	0.306	0.163	0.249	0.369	0.721
Haitian Creole	(French-based)	10 million	0.839	0.615	0.381	0.443	0.24	0.281	0.169	0.304	0.406	0.739
Papiamento	(Iberian-based)	340,000	0.831	0.702	0.505	0.536	0.426	0.439	0.352	0.504	0.499	0.783
Kabuverdianu	(Portuguese-based)	1.2 million	0.786	0.587	0.436	0.496	0.38	0.412	0.319	0.459	0.454	0.672
Kannada	Dravidian	44 million	0.825	0.77	0.663	0.775	0.016	0.026	0.081	0.314	0.624	0.816
Malayalam		38 million	0.845	0.797	0.664	0.777	0.015	0.027	0.102	0.341	0.663	0.844
Tamil		75 million	0.821	0.799	0.675	0.739	0.053	0.093	0.061	0.19	0.669	0.814
Telugu		81 million	0.846	0.802	0.731	0.772	0.031	0.045	0.108	0.337	0.667	0.831
Tosk Albanian	Albanian	3 million	0.884	0.828	0.655	0.806	0.263	0.288	0.213	0.365	0.622	0.836
Armenian	Armenian	6.7 million	0.867	0.835	0.569	0.838	0.086	0.124	0.078	0.22	0.634	0.841
Latgalian	Baltic	150,000	0.581	0.361	0.182	0.276	0.138	0.173	0.115	0.218	0.233	0.442
Lithuanian		3 million	0.877	0.815	0.668	0.801	0.297	0.292	0.326	0.541	0.787	0.864
Standard Latvian		1.75 million	0.886	0.822	0.665	0.812	0.322	0.35	0.353	0.59	0.785	0.872
Welsh	Celtic	875,000 (L2)	0.896	0.816	0.577	0.749	0.136	0.183	0.118	0.285	0.419	0.813
Irish		1.2 million (L2)	0.86	0.731	0.428	0.58	0.107	0.137	0.082	0.21	0.249	0.72
Scottish Gaelic		60,000	0.8	0.567	0.276	0.249	0.098	0.134	0.073	0.174	0.144	0.564
Afrikaans	Germanic	7 million	0.901	0.878	0.82	0.855	0.684	0.72	0.687	0.786	0.847	0.89
Danish		5.8 million	0.901	0.884	0.855	0.879	0.767	0.81	0.756	0.838	0.873	0.891
German		95 million (L1)	0.898	0.89	0.88	0.891	0.887	0.884	0.863	0.881	0.885	0.894
Limburgish		1.3 million	0.784	0.719	0.535	0.533	0.381	0.418	0.354	0.492	0.601	0.796
Eastern Yiddish		1 million	0.834	0.618	0.1	0.166	0.039	0.053	0.017	0.117	0.261	0.78
Faroese		70,000	0.845	0.639	0.417	0.491	0.254	0.279	0.183	0.317	0.375	0.709
Icelandic		350,000	0.876	0.768	0.526	0.714	0.241	0.252	0.173	0.315	0.476	0.789
Norwegian Bokmal		4 million	0.888	0.87	0.84	0.865	0.748	0.784	0.726	0.814	0.858	0.881
Norwegian Nynorsk		750,000	0.89	0.864	0.816	0.86	0.65	0.687	0.637	0.756	0.838	0.88
Swedish		10 million	0.899	0.892	0.875	0.879	0.791	0.822	0.777	0.841	0.874	0.893
Dutch		24 million	0.883	0.874	0.859	0.873	0.81	0.86	0.828	0.856	0.864	0.878
Luxembourgish		400,000	0.874	0.767	0.565	0.557	0.396	0.404	0.281	0.41	0.493	0.792
Greek	Greek	13 million	0.88	0.854	0.791	0.852	0.604	0.635	0.475	0.672	0.82	0.868
Assamese	Indo-Aryan	15 million	0.785	0.666	0.467	0.32	0.035	0.067	0.167	0.396	0.464	0.719
Awadhi		38 million	0.841	0.769	0.655	0.696	0.243	0.519	0.313	0.53	0.689	0.796
Bengali		265 million	0.855	0.81	0.742	0.791	0.097	0.14	0.392	0.644	0.728	0.831
Bhojpuri		50 million	0.834	0.702	0.56	0.596	0.191	0.444	0.239	0.418	0.602	0.768
Chhattisgarhi		16 million	0.821	0.672	0.541	0.605	0.191	0.471	0.256	0.445	0.589	0.735
Eastern Panjabi		33 million	0.848	0.831	0.686	0.733	0.017	0.037	0.103	0.417	0.587	0.824
Gujarati		55 million	0.853	0.807	0.693	0.725	0.012	0.024	0.197	0.497	0.649	0.838
Hindi		600 million (L2)	0.871	0.841	0.806	0.832	0.408	0.727	0.49	0.705	0.822	0.862
Magahi		14 million	0.843	0.741	0.634	0.667	0.242	0.497	0.293	0.509	0.682	0.801
Maithili		35 million	0.855	0.722	0.589	0.57	0.191	0.454	0.245	0.422	0.624	0.788
Marathi		83 million	0.864	0.809	0.716	0.726	0.131	0.253	0.227	0.464	0.69	0.831
Nepali		25 million	0.851	0.75	0.576	0.717	0.205	0.375	0.233	0.465	0.688	0.825
Odia		37 million	0.796	0.692	0.242	0.027	0.014	0.025	0.055	0.365	0.041	0.637
Sanskrit		14000+	0.624	0.536	0.389	0.41	0.18	0.31	0.165	0.327	0.341	0.596
Sindhi		32 million	0.824	0.721	0.346	0.126	0.042	0.081	0.064	0.167	0.214	0.625

Sinhala		17 million	0.793	0.703	0.026	0.019	0.011	0.016	0.017	0.118	0.233	0.729
Urdu		100+ million L2	0.855	0.828	0.701	0.736	0.188	0.215	0.276	0.505	0.674	0.822
Kashmiri (Arabic script)		7 million	0.497	0.315	0.17	0.221	0.051	0.089	0.062	0.145	0.202	0.383
Kashmiri (Devanagari script)		7 million	0.411	0.213	0.146	0.191	0.069	0.132	0.073	0.144	0.16	0.299
Central Kurdish	Iranian	6 million	0.594	0.763	0.224	0.071	0.014	0.026	0.033	0.099	0.127	0.574
Dari		10-12 million	0.86	0.873	0.745	0.793	0.405	0.415	0.561	0.684	0.775	0.84
Northern Kurdish		15 million	0.615	0.454	0.187	0.455	0.078	0.114	0.1	0.16	0.131	0.447
Southern Pashto		20 million	0.792	0.725	0.395	0.601	0.077	0.12	0.127	0.241	0.234	0.588
Tajik		8-9 million	0.848	0.766	0.212	0.178	0.05	0.1	0.075	0.193	0.141	0.682
Western Persian		55 million	0.873	0.894	0.804	0.839	0.438	0.463	0.601	0.741	0.822	0.864
Catalan	Romance	4 million	0.895	0.885	0.851	0.88	0.781	0.792	0.785	0.843	0.859	0.886
French		80+ million (L1)	0.896	0.891	0.885	0.892	0.892	0.889	0.881	0.887	0.886	0.894
Friulian		600,000	0.796	0.689	0.501	0.577	0.45	0.46	0.376	0.504	0.492	0.751
Galician		2.4 million	0.893	0.869	0.84	0.875	0.832	0.827	0.804	0.85	0.853	0.883
Italian		65 million	0.891	0.882	0.872	0.887	0.884	0.879	0.863	0.875	0.878	0.889
Ligurian		500,000	0.759	0.65	0.493	0.581	0.499	0.498	0.394	0.538	0.522	0.731
Lombard		3.5 million (est.)	0.817	0.663	0.49	0.597	0.447	0.458	0.348	0.503	0.504	0.747
Occitan		2 million	0.889	0.847	0.765	0.806	0.698	0.692	0.622	0.731	0.73	0.858
Portuguese		230 million	0.899	0.891	0.879	0.892	0.888	0.884	0.873	0.883	0.886	0.892
Romanian		24 million	0.898	0.889	0.867	0.873	0.729	0.77	0.754	0.829	0.867	0.893
Sardinian		1 million	0.758	0.68	0.505	0.538	0.426	0.426	0.34	0.476	0.51	0.746
Spanish		483 million L1	0.887	0.877	0.866	0.883	0.877	0.876	0.863	0.875	0.877	0.885
Venetian		2 million	0.858	0.792	0.677	0.772	0.614	0.612	0.542	0.695	0.703	0.842
Asturian		400,000	0.864	0.844	0.78	0.814	0.727	0.73	0.677	0.749	0.797	0.861
Sicilian		4.7 million	0.829	0.704	0.537	0.628	0.419	0.454	0.343	0.509	0.544	0.782
Belarusian	Slavic	6.5 million	0.865	0.815	0.651	0.812	0.171	0.223	0.333	0.567	0.744	0.846
Russian		150 million (L1)	0.889	0.883	0.86	0.884	0.791	0.846	0.855	0.872	0.867	0.888
Ukrainian		35 million	0.892	0.875	0.822	0.873	0.616	0.762	0.729	0.818	0.858	0.885
Bosnian		3 million	0.895	0.869	0.804	0.871	0.612	0.576	0.644	0.788	0.823	0.883
Bulgarian		8 million	0.891	0.869	0.821	0.865	0.624	0.635	0.728	0.812	0.856	0.883
Croatian		5.6 million	0.891	0.87	0.826	0.866	0.595	0.563	0.646	0.781	0.828	0.88
Macedonian		2 million	0.89	0.858	0.762	0.858	0.432	0.45	0.592	0.742	0.797	0.872
Serbian		6.5 million	0.893	0.875	0.801	0.86	0.423	0.456	0.585	0.753	0.825	0.884
Slovenian		2.1 million	0.889	0.85	0.767	0.839	0.531	0.518	0.578	0.727	0.819	0.878
Czech		10.5 million	0.892	0.882	0.856	0.87	0.697	0.771	0.779	0.847	0.862	0.887
Polish		38 million	0.885	0.873	0.846	0.867	0.714	0.763	0.777	0.847	0.861	0.881
Silesian		1 million	0.808	0.698	0.557	0.592	0.362	0.401	0.38	0.541	0.587	0.784
Slovak		5.2 million	0.892	0.864	0.802	0.862	0.602	0.693	0.689	0.807	0.852	0.882
Japanese	Japonic	125 million	0.878	0.858	0.825	0.851	0.761	0.819	0.799	0.846	0.833	0.869
Georgian	South Caucasian	4 million	0.856	0.776	0.449	0.801	0.104	0.138	0.137	0.273	0.541	0.794
Korean	Koreanic	81 million	0.875	0.843	0.786	0.842	0.573	0.766	0.76	0.823	0.792	0.861
Basque	Isolate	750,000	0.865	0.79	0.563	0.786	0.184	0.233	0.128	0.24	0.558	0.832
Halh Mongolian	Eastern Mongolic	3 million	0.834	0.699	0.151	0.514	0.042	0.084	0.065	0.136	0.147	0.613
Wolof	Atlantic	10 million	0.3	0.141	0.088	0.109	0.107	0.147	0.08	0.12	0.11	0.173
Nigerian Fulfulde		14 million	0.191	0.105	0.061	0.072	0.075	0.092	0.05	0.085	0.081	0.128
Bemba	Bantu	4 million	0.302	0.13	0.092	0.107	0.098	0.11	0.068	0.103	0.124	0.249
Chokwe		1.3 million	0.147	0.096	0.071	0.077	0.075	0.117	0.062	0.092	0.098	0.136
Ganda		7 million	0.45	0.156	0.091	0.107	0.08	0.092	0.065	0.097	0.099	0.247
Kamba		4 million	0.202	0.126	0.087	0.095	0.098	0.118	0.068	0.108	0.101	0.171
Kikongo		7 million	0.267	0.118	0.074	0.103	0.101	0.11	0.076	0.12	0.112	0.189
Kikuyu		8 million	0.239	0.158	0.095	0.116	0.112	0.139	0.085	0.119	0.122	0.199
Kimbundu		3 million	0.133	0.077	0.056	0.075	0.071	0.087	0.054	0.077	0.082	0.125
Kinyarwanda		12 million	0.788	0.296	0.096	0.098	0.071	0.091	0.068	0.115	0.114	0.494
Lingala		8-10 million	0.554	0.156	0.095	0.134	0.117	0.135	0.094	0.141	0.118	0.225
Luba-Kasai		6.5 million	0.201	0.1	0.083	0.115	0.104	0.125	0.087	0.112	0.121	0.188
Northern Sotho		5 million	0.632	0.205	0.104	0.117	0.103	0.124	0.092	0.148	0.118	0.38
Nyanja		12 million	0.7	0.215	0.11	0.129	0.101	0.127	0.086	0.133	0.166	0.436
Rundi		9 million	0.679	0.194	0.083	0.083	0.07	0.086	0.062	0.113	0.101	0.322
Shona		11 million	0.764	0.208	0.103	0.149	0.095	0.124	0.086	0.123	0.143	0.531
Southern Sotho		5.6 million	0.744	0.196	0.095	0.1	0.089	0.111	0.087	0.136	0.125	0.461
Swahili		100+ million L2	0.857	0.768	0.665	0.602	0.212	0.233	0.09	0.188	0.736	0.839
Swati		2.5 million	0.55	0.168	0.111	0.112	0.081	0.103	0.073	0.122	0.116	0.382
Tsonga		3 million	0.525	0.15	0.081	0.095	0.082	0.108	0.057	0.092	0.096	0.242
Tswana		5 million	0.624	0.193	0.092	0.104	0.088	0.111	0.075	0.122	0.113	0.377
Tumbuka		2 million	0.504	0.166	0.094	0.105	0.089	0.114	0.069	0.114	0.125	0.284
Umbundu		6 million	0.135	0.076	0.063	0.069	0.064	0.086	0.045	0.078	0.087	0.122
Xhosa		8.2 million	0.776	0.248	0.124	0.154	0.103	0.132	0.077	0.139	0.192	0.612
Zulu		12 million	0.799	0.264	0.101	0.111	0.082	0.107	0.095	0.127	0.168	0.619
Fon	Gbe	1.7 million	0.108	0.075	0.054	0.065	0.068	0.079	0.041	0.062	0.075	0.107
Ewe		7 million	0.138	0.097	0.071	0.08	0.068	0.083	0.054	0.074	0.077	0.124
Kabiye	Gur	1.2 million	0.099	0.101	0.065	0.072	0.051	0.074	0.035	0.061	0.078	0.138
Mossi		7.5 million	0.124	0.076	0.064	0.077	0.066	0.081	0.057	0.076	0.077	0.117
Akan	Kwa	11 million	0.511	0.201	0.109	0.127	0.128	0.148	0.088	0.135	0.147	0.306
Twi		17 million	0.504	0.226	0.133	0.14	0.129	0.161	0.09	0.143	0.158	0.341
Bambara	Mande	14 million	0.119	0.086	0.067	0.076	0.069	0.094	0.051	0.077	0.084	0.12
Dyula		3 million	0.12	0.066	0.054	0.073	0.076	0.097	0.051	0.074	0.073	0.105
Igbo	Volta	27 million	0.691	0.397	0.137	0.091	0.074	0.092	0.063	0.078	0.148	0.483
Yoruba		28 million	0.579	0.216	0.087	0.081	0.068	0.097	0.059	0.077	0.088	0.311
Sango	Ubangian	5 million (L2)	0.154	0.101	0.076	0.091	0.098	0.113	0.074	0.096	0.108	0.145
Luo	Nilotic	4.2 million	0.169	0.087	0.068	0.08	0.094	0.1	0.066	0.078	0.086	0.139
Nuer		1.4 million	0.065	0.038	0.033	0.036	0.023	0.037	0.02	0.05	0.038	0.065
Southwestern Dinka		2 million	0.134	0.111	0.089	0.096	0.096	0.11	0.072	0.098	0.107	0.136
Central Kanuri (Arabic script)	Saharan	4 million	0.043	0.02	0.01	0.019	0.017	0.027	0.011	0.017	0.015	0.026
Central Kanuri (Latin script)		4 million	0.153	0.1	0.073	0.092	0.112	0.12	0.074	0.104	0.087	0.143
Ayacucho Quechua	Quechua II	1 million	0.232	0.182	0.109	0.112	0.113	0.139	0.084	0.129	0.126	0.194
Chinese (Simplified)	Sinitic	920 million (L1)	0.884	0.872	0.847	0.871	0.775	0.829	0.859	0.868	0.855	0.878
Chinese (Traditional)		31 million	0.881	0.861	0.825	0.857	0.714	0.807	0.847	0.855	0.842	0.871
Yue Chinese		60 million	0.884	0.896	0.828	0.858	0.724	0.8	0.84	0.862	0.846	0.873
Burmese	Tibeto-Burman	33 million	0.748	0.672	0.075	0.616	0.021	0.033	0.033	0.094	0.178	0.638
Dzongkha		700,000	0.068	0.11	0.004	0.007	0.004	0.008	0.001	0.005	0.006	0.119
Jingpho		900,000	0.131	0.093	0.075	0.08	0.084	0.106	0.065	0.097	0.072	0.111
Meitei (Bengali script)		1.8 million	0.155	0.065	0.046	0.061	0.012	0.031	0.02	0.052	0.043	0.129
Mizo		900,000	0.334	0.325	0.203	0.185	0.189	0.217	0.158	0.219	0.328	0.593
Standard Tibetan		1.2 million	0.103	0.185	0.011	0.007	0.012	0.014	0.01	0.015	0.018	0.191
Shan	Tai	3 million	0.128	0.417	0.085	0.092	0.107	0.132	0.08	0.1	0.118	0.191
Lao		7.5 million	0.658	0.384	0.073	0.081	0.069	0.093	0.071	0.132	0.125	0.521
Thai		36 million	0.879	0.868	0.819	0.828	0.451	0.591	0.773	0.831	0.818	0.872
Guarani	Tupi	6-7 million	0.547	0.269	0.186	0.181	0.182	0.221	0.14	0.198	0.207	0.331

Northern Uzbek	Karluk	27 million	0.866	0.765	0.539	0.733	0.115	0.151	0.168	0.349	0.501	0.787
Uyghur		10 million	0.773	0.674	0.157	0.12	0.011	0.032	0.023	0.11	0.026	0.44
Bashkir	Kipchak	1.2 million	0.837	0.762	0.311	0.463	0.128	0.192	0.143	0.243	0.384	0.746
Crimean Tatar		300,000	0.765	0.609	0.42	0.518	0.175	0.257	0.215	0.366	0.418	0.705
Kazakh		13 million	0.868	0.788	0.399	0.755	0.102	0.149	0.187	0.325	0.498	0.808
Kyrgyz		4.5 million	0.827	0.731	0.333	0.655	0.086	0.15	0.162	0.278	0.308	0.709
Tatar		5 million	0.863	0.776	0.376	0.715	0.112	0.177	0.158	0.266	0.375	0.739
North Azerbaijani	Oghuz	9-10 million	0.837	0.776	0.618	0.749	0.21	0.262	0.267	0.491	0.636	0.804
South Azerbaijani		15-20 million	0.572	0.437	0.236	0.413	0.065	0.117	0.094	0.146	0.273	0.546
Turkish		75 million	0.884	0.857	0.809	0.82	0.497	0.614	0.625	0.775	0.825	0.878
Turkmen		7 million	0.834	0.538	0.289	0.287	0.102	0.153	0.115	0.211	0.257	0.656
Estonian	Finnic	1.1 million	0.89	0.838	0.708	0.811	0.175	0.222	0.314	0.531	0.777	0.869
Finnish		5.4 million	0.89	0.867	0.805	0.843	0.453	0.606	0.42	0.61	0.821	0.881
Hungarian	Ugric	13 million	0.887	0.871	0.839	0.852	0.486	0.641	0.399	0.61	0.829	0.879

Table 9: The Corpus BLEU results on the FLORES-200 dataset are derived from evaluations of 10 distinct large language models. Population estimates are based on heterogeneous sources, and the reported population are not guaranteed to be accurate. Therefore, they should be interpreted with appropriate caution.

Language Name	Language Branch	Population	GPT4o Mini	Llama 3.1 8B	Llama 3.2 3B	Ministral 8B	Phi-3	Phi-3.5	Qwen2.5 1.5B	Qwen2.5 3B	gemma-2 2B	gemma-2 9B
Central Atlas Tamazight	**Berber**	3-4 million	1.4	0.4	0.4	0.2	1.0	0.8	0.2	0.8	0.4	1.4
Kabyle		5 million	4.0	3.3	1.4	0.9	1.7	0.7	0.5	1.5	1.4	4.3
Tamasheq (Latin script)		500,000	5.2	3.9	2.7	1.9	4.3	1.7	1.0	3.4	3.3	4.9
Tamasheq (Tifinagh script)		500,000	1.3	0.4	0.3	0.2	1.0	0.7	0.1	0.5	0.6	1.1
Hausa	Chadic	40 million	30.4	20.0	7.5	2.9	3.9	1.6	1.5	4.5	8.9	25.9
Somali	Cushitic	20 million	26.6	10.8	5.3	3.2	4.0	1.3	1.9	4.0	4.2	19.1
West Central Oromo		10 million	17.2	3.5	1.9	0.9	1.7	0.7	0.3	1.5	1.1	4.2
Amharic	Semitic	32 million	18.0	8.4	1.1	0.4	1.0	0.8	0.6	2.7	4.8	19.1
Hebrew		9 million	43.6	36.4	21.2	36.9	18.1	9.3	22.3	31.7	33.1	42.6
Maltese		520,000	51.8	41.1	26.1	16.8	9.1	3.6	4.4	12.2	28.3	49.4
Modern Standard Arabic		330 million	39.2	30.1	29.5	33.9	19.0	16.0	27.2	32.6	31.3	38.6
Modern Standard Arabic (Romanized)		330 million	25.1	10.1	4.5	4.8	2.9	1.3	1.3	6.3	2.2	14.2
Tigrinya		9 million	4.7	1.8	0.7	0.3	0.7	0.7	0.2	1.3	1.1	5.5
Egyptian Arabic		60 million	30.9	11.6	21.6	24.9	13.0	10.5	18.4	23.6	21.7	29.5
Mesopotamian Arabic		15 million	33.8	12.2	23.0	26.7	14.9	12.5	20.8	25.9	24.7	31.9
Moroccan Arabic		30 million	29.1	13.7	17.0	18.1	9.9	7.3	13.2	18.4	16.3	25.7
Najdi Arabic		10 million	38.5	19.3	29.0	32.5	17.8	19.6	25.7	31.1	30.1	37.4
North Levantine Arabic		20 million	37.5	15.9	25.0	27.8	15.1	12.5	21.2	27.4	25.0	34.4
South Levantine Arabic		24 million	40.5	15.5	27.1	31.3	17.3	12.7	23.7	30.3	28.1	37.3
Ta'izzi-Adeni Arabic		11 million	35.6	11.2	25.6	29.2	16.3	15.7	23.3	28.0	27.3	33.9
Tunisian Arabic		11 million	30.7	15.3	19.9	22.2	12.8	10.0	17.5	21.8	19.9	28.1
Khmer	Khmer	16 million	25.3	17.4	12.5	2.0	3.1	1.7	3.5	9.2	6.3	22.3
Santali	**Munda**	7.5 million	0.7	3.9	0.5	0.1	0.4	0.3	0.1	0.1	2.1	12.7
Vietnamese	Vietic	76 million	35.8	33.4	30.0	31.4	19.7	12.5	28.6	32.1	29.7	36.6
Acehnese (Arabic script)	Malayo-Polynesian	3.5 million	4.8	1.5	1.0	0.9	0.6	0.5	0.4	1.6	0.5	3.1
Acehnese (Latin script)		3.5 million	12.7	10.7	6.9	5.4	6.1	2.8	2.7	6.2	6.2	13.5
Balinese		3.3 million	22.9	17.9	12.4	8.0	8.5	3.6	4.9	10.1	11.9	22.4
Banjar (Arabic script)		4 million	6.2	1.4	1.2	0.8	0.6	0.5	0.4	1.9	0.5	3.1
Banjar (Latin script)		4 million	24.9	22.4	15.9	12.7	10.0	4.7	7.3	14.4	15.8	27.1
Buginese		4 million	10.2	6.7	5.2	4.5	5.1	2.6	2.7	5.9	6.0	9.4
Cebuano		21 million	42.8	32.6	20.7	19.4	14.3	5.6	9.3	16.3	24.1	39.2
Ilocano		8 million	29.2	20.5	13.6	7.2	8.4	3.8	4.1	9.3	12.6	26.5
Indonesian		43 million L1	44.4	40.9	37.0	38.0	32.4	22.9	33.5	37.3	38.0	44.9
Javanese		82 million	37.7	27.2	18.1	10.3	8.3	3.0	6.7	14.2	18.1	33.4
Minangkabau (Arabic script)		6.5 million	5.7	1.3	0.8	0.7	0.6	0.5	0.3	1.3	0.3	2.9
Minangkabau (Latin script)		6.5 million	24.9	23.1	16.0	9.8	8.9	4.3	6.9	12.4	13.4	27.8
Pangasinan		1.5 million	17.8	14.7	11.7	9.7	10.6	5.4	5.8	10.3	11.0	18.1
Plateau Malagasy		5 million	27.4	11.0	5.2	9.5	3.7	1.5	1.5	3.9	4.5	17.1
Standard Malay		18 million L1	44.5	38.6	34.9	37.7	28.4	17.1	30.1	35.3	36.7	44.5
Sundanese		42 million	35.7	23.5	15.0	10.2	8.0	3.0	6.8	13.6	14.6	29.2
Tagalog		28 million	45.4	40.2	32.5	32.7	24.9	17.8	14.6	26.1	34.7	44.9
Waray		3.7 million	43.3	30.2	18.8	21.4	13.0	6.0	8.5	17.1	21.4	38.1
Fijian		330,000	13.3	5.9	3.5	3.0	3.7	1.5	1.5	3.7	3.6	8.9
Maori		50,000 L1	23.1	14.5	7.8	9.5	7.5	1.4	3.8	8.2	7.1	16.8
Samoan		500,000	26.2	12.5	5.9	3.9	4.5	1.3	1.9	4.6	4.4	16.0
Central Aymara	**Aymara**	2 million	5.7	2.8	2.8	2.3	3.5	1.5	1.0	2.8	2.6	4.8
Esperanto	N/A		45.1	40.3	35.2	40.6	30.2	14.0	23.7	30.5	35.1	44.3
Tok Pisin	(English-based)	120,000 L1	19.8	15.2	9.9	11.4	10.4	2.9	3.7	8.0	11.2	22.6
Haitian Creole	(French-based)	10 million	37.8	24.7	15.3	15.7	8.5	1.9	4.2	11.3	14.9	32.2
Papiamento	(Iberian-based)	340,000	42.1	32.1	21.1	19.2	15.7	5.0	10.3	19.2	18.0	38.9
Kabuverdianu	(Portuguese-based)	1.2 million	39.6	24.2	17.3	18.1	14.8	5.9	9.3	17.7	16.4	31.1
Kannada	South Dravidian	44 million	29.1	17.8	19.2	23.0	1.2	1.3	2.1	8.6	16.3	28.8
Malayalam		38 million	30.8	21.6	18.6	22.7	1.4	0.9	2.3	8.8	18.1	31.4
Tamil		75 million	27.7	16.0	19.3	21.3	2.5	1.8	1.9	6.8	17.4	29.0
Telugu	South-Central Dravidian	81 million	34.8	25.0	23.9	25.0	2.2	1.9	3.0	9.5	19.5	33.5
Tosk Albanian	Albanian	3 million	39.1	28.9	22.8	31.5	8.7	3.0	5.6	12.1	21.1	36.3
Armenian	Armenian	6.7 million	37.6	28.7	18.6	31.9	3.1	1.3	2.8	8.2	20.9	35.3
Latgalian	Baltic	150,000	19.5	11.3	6.3	6.9	3.9	1.4	2.1	5.9	5.5	14.7
Lithuanian		3 million	33.7	28.0	20.2	26.1	8.6	3.9	8.7	16.7	25.7	33.9
Standard Latvian		1.75 million	36.1	28.0	20.1	27.8	8.5	3.0	9.2	18.3	27.0	35.0
Welsh	Celtic	875,000	55.0	45.4	29.5	37.8	7.4	2.2	5.5	14.7	19.5	47.0
Irish	Celtic (Goidelic)	170k L1	37.1	27.8	16.0	20.9	5.6	2.0	3.5	10.2	10.0	30.2
Scottish Gaelic		60,000	30.6	19.6	10.5	8.6	4.4	1.2	2.8	7.1	5.8	21.0
Afrikaans	Germanic	7 million	56.7	52.7	47.2	50.4	36.0	18.6	36.1	45.0	48.7	56.5
Danish		5.8 million	48.3	45.0	40.3	44.1	35.0	30.4	34.2	40.7	43.6	48.5
German		95 million (L1)	44.0	41.3	38.7	41.3	40.0	34.9	35.6	38.4	40.4	44.1
Limburgish		1.3 million	36.4	32.9	23.2	21.6	14.8	6.3	13.1	20.7	25.5	38.2
Eastern Yiddish		1 million	49.5	25.9	7.5	9.1	3.8	1.0	0.5	7.0	14.0	45.9
Faroese		70,000	36.9	25.8	16.5	17.9	10.4	3.9	5.9	12.5	14.0	29.9
Icelandic		350,000	35.2	27.0	17.5	24.4	9.6	4.0	6.9	12.4	16.5	30.0

Norwegian Bokmål		4 million	43.5	40.6	36.8	40.1	30.6	23.8	30.3	36.3	39.2	44.0
Norwegian Nynorsk		750,000	45.0	41.1	37.2	40.5	26.4	14.4	26.4	34.0	39.4	45.0
Swedish		10 million	48.1	46.0	42.9	43.5	35.6	31.2	36.1	40.9	43.0	48.6
Dutch		24 million	31.6	29.7	28.5	29.7	25.8	25.0	25.6	28.6	29.9	32.1
Luxembourgish		400,000	46.6	34.4	23.7	22.5	14.0	5.7	7.0	15.4	19.0	38.6
Greek	Greek	13 million	35.5	32.4	28.2	31.2	19.3	13.9	15.5	23.7	29.8	35.8
Assamese	Indo-Aryan	15 million	26.3	15.5	12.7	6.9	1.8	1.2	4.2	9.2	11.6	23.3
Awadhi		38 million	33.0	6.0	18.6	19.0	6.8	6.1	7.7	13.7	19.1	29.3
Bengali		265 million	33.0	22.6	24.0	24.3	3.8	2.0	10.8	19.1	21.8	31.7
Bhojpuri		50 million	26.5	13.8	14.0	13.4	5.6	3.8	5.0	9.7	14.1	22.7
Chhattisgarhi		16 million	36.6	12.7	17.0	16.7	5.7	5.1	5.5	13.2	17.6	29.3
Eastern Panjabi		33 million	34.8	12.2	23.7	23.9	1.3	0.7	2.9	12.6	18.0	34.5
Gujarati		55 million	36.0	18.8	23.5	22.6	1.3	1.0	5.1	15.2	19.9	35.0
Hindi		600 million	38.8	33.2	29.9	30.6	12.5	16.3	13.8	23.2	30.1	39.1
Magahi		14 million	38.2	14.1	20.9	19.7	7.0	6.1	7.2	13.9	22.1	33.7
Maithili		35 million	36.9	12.0	16.1	12.6	5.1	3.3	4.9	9.4	15.3	28.4
Marathi		83 million	34.1	21.0	21.9	20.1	3.7	2.2	4.9	12.7	19.9	33.3
Nepali		25 million	37.6	24.0	17.1	22.4	5.8	4.6	5.3	13.3	20.4	34.9
Odia		37 million	27.3	21.2	5.7	0.6	1.4	1.1	1.9	9.5	1.1	18.9
Sanskrit		Few thousand L1	15.7	12.7	8.6	7.3	4.3	1.9	2.8	6.7	6.5	15.4
Sindhi		32 million	35.9	8.2	11.6	2.8	1.9	0.9	1.6	4.9	5.7	24.4
Sinhala		17 million	25.8	20.0	1.0	0.4	1.0	0.6	0.6	3.7	5.3	23.1
Urdu		70 million L1	33.3	8.8	22.7	22.7	5.5	2.6	7.4	14.9	20.4	32.2
Kashmiri (Arabic script)		7 million	14.2	6.4	4.9	3.0	2.3	1.1	1.2	3.8	4.3	10.3
Kashmiri (Devanagari script)		7 million	11.3	5.1	3.9	3.0	3.4	2.0	1.2	4.0	3.5	8.1
Central Kurdish	Iranian	6 million	19.3	5.9	8.1	2.2	1.1	0.6	1.1	3.3	4.1	19.7
Dari		10-12 million	37.0	10.1	27.7	29.7	12.6	4.6	17.5	24.2	28.4	36.8
Northern Kurdish		15 million	19.3	14.5	6.3	13.2	3.2	1.2	1.4	3.9	4.0	15.5
Southern Pashto		20 million	29.0	9.0	12.2	17.3	2.9	1.1	3.6	7.0	5.8	19.9
Tajik		8-9 million	30.9	11.4	6.1	4.2	2.2	1.0	1.7	5.4	3.7	23.1
Western Persian		55 million	34.8	15.6	27.8	29.7	12.6	3.7	17.5	24.6	28.4	35.8
Catalan	Romance	4 million	46.4	43.2	39.6	42.3	33.1	25.0	32.8	38.9	40.6	46.6
French		80+ million (L1)	45.2	42.9	39.9	42.6	41.6	37.3	38.2	41.3	42.1	45.5
Friulian		600,000	33.7	28.2	19.3	20.1	14.8	5.0	12.2	17.5	16.9	31.8
Galician		2.4 million	41.4	37.0	33.5	36.7	33.8	24.2	30.9	34.6	36.0	40.5
Italian		65 million	32.9	31.2	29.8	31.8	30.6	27.4	27.6	30.5	31.4	34.2
Ligurian		500,000	35.1	28.3	20.3	22.6	19.2	7.0	13.1	21.0	20.7	33.7
Lombard		3.5 million (est.)	35.8	25.9	19.6	22.4	16.1	5.9	10.4	18.8	19.2	32.2
Occitan		2 million	52.1	46.1	38.5	40.5	31.6	11.3	25.8	35.9	34.4	47.7
Portuguese		230 million	49.8	47.3	44.1	46.7	45.0	41.5	42.0	45.1	46.1	49.9
Romanian		24 million	43.1	40.0	36.9	37.9	27.5	15.9	29.4	34.8	38.6	43.9
Sardinian		1 million	34.4	31.2	22.0	21.6	15.6	6.1	11.8	19.1	20.7	35.7
Spanish		483 million L1	30.9	28.4	27.0	29.7	28.5	23.8	26.2	27.9	29.3	31.1
Venetian		2 million	40.0	34.7	27.0	31.7	23.9	6.6	18.6	28.3	28.8	40.5
Asturian		400,000	39.8	37.5	32.9	34.7	29.2	14.9	26.0	29.7	33.1	40.1
Sicilian		4.7 million	35.5	28.9	21.7	24.4	15.3	3.8	11.4	19.1	20.1	34.4
Belarusian	Slavic (East)	6.5 million	20.8	16.5	13.1	17.4	4.7	2.6	6.3	11.7	15.3	20.2
Russian		150 million (L1)	35.9	33.0	30.5	33.2	26.6	24.3	28.7	31.5	32.4	35.9
Ukrainian		35 million	39.7	36.2	31.2	35.3	22.1	21.6	24.7	31.1	34.3	39.9
Bosnian	Slavic (South)	3 million	42.5	38.1	32.0	37.1	22.5	12.2	23.9	31.9	33.6	42.2
Bulgarian		8 million	40.9	37.3	33.2	35.6	22.2	17.9	25.5	31.9	35.2	41.3
Croatian		5.6 million	37.7	34.9	31.3	33.4	20.4	12.0	22.3	29.0	30.7	37.8
Macedonian		2 million	42.0	37.7	30.7	36.1	16.0	7.9	21.3	30.3	32.0	41.7
Serbian		6.5 million	43.3	39.7	33.0	36.9	15.7	7.7	21.1	30.6	34.4	42.8
Slovenian		2.1 million	35.9	30.9	26.5	29.2	17.0	9.3	17.2	24.5	28.4	35.4
Czech	Slavic (West)	10.5 million	40.2	37.8	34.2	35.5	24.6	23.1	27.2	33.8	35.1	40.4
Polish		38 million	30.1	27.5	25.3	26.6	19.9	14.1	21.9	25.2	27.0	30.5
Silesian		<1 million	36.1	27.4	22.5	21.9	13.0	6.0	13.5	20.7	21.7	35.2
Slovak		5.2 million	39.7	34.6	30.1	34.2	20.5	14.6	23.6	30.5	33.6	39.3
Japanese	Japonic	125 million	26.5	23.2	20.5	21.9	17.8	16.6	18.9	22.4	21.7	26.3
Georgian	South Caucasian	4 million	27.5	20.3	11.3	21.5	3.2	1.4	3.0	7.0	12.1	24.4
Korean	Koreanic	81 million	29.3	25.1	21.1	24.4	13.9	16.5	19.4	23.8	20.9	29.0
Basque	N/A	750,000	30.1	24.7	15.3	23.6	4.9	1.6	2.8	6.2	15.3	28.8
Halh Mongolian	Eastern Mongolic	3 million	28.1	8.9	4.4	12.1	1.6	0.9	1.2	4.3	3.5	17.6
Wolof	**Atlantic**	10 million	10.2	5.7	3.9	2.9	4.4	1.4	2.0	5.0	3.5	6.7
Nigerian Fulfulde	**Atlantic–Fula**	14 million	6.8	4.1	2.5	2.5	3.9	1.6	1.3	3.5	2.6	5.3
Bemba	Bantu	4 million	10.4	6.1	4.3	3.9	5.5	2.1	1.8	4.5	5.1	9.9
Chokwe		1.3 million	5.7	3.5	2.9	1.9	4.0	1.6	1.5	3.1	3.2	5.0
Ganda		7 million	15.0	7.1	4.5	3.0	4.6	1.7	1.9	4.1	4.2	10.1
Kamba		4 million	7.6	5.8	4.3	2.9	4.9	1.6	1.5	4.2	3.4	6.9
Kikongo		7 million	8.8	4.4	3.2	2.6	4.4	1.7	1.4	4.4	3.5	6.0
Kikuyu		8 million	8.2	5.7	3.3	3.2	4.8	1.9	1.3	3.8	3.8	6.5
Kimbundu		3 million	6.0	3.3	2.6	2.3	3.6	1.4	1.2	3.5	3.4	5.5
Kinyarwanda		12 million	27.7	11.3	4.6	3.5	4.1	1.2	1.4	3.8	4.6	17.9
Lingala		8-10 million	16.0	5.8	4.2	3.9	4.9	1.5	1.9	4.7	3.7	7.8
Luba-Kasai		6.5 million	7.7	3.8	2.7	2.9	4.1	2.0	1.8	4.4	3.9	6.8
Northern Sotho		5 million	27.9	9.9	5.4	3.6	4.7	1.8	1.3	5.0	4.4	18.0
Nyanja		12 million	21.9	8.7	4.4	3.8	4.7	1.5	2.3	5.4	6.1	15.3
Rundi		9 million	18.0	6.8	3.6	2.4	3.2	1.4	1.3	3.4	3.1	10.3
Shona		11 million	23.7	8.7	4.6	3.4	4.9	1.7	1.5	5.3	5.4	17.7
Southern Sotho		5.6 million	29.0	9.3	5.0	3.3	5.0	1.6	1.2	4.9	4.4	18.5
Swahili		16 million L1	43.1	35.0	28.8	23.8	8.5	1.5	3.4	9.2	29.5	42.3
Swati		2.5 million	18.2	7.3	4.2	3.3	4.0	1.7	1.6	4.6	3.6	14.1
Tsonga		3 million	18.6	7.3	4.3	3.0	4.7	1.7	1.7	4.1	3.5	9.9
Tswana		5 million	19.5	7.5	4.4	2.7	4.2	1.6	1.0	4.1	4.1	12.9
Tumbuka		2 million	11.7	6.2	3.7	3.2	4.3	1.5	1.4	4.1	4.4	8.6
Umbundu		6 million	5.5	3.0	2.7	2.2	3.6	1.3	1.0	3.1	3.0	5.0
Xhosa		8.2 million	31.8	10.5	5.4	4.6	5.1	1.5	1.6	5.6	6.8	25.0
Zulu		12 million	33.4	11.1	4.6	3.2	4.2	1.5	1.4	4.7	5.1	24.7
Fon	**Gbe**	1.7 million	3.7	2.4	1.7	1.4	2.8	1.2	0.9	2.3	2.2	3.5
Ewe		7 million	5.1	2.9	2.5	2.1	3.3	1.3	0.8	2.4	2.2	4.3
Kabiyè	**Gur**	1.2 million	3.8	3.1	1.9	1.6	2.7	1.2	0.5	2.2	2.2	4.5
Mossi		7.5 million	4.5	2.7	2.3	2.4	3.3	1.1	1.4	3.0	2.9	4.5
Akan	Kwa	11 million	13.4	7.5	5.0	3.6	5.9	2.2	1.5	5.2	5.3	10.4
Twi		17 million	14.6	9.0	5.4	3.4	5.8	2.3	1.6	5.4	5.6	11.8
Bambara	Mande	14 million	5.8	3.0	2.6	2.4	3.9	1.1	1.0	3.7	3.0	5.0
Dyula		3 million	4.2	2.0	1.6	1.8	3.0	1.0	0.8	2.6	2.6	3.6
Igbo	Volta–Niger	27 million	24.0	14.2	5.7	1.6	3.5	1.6	0.9	3.7	5.7	17.6

Yoruba		28 million	17.3	8.6	3.9	2.8	3.5	1.2	1.7	4.4	3.4	11.0
Sango	Creolized Ubangian	400,000 L1	4.7	3.0	2.3	2.4	3.6	1.1	1.4	3.3	2.7	4.1
Luo	**Nilotic**	4.2 million	6.3	3.6	3.3	2.9	3.9	1.6	1.7	3.9	3.2	5.3
Nuer		1.4 million	3.4	2.0	1.8	1.1	2.2	0.9	0.6	1.7	1.8	3.0
Southwestern Dinka		2 million	6.1	5.0	3.8	3.5	5.0	2.0	1.8	4.0	4.5	6.0
Central Kanuri (Arabic script)	**Saharan**	4 million	2.2	1.1	0.7	0.6	0.9	0.6	0.3	1.3	0.5	1.4
Central Kanuri (Latin script)		4 million	5.9	3.1	2.8	2.9	4.9	2.3	1.2	4.0	2.6	5.3
Ayacucho Quechua	**Quechua**	1 million	6.3	5.6	3.7	2.7	4.3	2.0	1.2	3.6	3.4	5.5
Chinese (Simplified)	Sinitic	920 million	28.8	25.4	23.9	24.8	19.8	19.7	24.5	26.4	24.5	28.6
Chinese (Traditional)		31 million	27.4	23.8	21.8	23.4	17.3	16.5	22.5	25.0	22.0	27.3
Yue Chinese		60 million	29.6	14.8	23.5	25.7	19.6	15.7	24.6	26.7	23.6	29.5
Burmese	**Tibeto-Burman**	33 million	21.5	12.1	2.1	14.3	1.3	0.9	1.3	4.2	4.0	17.7
Dzongkha		700,000	0.8	1.5	0.1	0.0	0.1	0.1	0.0	0.3	0.1	1.6
Jingpho		900,000	4.0	2.5	1.8	1.8	2.7	1.4	0.9	2.5	2.3	3.9
Meitei (Bengali script)		1.8 million	4.4	1.9	1.8	1.0	0.8	0.7	0.3	1.8	0.9	4.1
Mizo		900,000	9.3	8.6	6.8	5.2	5.9	3.1	2.7	5.4	8.3	14.2
Standard Tibetan		1.2 million	1.9	3.5	0.4	0.1	0.6	0.5	0.3	0.7	0.5	3.8
Shan	**Southwestern Tai**	3 million	4.0	6.0	1.7	1.1	2.4	1.7	0.7	1.6	3.2	5.1
Lao	Tai	7.5 million	20.1	10.3	2.2	2.1	3.5	2.5	1.8	6.3	3.7	17.8
Thai		36 million	29.6	21.0	23.6	23.0	11.4	10.6	20.1	25.1	23.7	30.6
Guarani	Tupi–Guarani	6-7 million	16.1	8.9	5.6	4.3	5.6	1.8	2.0	5.5	5.7	10.4
Northern Uzbek	Karluk	27 million	32.2	21.5	14.0	21.0	3.3	1.0	3.7	8.7	12.0	28.5
Uyghur		10 million	20.3	7.3	4.4	3.0	0.8	0.4	0.6	2.9	1.5	11.0
Bashkir	Kipchak	1.2 million	27.4	16.3	7.9	10.2	3.5	1.2	2.6	6.0	8.7	23.1
Crimean Tatar		300,000	24.6	16.9	11.7	13.8	5.6	2.4	4.9	9.7	11.3	23.0
Kazakh		13 million	33.8	19.6	11.6	20.9	3.1	1.5	4.5	9.3	12.3	28.6
Kyrgyz		4.5 million	22.6	11.1	7.6	13.9	2.5	1.1	3.1	6.4	6.6	17.9
Tatar		5 million	29.1	13.9	10.2	19.1	3.5	1.4	3.0	7.2	8.8	23.3
North Azerbaijani	Oghuz	9-10 million	22.8	13.2	13.9	17.2	5.0	2.5	5.0	10.3	13.3	21.7
South Azerbaijani		15-20 million	14.7	5.4	5.6	8.9	2.3	0.9	1.3	3.7	5.5	14.4
Turkish		75 million	37.9	33.4	27.3	28.9	12.8	9.3	18.5	26.0	28.4	37.9
Turkmen		7 million	29.2	15.5	8.7	6.7	3.2	1.6	2.1	5.6	5.9	21.3
Estonian	Finnic	1.1 million	38.2	31.3	23.2	28.7	6.2	2.4	8.9	17.5	26.6	36.6
Finnish		5.4 million	35.0	30.5	26.0	28.5	12.2	10.0	11.8	19.6	26.6	34.0
Hungarian	Ugric	13 million	35.5	31.7	28.4	29.3	13.8	11.5	11.3	19.6	28.3	35.5

Table 10: Performance testing after SFT on Corresponding Validation Dataset (#1000 samples)

Language Pair	Methods	spBLEU	ChrF++	Jaccard	LLMaaJ
As-En	BM	8.75	22.72	0.16	0.64
	DN	9.00	23.03	0.16	0.65
	DL	8.87	23.04	0.16	0.59
	DG	9.43	23.69	0.16	0.62
En-As	BM	2.27	10.84	0.03	0.37
	DN	8.75	22.72	0.16	0.64
	DL	8.09	29.03	0.18	0.61
	DG	8.07	29.23	0.18	0.65
Kh-En	BM	0.63	14.66	0.06	0.05
	DN	NA	NA	NA	NA
	DL	2.79	18.66	0.10	0.10
	DG	4.81	23.43	0.14	0.30
En-Kh	BM	0.22	0.50	0.00	0.00
	DN	NA	NA	NA	NA
	DL	4.81	16.95	0.15	0.17
	DG	11.58	29.19	0.23	0.51
Uk-En	BM	22.50	41.35	0.30	0.72
	DN	25.34	44.06	0.33	0.77
	DL	25.29	44.08	0.33	0.76
	DG	24.81	43.76	0.32	0.78
En-Uk	BM	13.57	30.19	0.15	0.60
	DN	17.87	34.83	0.18	0.70
	DL	17.97	34.83	0.19	0.69
	DG	18.10	34.97	0.19	0.72
En-Lb	BM	6.46	26.78	0.12	0.36
	DN	37.98	55.41	0.37	0.82
	DL	40.71	59.02	0.44	0.87
	DG	44.58	59.73	0.45	0.87
Lb-En	BM	26.31	45.98	0.33	0.58
	DN	42.78	59.33	0.48	0.82
	DL	54.64	70.98	0.57	0.82
	DG	59.88	74.97	0.63	0.90