LEGOMT2: NON-BLOCKING FEDERATED LEARNING FOR MASSIVE MULTILINGUAL MACHINE TRANSLATION

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ABSTRACT

What is the maximal number of languages that a single machine translation model can translate? It is a critical challenge to learn a single model for massive languages. Prior methods focus on increasing the model size and training data size. However, large models are difficult to optimize efficiently even with distributed parallel training and translation capacity can interfere among languages. To address the challenge, we propose LegoMT2, an efficient approach with a tailored model architecture for massive multilingual neural machine translation. LegoMT2 organizes 435 languages into 8 language-centric groups and attributes one local encoder-decoder for each group and a global encoder-decoder for all languages. LegoMT2 then trains each local and global encoder-decoder on a group-dedicated set of clients through asynchronous updating of parameters. We trained LegoMT2 on a large dataset with 25 billion sentence pairs beyond English-centric. LegoMT2 is 16.2× faster than the distributed training method for the same-size NLLB while improving the translation results by an average of 2.2 BLEU on *Flores-101* [1].

1 INTRODUCTION

Recent years have witnessed great success in multilingual neural machine translation (MNMT) (Ha et al., 2016; Johnson et al., 2017; Bapna et al., 2019; Liu et al., 2020; Fan et al., 2021; Costa-jussà et al., 2022) that uses a single model for translating all directions. To construct an MNMT system that supports high-quality translation for massive directions, many efforts have been put into scaling up the model size and training corpus (Liu et al., 2020; Fan et al., 2021). For example, Costa-jussà et al. (2022) constructed a 54.5B NLLB model to support translation among 200 languages. Additionally, recent advancements in large language models, such as GPT-4 (OpenAI, 2023) and LLAMA (Touvron et al., 2023), have shown promising potential in multilingual machine translation. Generally, these multilingual models are also trained using a single model.

However, with the increasing model size, training a single model over massive data brings new challenges. Specifically, the challenge is two-fold: (1) *huge training costs*. Training and serving a large MNMT model requires a pile of GPUs associated with massive communication costs for aggregation among different devices (Johnson et al., 2017; Fan et al., 2021), which brings huge training delays and thus largely reduces training efficiency (Rasley et al., 2020; Narayanan et al., 2021); (2) *parameter interference*. Parameter interference is a fundamental problem in multilingual machine translation. It refers to the competition between different languages for the limited parameters of a model when we hope to use a single model to handle all translation directions. This can result in good translation results for some languages, while the translation results for other languages may be less satisfactory. Previous studies have observed parameter interference, especially when dealing with numerous translation directions (Aharoni et al., 2019; Gordon et al., 2021; Yang et al., 2022; Fan et al., 2021). Test error often falls off as a power law with model size in machine translation. Mixture-of-Experts (MoE) (Jacobs et al., 1991; Shazeer et al., 2017; Lepikhin et al., 2020; Fedus et al., 2021; Du et al., 2022; Fan et al., 2021; Costa-jussà et al., 2022) is a popular solution to reduce parameter interference, but it also introduces substantial memory and computational requirements.

[1]We will release the model and code to the public.

To address these challenges, we propose LegoMT2, an efficient approach to massive MNMT. LegoMT2 consists of three key designs: a proper language grouping scheme, a tailored multi-way model architecture, and a non-blocking federated learning algorithm.

First, LegoMT2 splits data into carefully designed language groups. This grouping affects our method design and training algorithm. Under this scheme, we arrange all languages based on the size of the language-centric data (sentence pairs that are from or to a specific language) and divide this language-centric data into 8 different groups of equal size. Each group may contain a different numbers of languages. Each group's data is stored on a dedicated set of GPU servers, therefore no moving of training data is needed.

Second, we design a multi-way detachable model to alleviate parameter interference. Our key insight is the separation of the model used for training and inference and splitting language capacity into different model components. The model at training time includes but can be much larger than the inference model. Our multi-way model consists of a global encoder-decoder for all languages and one local encoder-decoder for each language group. In total, the model has 9 encoder-decoders at training time. At inference time, it only uses the global encoder-decoder. The model architecture also affects our algorithm design decisions.

Third, we design a non-blocking distributed learning algorithm to accelerate the training. Our key insight is that at training time, we no longer need to load all model parameters (for 9 encoder-decoder) into all servers, thanks to our language grouping scheme and associated multi-way architecture. We dedicate one set of servers to one language group. We only load and train the encoder-decoder parameters responsible for the group, plus the global encoder-decoder. A separate thread is responsible for aggregating the global parameters across different servers. Parameter communication is asynchronous and efficient, which does not block the training on local servers. We only need to transfer the global parameters from servers at intervals. The need for transferring local encoder-decoder is eliminated, thereby reducing communication costs. While asynchronous training has been studied before, our work is the first to demonstrate its effectiveness in massive MNMT training.

We construct a large-scale MNMT translation dataset to train LegoMT2. The proposed dataset contains 25B parallel pairs, covering 435 languages and 22,613 translation directions. Our contribution can be summarized below:

- We propose an efficient training framework LegoMT2 for MNMT. LegoMT2 is empowered by an efficient non-blocking optimization algorithm to accelerate training and a tailored multi-way detachable model architecture.
- We design a proper grouping scheme of 435 languages and 22k language directions. Our approach properly attributes one encoder-decoder to each group, with which we train a 1.6B LegoMT2 model for 435 languages.
- Our experiments on *Flores-101* show that LegoMT2 achieves 16.2× speedups and 2.2 BLEU gains over the prior best approach.

2 Related Work

The most common approach in MNMT is using a single model to handle all translation directions Ha et al. (2016); Johnson et al. (2017); Bapna et al. (2019); Liu et al. (2020); Fan et al. (2021), which has promising generalization abilities by transferring knowledge from high-resources and low-resources. Nevertheless, researchers Aharoni et al. (2019) have observed that there is the trade-off between translation quality and language number when using a single model for inference. Federated learning is originally proposed to address privacy problems. McMahan et al. (2017) first introduced *Federated Learning* and applied this algorithm in both computer vision and NLP tasks. Since then, more and more studies have explored NLP models with federated learning (Sui et al., 2020; Lin et al., 2021; Passban et al., 2022; Weller et al., 2022; Tian et al., 2022). Sui et al. (2020) focused on efficient federated communication methods. Lin et al. (2021) evaluated different federated methods on various NLP tasks. Passban et al. (2022) introduced federated learning into multi-domain translation. Most of them focused on using federated learning to better fine-tune a pre-trained model. Unlike these studies, Tian et al. (2022) proposed a framework that collaboratively pre-trained a BERT model with privacy data in a federated way. In this paper, we propose a new training recipe for MNMT pre-training based on the Federated Learning framework.

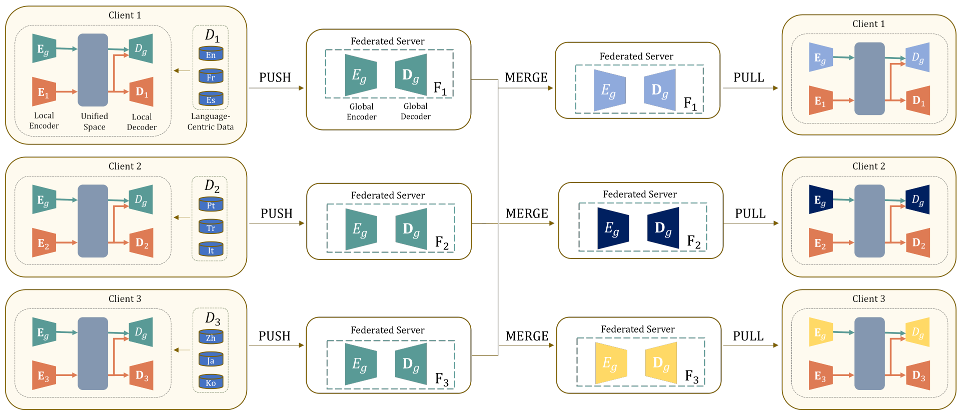

Figure 1: Overview of LegoMT2. It partitions data into language-centric groups. E.g. all parallel sentences from/to English, French, and Spanish are in Group 1 and stored on client 1. The model consists of a global encoder-decoder for all languages and multiple local encoder-decoder for specific language groups. During training, each client transmits its global encoder-decoder parameters to the federated server (PUSH) and gets the updated global parameters from the server (PULL) at pre-determined intervals. Parameter communication is asynchronous, which does not block the training on local clients.

3 The LegoMT2 Approach

3.1 Overview

Our goal is to develop a single model to translate massive languages (over 400). Prior approach needs to scale the model to extremely large (e.g. 54 billion parameters for NLLB), which is costly to train. We aim to tackle this challenge through a holistic approach considering three aspects: a proper language/data grouping scheme, a tailored architecture, and a more efficient distributed training algorithm. We design LegoMT2 approach with tailored components in all three aspects (Figure 1).

First, LegoMT2 includes a group scheme that arranges all sentence pairs from and to a specific language into a group. Our goal is to balance the number of parallel sentences in each group so that each contains equal data size. Figure 1 shows 3 groups while in our experiment we use 8 groups.

Second, LegoMT2 uses a multi-way model that includes multiple encoder-decoders with shared embedding space. LegoMT2 includes one local encoder-decoder for each language group and one global encoder-decoder for all languages. The purpose is to alleviate parameter interference while keeping the multilingual capability. As shown in Figure 1, by incorporating global encoder-decoder ($E_g - D_g$), LegoMT2 ensures the sharing of essential knowledge across all language groups, facilitating the accumulation of collective intelligence during the training process. Simultaneously, the local encoder-decoder, such as $E_1 - D_1$, $E_2 - D_2$ or $E_3 - D_3$, allow for fine-tuning the adaptation to address the unique characteristics and challenges of individual languages.

Third, LegoMT2 provides a non-blocking training algorithm, as illustrated in Figure 1. Each server stores a local and a global encoder-decoder. It calculates gradient updates for two encoder-decoders using the language group data stored on the server. Each server only pushes the global encoder-decoder parameter to the central server and pulls from that at pre-defined intervals. This update is asynchronous and minimizes the parameters for transferring across servers.

3.2 Language Grouping Scheme

We assign different data groups to different clients. Given a multilingual parallel dataset $\mathcal{D}$ with N languages, $\mathcal{D} = \{\mathcal{D}_{1\rightarrow\cdot}, \mathcal{D}_{\cdot\rightarrow 1}, \cdots, \mathcal{D}_{n\rightarrow\cdot}, \mathcal{D}_{\cdot\rightarrow n}, \cdots, \mathcal{D}_{N\rightarrow\cdot}, \mathcal{D}_{\cdot\rightarrow N}\}$, where $\mathcal{D}_{n\rightarrow\cdot}$ refers to a parallel data from the n-th source language to any language except itself. $\mathcal{D}_{\cdot\rightarrow n}$ refers to a parallel data from other languages to the n-th language. The combination of $\mathcal{D}_{\cdot\rightarrow n}$ and $\mathcal{D}_{n\rightarrow\cdot}$ is language-centric data. Then we split all N language-centric data into P clients, that is, reorganizing $\mathcal{D}$ into

$\{\mathcal{D}_{S_1}, \cdots, \mathcal{D}_{S_P}\}$. The non-identical distribution for clients i and j is $\mathcal{D}_{S_i} \neq \mathcal{D}_{S_j}$.

$$|S_1| + \cdots + |S_i| + \cdots + |S_P| = N,\ S_i \cap S_j = \varnothing,\ |S_i| \neq 0 \tag{1}$$

where S_i is a language set contains one or many languages; $|S_i|$ refers to the number of languages. $\mathcal{D}_{S_j}$ is the combination of language-centric data covering all languages in S_j.

For instance, a dataset $\mathcal{D} = \{\mathcal{D}_{\text{En}\to\text{Fr}}, \mathcal{D}_{\text{Fr}\to\text{En}}, \mathcal{D}_{\text{Zh}\to\text{Nl}}, \mathcal{D}_{\text{Nl}\to\text{Zh}}, \mathcal{D}_{\text{Fr}\to\text{Nl}}, \mathcal{D}_{\text{Nl}\to\text{Fr}}\}$ with $N = 4$ languages needs to split into 3 different clients with $S_1 = \{\text{En}, \text{Fr}\}$, $S_2 = \{\text{Zh}\}$ and $S_3 = \{\text{Nl}\}$ language sets. The result is $\mathcal{D}_{S_1} = \{\mathcal{D}_{\text{En}\to\text{Fr}}, \mathcal{D}_{\text{Fr}\to\text{En}}, \mathcal{D}_{\text{Fr}\to\text{Nl}}, \mathcal{D}_{\text{Nl}\to\text{Fr}}\}$, $\mathcal{D}_{S_2} = \{\mathcal{D}_{\text{Zh}\to\text{Nl}}, \mathcal{D}_{\text{Nl}\to\text{Zh}}\}$, $\mathcal{D}_{S_3} = \{\mathcal{D}_{\text{Fr}\to\text{Nl}}, \mathcal{D}_{\text{Nl}\to\text{Fr}}, \mathcal{D}_{\text{Zh}\to\text{Nl}}, \mathcal{D}_{\text{Nl}\to\text{Zh}}\}$. Here, we arrange languages based on the size of the language-centric data and divide them into different groups of equal size. Further details in our implementation are described in Appendix C.

3.3 Multi-way Model Architecture

LegoMT2 is not constrained to a specific implementation of the backbone model (e.g, Shared mode +Adapter (Houlsby et al., 2019), multi-way model (Fan et al., 2021; Yuan et al., 2022)). For simplification, we adopt a multi-way detachable model Yuan et al. (2022) with standard Transformer architecture, which decomposes the MNMT model with a global encoder-decoder and a local encoder-decoder. To clarify, each client possesses a local language-specific encoder-decoder and a duplicate of the global encoder-decoder. This setup can also be applied to structures that only contain a decoder. It's important to note that only the global module is shared across all devices. Although the local module is not shared, its parameters are subject to adjustment through the shared global module.

LegoMT2 is also not limited to a specific initialization. To minimize training costs, we utilize NLLB-200-1.3B to initialize both global and local parameters. To accommodate a large number of languages, we expanded the size of the vocabulary from 256K to 490K tokens. This is achieved by training Byte Pair Encoding (BPE) separately for each language and then merging these vocabularies. We use pre-trained embeddings for the tokens that are already in the original vocabulary and randomly initialized embeddings for the new ones.

To train the global and local parameters, we follow the three data flows in Yuan et al. (2022) to train client parameters: a global encoder with a local decoder (Dec-Flow), a global encoder with a global decoder (Mix-Flow), and a local encoder with a global decoder (Enc-Flow). Each flow can be used independently during the inference phase.

Mix-Flow Mix-Flow uses a global encoder and global decoder. The loss for it of client i:

$$F_{i_M} = \sum_{\mathbf{x},\mathbf{y}\sim\mathcal{D}_{i_{\text{multi}}}} -\log P_{\theta^i_m}(\mathbf{y}|\mathbf{x}) \tag{2}$$

where $(\mathbf{x}, \mathbf{y})$ is a sample from multilingual data, the parameters of Mix-Flow are θ_m and the probabilities output by the decoder is $P_{\theta^i_m}$. The multilingual data, including one-to-many dataset ($\mathcal{D}_{S_i\to\cdot}$) and many-to-one dataset ($\mathcal{D}_{\cdot\to S_i}$), for client i is denoted as $\mathcal{D}_{i_{\text{multi}}} = \mathcal{D}_{\cdot\to S_i} \cup \mathcal{D}_{S_i\to\cdot}$.

Enc-Flow The loss for the Enc-Flow, which employs a local encoder and a global decoder:

$$F_{i_E} = \sum_{\mathbf{x},\mathbf{y}\sim\mathcal{D}_{S_i\to\cdot}} -\log P_{\theta^i_e}(\mathbf{y}|\mathbf{x}) \tag{3}$$

where $(\mathbf{x}, \mathbf{y})$ is a sample from one-to-many ($\mathcal{D}_{S_i\to\cdot}$) training data, P_{θ_e} is probability output by the decoder of Mix-Flow, θ_e is the parameters of Enc-Flow, and i is client id.

Dec-Flow Dec-Flow uses a global encoder and a local decoder. The loss for client i is:

$$F_{i_D} = \sum_{\mathbf{x},\mathbf{y}\sim\mathcal{D}_{\cdot\to S_i}} -\log P_{\theta^i_d}(\mathbf{y}|\mathbf{x}) \tag{4}$$

where $(\mathbf{x}, \mathbf{y})$ is a sample from many-to-one ($\mathcal{D}_{\cdot\to S_i}$) data, P_{θ_d} is the parameters of Dec-Flow.

The training strategy follows the approach outlined by Yuan et al. (2022) for individual clients i:

Stage 1: Training $f_i = F_{iM} + F_{iE}$ on client i where the multilingual encoder/decoder and local encoder are trained together. This stage necessitates collaboration among all clients.

Stage 2: After stage 1 is completed, fixing the multilingual decoder and utilizing F_{iD} to train the local decoder. This step is executed independently on a single client.

As observed, the performance of the global decoder is directly affected by the local encoders. However, the local decoder has no impact on the global module. Research conducted by Yuan et al. (2022) demonstrates employing local decoders potentially causes a significant shift in the distribution of multilingual encoders, leading to catastrophic forgetting.

Formally, the training objective for the whole system is $F(\theta) = \mathbb{E}_{i\sim P}[F_i(\theta)]$, where $F_i(\theta) = \mathbb{E}_{x\sim\mathcal{D}_i}[f_i(\theta, x)]$, θ refers to the parameter of the target model; F_i represents the local objective function at client i; P is the total number of client; $\mathcal{D}_i$ is the data distribution in client i and $f_i = F_{iM} + F_{iE}$. The function F_{i_D} is used on the client i and does not impact the overall system.

3.4 Non-Blocking Optimization Algorithm

Large-scale training usually requires massive communication costs to collect gradients from each client. LegoMT2 develops an effective communication approach by exchanging parameters in an asynchronous way to broadcast global parameters across different clients and a federated server. In this work, the file system serves as the actual server, and the number of requests from LegoMT2 is significantly lower than the file system's maximum load capacity. The whole non-blocking federated learning comprises three main operations: ***PUSH***, ***MERGE***, ***PULL***, as shown in Figure 1.

PUSH: In contrast to traditional federated learning approaches, where the shared module is uploaded to the server only after local training, LegoMT2 operates differently. It employs an asynchronous approach by saving the global module to the federated server at regular intervals α during training.

MERGE: In traditional federated learning, the server is required to wait until it collects the global encoder-decoder from all clients before merging them to generate a unified global model. In LegoMT2, the server can directly merge (simply average) global models that have been pushed to the federated server without waiting for the arrival of all models from all clients.

PULL: Each client will pull the latest fusion model from the federated server to update (the newest version overwrites the existing one) its local server every fixed interval β.

LegoMT2 uses these three operations to complete parameter communication across all clients. These functions do not pause the training of local clients, therefore largely improving the throughput of models. The whole training algorithm is shown in Algorithm 1.

4 Experiments

4.1 Dataset, Models and Training Details

Training Set: We gather many-to-many dataset from OPUS, an open corpus that compiles numerous parallel sentences from the internet, covering a wide range of domains, from legislative to religious texts. The dataset we constructed consists of 435 languages and approximately 22,000 language pairs, comprising around 25 billion sentence pairs. In the training set, over 11,000 language pairs contain more than 1,000 sentence pairs, and 1,151 of them have more than 1 million sentence pairs. Among all the languages, 19 have more than 1 billion sentence pairs (see more in Appendix B).

Metric: To evaluate the effectiveness of our model, we have taken a comprehensive approach. Since no dataset currently covers 400 languages, we have partially followed the standard testing process and assessed our model's performance on the widely-used multilingual dataset known as *Flores-101*. We use the same evaluation metric of sentence piece BLEU (abbreviated as **spBLEU**) to compare our approach with strong baselines and present the average performance of the 86 languages[2] that overlap with *Flores-101* for all M2M-100 models. Additionally, there is no parallel evaluation data for the majority low-resource languages that are not in *Flores-101*. we have employed back translation (*src-tgt-srcb*) to evaluate our model's performance over 435 language translations. This process involves translating text from the source language (*src*) to the target language (*tgt*) and then back to the source language (*srcb*). **Back-spBLEU** evaluates the spBLEU score between *src* and *srcb*. To avoid counting direct copies, we also report the translation performance between *src* and *tgt*.

[2]These 86 languages are: af, am, ar, ast, be, bg, bn, bs, ca, ceb, cs, cy, da, de, el, en, es, et, fa, ff, fi, fr, ga, gl, gu, ha, he, hi, hr, hu, hy, id, ig, is, it, ja, jv, ka, kk, km, kn, ko, lb, lg, ln, lo, lt, lv, mk, ml, mn, mr, ms, my, ne, nl, no, ns, oc, or, pa, pl, ps, pt, ro, ru, sd, sk, sl, so, sr, sv, sw, ta, th, tl, tr, uk, ur, uz, vi, wo, xh, yo, zh, zu.

Algorithm 1: Non-Blocking Federated Training

Data: Given P clients and client-centric data, with predefined values for α and β such that $\alpha < \beta$. Here, α represents the frequency in minutes at which the latest model is pushed to the federated server, while β represents the frequency in minutes at which the latest model is pulled from the federated server.

```
for client i = 1 to P do
    Shuffle client-centric data to obtain a new client-centric training sequence B ;
    Record the save start time as t_s and the load start time as t_l ;
    for batch b = 1 to B do
        Record the current time as t_c ;
        if t_c - t_s >= β then
            θ^i_avg <- MERGE ({θ^1_m, θ^2_m, ..., θ^P_m}) ;   // running on the central server
            θ^i_m <- PULL (θ^i_avg) ;                         // running on the client i
            t_s <- t_c ;                                      // running on the client i
        end
        if t_c - t_l >= α then
            PUSH (θ^i_m) ;                                    // running on the client i
            t_l <- t_c ;                                      // running on the client i
        end
    end
end
```

Models: **Flores-175MB / 615MB** are two baselines released with the *Flores-101* dataset (Goyal et al., 2022), which are based on M2M-100 model. **M2M-100-1.2B** (Fan et al., 2021) is a powerful multilingual sequence-to-sequence model that can translate between 100 languages in 9,900 directions. It is an encoder-decoder model trained for Many-to-Many multilingual translation and built using the Transformer architecture. **M2M-100-12B** (Fan et al., 2021) is a multilingual encoder-decoder (seq-to-seq) model that builds on M2M-100-1.2B by adding language-specific information. Its main purpose is to perform translation tasks between any of the 100 languages. **NLLB-200-1.3B** (Costa-jussà et al., 2022) is a distilled variant of the NLLB-200 model, which is a pre-trained MNMT model that supports 200 languages.**NLLB-200-54.5B** (Costa-jussà et al., 2022) is a Mixture of Experts (MoE) model and is the largest MT model. To ensure a fair comparison, we fine-tune the NLLB-200-1.3B model on our datasets using a standard centralized training method, recorded as **Single-FT**.

LegoMT2 Parameters: We use a Transformer with 24 encoder-decoders. Given a vocabulary size of 490k and an embedding dimension of 1024, the total number of parameters for the embedding amounts to 0.5 billion, record as $\#\text{embedding} = 0.5\text{B}$. The embedding weight is shared between all encoder-decoder. A single encoder-decoder, comprising 24 transformer encoder layers and 24 transformer decoder layers, has a total parameter count of 1.1 billion, recorded as $\#\text{encoder} - \text{decoder} = 1.1\text{B}$. During training, the total number of parameters of LegoMT2 is: $\#\text{embedding} + \#\text{encoder} - \text{decoder} \times 9 = 0.5 + 1.1 \times 9 = 10.4\text{B}$. During inference, we only use the multilingual global encoder and the multilingual global decoder, therefore the total number of parameters is $\#\text{embedding} + \#\text{encoder} - \text{decoder} = 0.5 + 1.1 = 1.6\text{B}$.

Training Details: We split training into 8 language groups in our framework. For balanced training, we sort all languages based on language-centric data and uniformly split all languages into 8 groups. The language details of 8 groups can be found in Appendix C. The training code is developed on fairseq[3] repository. The model architecture follows the design in Yuan et al. (2022), with different configurations and vocabulary size. Both the global and private models are initialized with NLLB-200-1.3B weights. In order to synchronize the speed among different clients as much as possible, GPU resources are allocated to each group as follows: each client model is trained on 8 80G A100-chips using the Adam optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.999$, learning rate $1e-4$, the maximum number of tokens in a batch is $4,000$, update parameters every 48 batch, when in an epoch. The interval of save α and load β is set as 6 and 12, respectively. This setting primarily considers the fault tolerance time for three consecutive loading failures.

4.2 Experimental Results

LegoMT2 outperforms single-model fine-tuning by a large margin. As illustrated in Table 1, LegoMT2 outperforms *Single-FT* by a large marge with 2.2 spBLEU on many-to-one translation and

[3] `https://github.com/facebookresearch/fairseq`.

Table 1: Result on the *Flores-101* devtest. "Para." refers to the number of parameters required for inference. "H" and "L" represent average results from or to high/low-resource languages, where high-resource languages include all languages in Families 1-6 while low-resource languages include all languages in Families 7-8. Single-FT and LegoMT2 have the same training data and can be fairly compared. LegoMT2, supporting 435 languages, outperforms Single-FT by a large margin.

Model	H	L	H	L	H	L	H	L	H	L	H	L	H	L	AVG.
	X → En		X → Pt		X → Hu		X → Da		X → Zh		X → Sw		X → Pa		
NLLB-200-54.5B	44.9	39.0	35.8	30.8	27.8	22.8	34.6	28.7	17.3	16.7	28.4	25.4	30.7	27.0	29.3
Flores-175M	23.5	8.4	23.5	7.8	15.8	5.3	20.9	5.4	10.7	3.6	12.3	4.5	2.3	1.3	10.4
Flores-615M	30.9	12.8	30.1	11.8	22.0	8.0	27.5	9.6	15.9	6.2	18.6	7.4	3.7	2.1	14.8
M2M-100-1.2B	36.3	16.8	33.1	14.8	24.8	10.4	31.0	13.0	18.3	7.8	20.6	9.7	3.7	2.5	17.3
M2M-100-12B	38.2	18.6	34.8	17.0	26.1	12.2	32.2	14.5	18.3	8.7	23.9	12.9	12.5	7.0	19.8
NLLB-200-1.3B	41.6	**35.9**	34.0	28.5	23.9	19.3	32.1	25.9	14.5	13.7	27.5	**24.3**	**29.4**	**25.9**	26.9
Single-FT-1.6B	40.1	33.0	34.1	27.6	23.5	18.0	31.6	24.9	18.0	15.1	26.3	22.2	26.5	22.8	26.0
LegoMT2-435-1.6B	**42.9**	35.6	**36.8**	**29.5**	**26.0**	**20.6**	**33.9**	**27.0**	**20.5**	**16.8**	**28.1**	24.2	28.6	24.9	**28.2**
Model	**En → X**		**Pt → X**		**Hu → X**		**Da → X**		**Zh → X**		**Sw → X**		**Pa → X**		**AVG.**
NLLB-200-54.5B	40.3	30.6	34.2	26.4	29.3	23.0	33.5	25.5	25.3	20.4	29.0	22.9	29.9	24.8	28.2
Flores-175M	21.2	4.8	20.3	4.4	16.4	3.4	20.2	4.1	12.4	2.7	12.9	3.2	3.2	1.1	9.3
Flores-615M	29.8	7.0	26.4	5.8	22.4	4.8	26.7	5.6	17.7	4.1	19.4	4.8	5.4	1.6	13.0
M2M-100-1.2B	33.8	9.6	29.2	7.7	25.4	6.5	29.2	7.4	20.8	5.5	21.5	6.6	9.7	3.1	15.4
M2M-100-12B	36.2	14.0	31.1	11.6	26.9	9.6	31.0	10.9	21.8	8.4	23.8	9.9	13.7	6.6	18.3
NLLB-200-1.3B	36.4	**28.3**	30.9	**24.4**	25.7	**20.9**	30.2	**23.5**	21.7	18.1	25.4	21.3	25.6	**22.3**	25.3
Single-FT-1.6B	35.8	24.6	30.2	21.0	24.9	18.2	30.1	21.2	22.0	17.0	25.0	19.5	25.1	18.6	23.8
LegoMT2-435-1.6B	**38.6**	27.5	**32.5**	23.3	**28.3**	20.7	**32.9**	23.2	**23.6**	**18.2**	**28.2**	**21.9**	**27.5**	21.4	**26.3**

Table 2: Back-translation evaluation results. Back-translation (*src-trg-srcb*) is an unsupervised evaluation method that involves translating source text to target text *src-trg (S-T, such as* ***En→X****)* and then translating target text back to source text *src-srcb (S-S*$_b$*, such as* ***En→X→En****)*. Lower S-T and higher S-S$_b$ are better. Experimental results demonstrate that LegoMT2 outperforms Single-FT on back-translation performance with almost the same *src-trg (S-T)* score.

Model	S-T↓	S-S$_b$↑	S-T↓	S-S$_b$↑	S-T↓	S-S$_b$↑	S-T↓	S-S$_b$	S-T↓	S-S$_b$↑	S-T↓	S-S$_b$↑	S-T↓	S-S$_b$↑	S-T↓	S-S$_b$↑
	En→X→En		Pt→X→Pt		Hu→X→Hu		Da→X→Da		Zh→X→Zh		Mt→X→Mt		Pa→X→Pa		Lo→X→Lo	
Single-FT	**8.3**	36.6	**2.8**	31.3	**1.7**	18.1	**2.6**	26.7	**1.3**	15.8	**1.4**	27.9	**0.2**	17.4	**1.1**	14.6
LegoMT2	9.6	**43.2**	3.0	**37.7**	1.8	**22.2**	2.7	**33.0**	**1.3**	**20.1**	1.5	**35.0**	**0.2**	**22.3**	1.2	**18.3**
Model	**Fr→X→Fr**		**Nl→X→Nl**		**Bg→X→Bg**		**Sk→X→Sk**		**Mk→X→Mk**		**Is→X→Is**		**Ig→X→Ig**		**Li→X→Li**	
Single-FT	**2.7**	32.1	**2.7**	25.0	**0.7**	27.5	**1.7**	22.9	**0.7**	24.3	**1.7**	17.7	**1.4**	13.4	2.5	7.1
LegoMT2	2.8	**38.4**	2.9	**31.5**	0.9	**31.1**	1.8	**28.0**	0.8	**30.3**	1.9	**22.5**	1.5	**14.6**	**2.4**	**9.8**
Model	**Ja→X→Ja**		**Es→X→Es**		**Ar→X→Ar**		**Lt→X→Lt**		**Fo→X→Fo**		**De→X→De**		**Uk→X→Uk**		**Zu→X→Zu**	
Single-FT	**0.2**	16.7	4.7	27.7	**0.8**	17.2	**1.1**	19.8	1.8	**13.2**	**2.8**	23.8	**0.5**	20.7	**1.2**	16.4
LegoMT2	0.3	**21.6**	**4.1**	**33.0**	**0.8**	**21.8**	1.2	**24.5**	**1.6**	12.9	2.9	**30.8**	0.6	**26.9**	1.5	**20.4**

2.5 spBLEU on one-to-many translation. For a fair comparison, we only report results by using the shared global encoder and global decoders for all translation directions. With additional language-specific parameters, LegoMT2 alleviates parameter interference and brings better results. Furthermore, unlike traditional synchronous aggregation methods, we adopt asynchronous aggregation to update global parameters to reduce communication costs and delays. The better results also demonstrate that asynchronous training is an effective method for training massive models.

LegoMT2 supports 435 languages, the supported language number outperforming all existing open-source multilingual machine translation systems. To build a fair comparison, we conduct a large-scale multilingual training set. The key challenge lies in balancing the trade-off between knowledge transferring and parameter interference. If not well-handled, involving more languages would result in performance degeneration. Due to the lack of high-quality test translations over 400+ languages, we adopt a practical unsupervised metric, Back-spBLEU to compute the BLEU score between source text and back-translated text. As shown in Table 2, we sample several language-centric results and LegoMT2 demonstrates an improvement in back-translation performance without copying source text issues (comparable src-trg scores).

Human evaluation results show that the performance of LegoMT2 reaches commercial translators' performance. We manually assessed the performance of Google Translator, Baidu Translator, LegoMT2, and NLLB-200-1.3B models on Chinese-centric translation tasks. The resulting evaluation scores ranged from 0 to 5. A score of 0 meant that the language was not supported or could not be

Figure 2: Analysis on deferred global parameters. The client is able to use delayed global parameters from other clients for inference without experiencing any decrease in performance. This observation substantiates the notion that the employment of deferred global parameters does not exert a significant influence on model training. The # Param is the total number of a system.

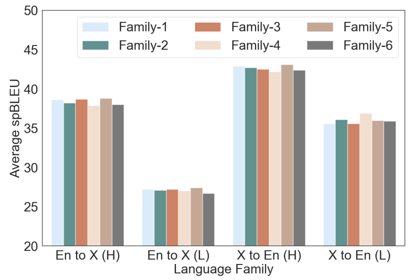

Figure 3: Analysis on α and β. We analyzed the save/load interval and performed two different settings: 1) save interval of $\alpha = 10$min and load interval of $\beta = 20$min; 2) save interval of $\alpha = 20$min and load interval of $\beta = 10$min, while recording the frequency of setting 1 over setting 2. Results indicate the system's performance is negatively affected by low update frequency.

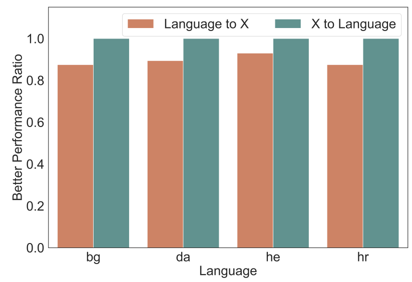

Table 3: The training speed. The number of tokens a model can handle per second is represented by 'Token/s'. The analysis on training demonstrates that LegoMT2 can process more tokens per second with higher GPU efficiency.

Module	Training Strategy	Parallelism	#Param (during training)	Training Token/s	Training Speedup
Single-FT	Centralized Learning	DDP	1.6B	76,116	40.6×
Single-FT + MOE	Centralized Learning	DDP + Pipeline	12B	1,873.4	1.0×
LLaMA	Centralized Learning	DDP + Tensor + Pipeline, Flash Attention	13B	7,091.3	3.8×
LegoMT2	Traditional Federated Learning	-	10.4B	18,719.2	10.0×
LegoMT2	Non-blocking Federated Learning	-	10.4B	30,280.9	16.2×

translated at all. A score of 5 implied that not only was the content preserved, but the expression was also very smooth. The performance of LegoMT2 is between Google and Baidu, while largely better than NLLB-200-1.3B. More human evaluation details are shown in Appendix D. Among the overlapped languages, LegoMT2 has an average translation score of 3.12, while Google Translator has an average score of 3.64. Among the overlapped languages, LegoMT2's average score is 3.03, while Baidu Translator's average score is 2.55.

LegoMT2 achieves 1.6× speedups over traditional federated training Training a single model on multiple GPUs can result in significant communication costs, limiting training efficiency. In this work, we propose LegoMT2 to reduce the bottlenecks caused by aggregation across GPUs. By splitting models into different clients, we can get almost 10× speedups. With reduced communication costs, LegoMT2 further achieves almost 1.6× speedups. Finally, LegoMT2 brings almost 16× speedups. As shown in Table 3, LegoMT2 can process more tokens per second and has higher GPU efficiency than a comparable single model with 12B parameters. We also compared LegoMT2 with widely-used distributed training acceleration frameworks, (e.g., deepspeed (Rajbhandari et al., 2020) and megatron (Shoeybi et al., 2019)), LegoMT2 also shows over 4× throughput improvements. In baseline "Single-FT", we implement DDP and pipeline parallelism (Huang et al., 2019) to accelerate training using the released code training NLLB. In addition, we also report a LLM baseline LLaMA (Touvron et al., 2023) having a similar model size with almost the SOTA distributed setting: DDP + tensor parallelism and pipeline parallelism. Additionally, we use an efficient version of Transformer Flash Attention (Dao et al., 2022) for faster inference. Compared to these advanced training methods, LegoMT2 is a simple but efficient method.

LegoMT2 brings better performance improvements on high-resource translation We find that multi-way training benefits high-resource translation by relieving parameter interference. On high-resource translation, LegoMT2 outperforms NLLB-200-1.3B with gains of 1.3 BLEU on many-to-one translation and 2.0 BLEU on one-to-many translation. LegoMT2 largely narrows the gap with the largest machine translation model, NLLB-200-54.5B. Specifically, some results even approach the NLLB-200-54.5B. Taking Family-5 as an example, LegoMT2 yields +3.2% spBLEU improvements over NLLB-200-54.5B on Family-5 on many-to-one settings. Meanwhile, LegoMT2 is on par with

Table 4: Using Dec-Flow, translation performance on *Flores-101* devtest can be improved. Remarkably, this improvement is achievable even for low-resource languages.

Module	X→Ne	X→Mi	X→Be	X→Km	AVG.
Mix-Flow	27.2	**19.0**	18.7	14.3	19.8
Dec-Flow	**28.7**	18.5	**20.0**	**16.9**	**21.0**

Table 5: The experiment results indicate that an extremely unbalanced grouping within the system is not conducive to its optimal performance.

Direction	Setting	Hr	Bg	Da	AVG.
LG→X	Similarity	14.7	14.9	16.1	15.2
	Random	**16.9**	**17.6**	**18.9**	**17.8**
X→LG	Similarity	12.9	18.5	19.1	16.8
	Random	**15.0**	**21.2**	**22.4**	**19.5**

NLLB-200-1.3B on low-resource settings. It is mainly because NLLB focuses on low-resource settings and extremely optimizes low-resource settings based on techniques like back-translation. We only cover limited resources for each translation pair to support more languages.

5 Analysis on LegoMT2

Language-specific decoder enhances model performance According to our results, we find that Dec-Flow largely improves low-resource inference results. To enhance low-resource translation performance, we train Family-7 and Family-8 via Dec-Flows in the second training stage. Table 4 shows that the introduction of Dec-Flow helps low-resource translation.

Explaining why asynchronous training works LegoMT2 introduces asynchronous training to reduce communication delays to accelerate training. Each client pulls the latest parameters every k steps and pushes current parameters into the federated server every m steps. It represents that all clients do not always enjoy and latest parameters. To prove whether such delay affects final performance, we conduct experiments by using global modules from other clients for inference.Figure 2 shows delayed global parameters basically do not affect model training. The client can use delayed global parameters from other clients for inference without any performance drops.

Impact of language groups In this work, we sort languages based on the size of language-centric data and split languages into different equal-size groups. We adopt this split method because we find that balanced training flows in different clients help multilingual machine translation. In addition, the common strategy of language clustering is by similarity. Therefore, we use similarity clustering to construct a baseline. Given an MNMT model, here we use the single multilingual model to get language id embedding, then directly apply KMeans [4] on those embedding. The clustering results are shown in Appendix E. It is clear that the number of languages in different clusters varies. Meanwhile, we also conduct an experiment by randomly splitting language groups. According to new language groups, we conduct experiments and show results in Table 5. Experiment results show the severely unbalanced distribution of clients hurt the system's performance.

Impact of save/load (α/β) intervals setting Test the effect of different save/load intervals on system performance, i.e. the effect of α and β in the algorithm. Theoretically, when α and β are small enough, the localized training by LegoMT2 is approximately equal to centralized training. Here, we conduct two different settings: 1) $\alpha = 10\text{min}, \beta = 20\text{min}$ and 2) $\alpha = 20\text{min}, \beta = 40\text{min}$. We test two settings LegoMT2 on the *Flores-101* devtest. If the result of setting 1 is better than setting 2, record to 1; otherwise 0. As shown in Figure 3, exchanging information too late may cause the loss of information and reduce the performance of the system.

6 Conclusion

The typical multilingual neural machine translation is training a single model for all directions with a centralized training schema, which faces many challenges in practice including parameter competition and efficiency problems. In this paper, we propose a new MNMT pre-training framework with federated learning, LegoMT2. Extensive experiments verify the effectiveness of LegoMT2. It brings 16.2× training speedups and large performance gains. We build a translation system that supports 435 languages, the supported language number outperforming all existing open-source multilingual machine translation systems.

[4]Implemented by sklearn.

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LIMITATION

This paper also has several limitations. Firstly, our analysis reveals that the augmentation of low-resource translation through the use of language-specific decoders and encoders is not as effective as anticipated, necessitating a deeper exploration of the interplay between parameter sharing and tension. Secondly, the assessment of few-shot languages continues to pose a significant challenge. Despite our training dataset encompassing 435 languages, our evaluation is limited to back-translation performance, underscoring the need for more rigorous benchmarks.

A MECHANISM OF NON-BLOCKING

The non-blocking mechanism is facilitated by asynchronous communication, which effectively minimizes the blocking time caused by communication.

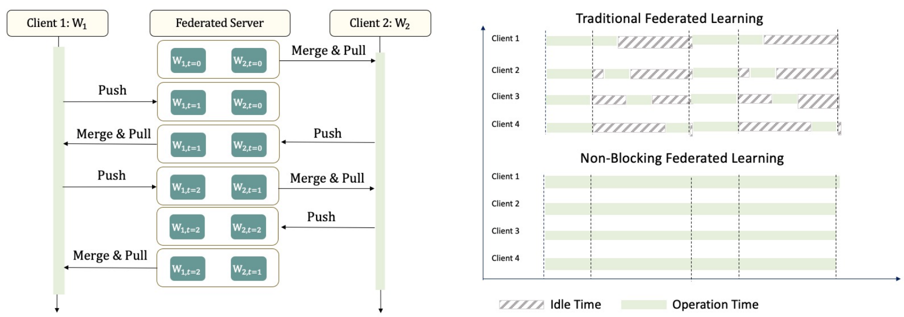


Figure 4: The mechanism of non-blocking. **(1)** Left figure presents an overview of non-blocking communication among different clients. To enable parallel training, LegoMT2 divides the training process into multiple clients, each having its own language-specific data and a copy of global parameters (W_1 and W_2). To minimize the blocking time caused by communication, we adopt an asynchronous approach. This asynchronous communication ensures that local training is not hindered by waiting for parameter updates. **(2)** The right figure compares traditional federated learning with MT. In traditional federated learning, parameter communication occurs synchronously, which often leads to blocking local training due to the additional synchronous wait.

B DATASET CONSTRUCTION

In this section, we will go through the details of constructing a Many-to-Many dataset. The entire pipeline is made up of six steps:

Step 1: Data Collection The unprocessed data is obtained from OPUS[5]. It is an open corpus that collects a large number of parallel sentences from the Web and covers a wide range of domains from legislative to religious texts.

Step 2: Data Unification OPUS has datasets from several sources, which causes the two important problems listed below.

1) Different Language Code: Language code is the abbreviation for a language. In OPUS, there are some languages has multiple language codes. One of the causes is that different corpora follow different standards, including ISO 639-1, ISO 639-2, ISO 639-3, or self-defined language codes. Another scenario is that some datasets use language code and region code together. We take ISO 639-1 as the unique code and replaced ISO 639-2 and ISO 639-3 language codes with ISO 639-1 language codes. All these language codes are released by SIL International (formerly known as the Summer Institute of Linguistics)[6].

[5] `https://opus.nlpl.eu/`

[6] `https://iso639-3.sil.org/sites/iso639-3/files/downloads/iso-639-3.tab`

2) Inconsistent Operation: There are some inconsistent operations in some datasets, for example, pre-tokenize for Chinese and Japanese.

To address the above issue, we first handle the case where the language code ends with the region code by removing the region code. Then we standardize all language codes by ISO 639-1. All replaced language codes are listed in Table 6. For the language codes out of ISO 639 series, we report the detail of the language and the corpus that they come from in Table 7. For ease of understanding, we report all used languages with their full name in Table 8. Finally, for the dataset with inconsistent operations, we uniformly perform a removal operation to restore them to natural text.

Step 3: Data Merging After unifying the language code and operation, the parallel data with the same language code will be merged into a file.

Step 4: Data Cleaning There are some low-quality text in OPUS. They are mainly caused by following reason.

1) Duplication: We apply fairseq[7] deduplication script for each language pair.

2) Missing Translation: Some low-quality parallel data lacked the correct translation results. We discard using the sentence where the source sentence is without a corresponding target sentence or simply repeat the source sentence as a target sentence.

3) Length Mismatching: The length mismatching mainly focuses on the case where the difference between the length of the source and the target is too large. The length of a sentence is defined as the number of words after segmenting with white space (individual characters for Chinese and Japanese). We reuse the filtering script from Moses[8].

Step 5: Train-Dev-Test Split The train-dev-test split scheme is specified by the data quantity.

1) A dataset has over 6.000 parallel sentences. For a dataset, 2,000 randomly selected parallel sentences are used as a test set, another 2000 randomly selected parallel sentences are used as a validation set, and the rest of the dataset is used as the training set.

2) A dataset has less than 6.000 parallel sentences. We use 80%, 10%, and 10% of all parallel sentences as train, validation, and test set.

Meanwhile, we remove the sentence included in the widely used benchmark (WMT, *Flores-101*) from our training and validation set to keep the fairness of comparison.

Step 6: Data Preprocessing The data preprocessing consists of two main steps:

1) Sampling: Because the full dataset is huge, we sample some data for our training. Our dataset contains 445 languages and about 25B sentence pairs. Table 9 shows the number of parallel sentences in the training set for each language. We present statistics on parallel sentence pairs for the top 100 languages in our constructed data, as shown in Figure 5. The dataset comprises 435 languages and approximately 25 billion sentence pairs. Among these, 19 languages have over 1 billion sentence pairs, while for most languages, the total number of sentence pairs in the dataset does not exceed 1 million.

2) Preprocessing: The data is preprocess using the SentencePiece tokenizer provided by Costa-jussà et al. (2022) with a expaned vocabulary of size 491,404.

C CLIENT INFORMATION

The language group result as shown in Table 10.

We surprisingly find that low-resource language groups harm pre-training During the training process of LegoMT2, we include all clients to update global parameters. However, we find that

[7]https://github.com/facebookresearch/fairseq/edit/main/examples/backtranslation/deduplicate_lines.py

[8]https://github.com/moses-smt/mosesdecoder

Figure 5: We present an analysis of parallel sentence pairs for the top 100 languages in our constructed dataset. Comprising 435 languages and approximately 25 billion sentence pairs, our dataset reveals that 19 languages have over 1 billion sentence pairs. In contrast, the majority of languages have a total number of sentence pairs that do not exceed 1 million.

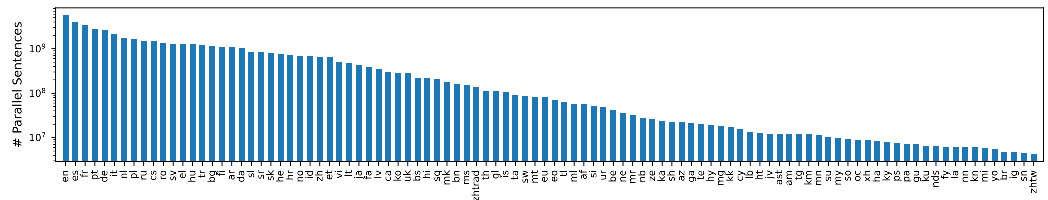


Table 6: Code Replacement List. We use the codes in the column "Original" to replace the codes in the column "replaced" if these replaced codes exist in OPUS.

Original	Replaced	Original	Replaced	Original	Replaced	Original	Replaced	Original	Replaced	Original	Replaced
ak	aka	es	es_HN	pt	pt_BR	es	es_CL	kr	kau	tr	tr_TR
am	amh	es	es_EC	pt	pt_br	es	es_SV	kv	kpv	ur	ur_PK
ar	ara	es	es_CO	pt	pt_PT	es	es_NI	ln	lin	vi	vi_VN
ar	ar_SY	fa	fa_IR	rn	run	es	es_UY	mg	mlg	wo	wol
ar	ar_TN	fa	fa_AF	rw	kin	es	es_PE	ms	ms_MY	xh	xho
ay	aym	ff	ful	sn	sna	es	es_VE	nb	nb_NO	yo	yor
az	az_IR	fr	fr_FR	so	som	es	es_AR	nds	nds_nl	ze	ze_zh
bg	bg_BG	fr	fr_CA	sr	srp	es	es_MX	nl	nl_NL	ze	ze_en
bm	bam	fr	fr_BE	sr	sr_ME	es	es_MX	nl	nl_NL	ze	ze_en
bn	bn_IN	fr	fr_ca	st	sot	es	es_PA	nl	nl_BE	zh	zh_cn
ca	cat	ha	hau	sw	swa	es	es_CR	nn	nn_NO	zh	zh_CN
da	da_DK	hi	hi_IN	ta	ta_LK	es	es_PR	no	no_nb	zhtrad	zh_HK
de	de_CH	ig	ibo	tg	tg_TJ	es	es_ES	ny	nya	zhtrad	zh_TW
de	de_AT	it	it_IT	ti	tir	es	es_GT	om	orm	zhtrad	zh_tw
de	de_DE	jp	jap	tl	tl_PH	es	es_DO	pa	pan	zu	zul

Table 7: Unkown Language Codes, which are out of ISO 639 series. We can't confirm their full names.

Code	Dataset	Code	Dataset	Code	Dataset	Code	Dataset	Code	Dataset
crp	bible-uedin	cb	MultiCCAligned	sz	MultiCCAligned	sgn	QED	cycl	Tatoeba
tc	EUbookshop	cx	MultiCCAligned	zz	MultiCCAligned	iro	QED	nah	Tatoeba
zhs	GlobalVoices	ns	MultiCCAligned	ze	OpenSubtitles	mo	QED,Ubuntu		
zht	GlobalVoices	qd	MultiCCAligned	bh	QED	ber	QED,Ubuntu		
tmp	GNOME	qa	MultiCCAligned	bnt	QED	toki	Tatoeba		
gr	GNOME	tz	MultiCCAligned	ry	QED	kzj	Tatoeba		

if we directly combine low-resource languages in Family-7 and Family-8 into pre-training, it will increase the proportion of low-resource excessively, thus reducing the performance of the entire system. As shown in Figure 6, we conduct two experiments by involving Family-7 and Faimly-8 or not and report the performance improvements caused by removing Family-7 and Family-8 from pre-training. Experiments show that low-resource languages bring negative effects on pre-training by overestimating the distribution of long-tailed languages.

D HUMAN EVALUATION PERFORMANCE

Human evaluation results show that the performance of LegoMT2 far exceeds that of Baidu and is on par with Google. We manually assessed the performance of Google Translator, Baidu Translator, LegoMT2, and NLLB-1.3B models on Chinese-centric translation tasks and found that, on average, Google Translator outperformed LegoMT2. LegoMT2 performed better than Baidu Translator and NLLB-1.3B, as shown in Table 11. Here are the specifics of our human evaluation:

1) Data source: We evaluated a total of 100 raw data samples, including 58 samples from the *Flores-101* dataset and 42 samples from the domains of sports, entertainment, and financial news.

Table 8: List of Languages. Our dataset mainly use ISO 639 series as language code. For traditional Chinese, we define “zhtrad” as code.

Language	Code	Language	Code	Language	Code	Language	Code	Language	Code	Language	Code
Abkhazian	ab	Corsican	co	Iban	iba	Lower Sorbian	dsb	Ossetian	os	Swahili (macrolanguage)	sw
Achinese	ace	Cree	cr	Icelandic	is	Lukpa	dop	Ottoman Turkish (1500-1928)	ota	Swati	ss
Achuar-Shiwiar	acu	Creek	mus	Ido	io	Luo (Kenya and Tanzania)	luo	Paite Chin	pck	Swedish	sv
Adyghe	ady	Crimean Tatar	crh	Igbo	ig	Lushootseed	lut	Palauan	pau	Swiss German	gsw
Afar	aa	Croatian	hr	Iloko	ilo	Luxembourgish	lb	Pali	pi	Syriac	syr
Afrihili	afh	Cusco Quechua	quz	Indonesian	id	Luyia	luy	Pampanga	pam	Tachawit	shy
Afrikaans	af	Czech	cs	Ingrian	izh	Macedonian	mk	Pangasinan	pag	Tachelhit	shi
Aguaruna	agr	Danish	da	Ingush	inh	Macedo-Romanian	rup	Panjabi	pa	Tagal Murut	mvv
Ainu (Japan)	ain	Dari	prs	Interlingua	ia	Madurese	mad	Papiamento	pap	Tagalog	tl
Akan	ak	Dinka	din	Interlingue	ie	Maithili	mai	Papuan Malay	pmy	Tahaggart Tamahaq	thv
Akawaio	ake	Drents	drt	Inuktitut	iu	Malagasy	mg	Pedi	nso	Tahitian	ty
Aklanon	akl	Dungan	dng	Inupiaq	ik	Malay (individual language)	zlm	Pennsylvania German	pdc	Tajik	tg
Albanian	sq	Dutch	nl	Iranian Persian	pes	Malay (macrolanguage)	ms	Persian	fa	Talossan	tzl
Algerian Arabic	arq	Dutton World Speedwords	dws	Irish	ga	Malayalam	ml	Phoenician	phn	Talysh	tly
American Sign Language	ase	Dzongkha	dz	Italian	it	Maltese	mt	Picard	pcd	Tamashek	tmh
Amharic	am	Eastern Canadian Inuktitut	ike	Jakun	jak	Mam	mam	Piemontese	pms	Tamil	ta
Ancient Greek (to 1453)	grc	Eastern Mari	mhr	Jamaican Creole English	jam	Mambae	mgm	Pipil	ppl	Tarifit	rif
Ancient Hebrew	hbo	Eastern Maroon Creole	djk	Japanese	ja	Mandarin Chinese	cmn	Plateau Malagasy	plt	Tase Naga	nst
Arabic	ar	Efik	efi	Javanese	jv	Manx	gv	Polish	pl	Tatar	tt
Aragonese	an	Egyptian Arabic	arz	Jewish Babylonian Aramaic	tmr	Maori	mi	Portuguese	pt	Telugu	te
Armenian	hy	Emilian	egl	Kabyle	kab	Marathi	mr	Potawatomi	pot	Tena Lowland Quichua	quw
Arpitan	frp	English	en	Kadazan Dusun	dtp	Marshallese	mh	Prussian	prg	Tetelcingo Nahuatl	nhg
Asháninka	cni	Erzya	myv	Kalaallisut	kl	Mesopotamian Arabic	acm	Pushto	ps	Tetum	tet
Assamese	as	Esperanto	eo	Kalmyk	xal	Miahuatlán Zapotec	zam	Quechua	qu	Thai	th
Asturian	ast	Estonian	et	Kamba (Kenya)	kam	Middle English (1100-1500)	enm	Quenya	qya	Tibetan	bo
Avaric	av	Evenki	evn	Kannada	kn	Middle French (ca. 1400-1600)	frm	Quiotepec Chinantec	chq	Tigrinya	ti
Avestan	ae	Ewe	ee	Kanuri	kr	Mikasuki	mik	Rapanui	rap	Tohono O’odham	ood
Awadhi	awa	Extremaduran	ext	Kaqchikel	cak	Mi’kmaq	mic	Romanian	ro	Tok Pisin	tpi
Aymara	ay	Faroese	fo	Karelian	krl	Min Dong Chinese	cdo	Romansh	rm	Tonga (Tonga Islands)	to
Azerbaijani	az	Fiji Hindi	hif	Kashmiri	ks	Min Nan Chinese	nan	Romany	rom	Traditional Chinese	zhtrad
Baluchi	bal	Fijian	fj	Kashubian	csb	Minangkabau	min	Rundi	rn	Tsonga	ts
Bambara	bm	Filipino	fil	Kazakh	kk	Mingrelian	xmf	Russian	ru	Tswana	tn
Banjar	bjn	Finnish	fi	Kekchí	kek	Mirandese	mwl	Rusyn	rue	Tupí	tpw
Barasana-Eduria	bsn	French	fr	Khakas	kjh	Mískito	miq	Samoan	sm	Turkish	tr
Bashkir	ba	Friulian	fur	Khasi	kha	Modern Greek (1453-)	el	Samogitian	sgs	Turkmen	tk
Basque	eu	Fulah	ff	Khmer	km	Mohawk	moh	Sango	sg	Tuvalu	tvl
Bavarian	bar	Galela	gbi	K’iche’	quc	Mongolian	mn	Sanskrit	sa	Twi	tw
Baybayanon	bvy	Galician	gl	Kikuyu	kik	Morisyen	mfe	Santali	sat	Uab Meto	aoz
Belarusian	be	Gan Chinese	gan	Kinyarwanda	rw	Moroccan Arabic	ary	Sardinian	sc	Udmurt	udm
Bemba (Zambia)	bem	Ganda	lg	Kirghiz	ky	Mossi	mos	Saterfriesisch	stq	Uighur	ug
Bengali	bn	Garhwali	gbm	Klingon	tlh	Nauru	na	Scots	sco	Ukrainian	uk
Berom	bom	Georgian	ka	Koasati	cku	Navajo	nv	Scottish Gaelic	gd	Uma	ppk
Bhojpuri	bho	German	de	Kölsch	ksh	Neapolitan	nap	Sediq	trv	Umbundu	umb
Bislama	bi	Gheg Albanian	aln	Komi	kv	Nepali (individual language)	npi	Serbian	sr	Upper Sorbian	hsb
Bodo (India)	brx	Gilbertese	gil	Komi-Permyak	koi	Nepali (macrolanguage)	ne	Serbo-Croatian	sh	Urdu	ur
Bosnian	bs	Goan Konkani	gom	Kongo	kg	Nigerian Fulfulde	fuv	Shan	shn	Uspanteco	usp
Breton	br	Gothic	got	Korean	ko	Niuean	niu	Shona	sn	Uzbek	uz
Brithenig	bzt	Gronings	gos	Kotava	avk	Nogai	nog	Shuar	jiv	Venda	ve
Buginese	bug	Guadeloupean Creole French	gcf	Kriang	ngt	North Levantine Arabic	apc	Shuswap	shs	Venetian	vec
Bulgarian	bg	Guarani	gn	Kuanyama	kj	North Moluccan Malay	max	Sicilian	scn	Vietnamese	vi
Buriat	bua	Guerrero Amuzgo	amu	Kurdish	ku	Northern Frisian	frr	Silesian	szl	Vlaams	vls
Burmese	my	Guerrero Nahuatl	ngu	Kven Finnish	fkv	Northern Kurdish	kmr	Sindarin	sjn	Volapük	vo
Cabécar	cjp	Gujarati	gu	Láadan	ldn	Northern Sami	se	Sindhi	sd	Walloon	wa
Camsá	kbh	Gulf Arabic	afb	Ladin	lld	Northwestern Ojibwa	ojb	Sinhala	si	Walser	wae
Catalan	ca	Haida	hai	Ladino	lad	Norwegian	no	Slovak	sk	Waray (Philippines)	war
Cebuano	ceb	Haitian	ht	Lakota	lkt	Norwegian Bokmål	nb	Slovenian	sl	Welsh	cy
Central Huasteca Nahuatl	nch	Hakha Chin	cnh	Lao	lo	Norwegian Nynorsk	nn	Somali	so	Western Frisian	fy
Central Kurdish	ckb	Hakka Chinese	hak	Latgalian	ltg	Novial	nov	South Azerbaijani	azb	Western Panjabi	pnb
Central Sama	sml	Hausa	ha	Latin	la	Nuer	nus	South Ndebele	nr	Wolaytta	wal
Chamorro	ch	Hawaiian	haw	Latvian	lv	Nyanja	ny	Southern Kurdish	sdh	Wolof	wo
Chavacano	cbk	Hebrew	he	Ligurian	lij	Occitan (post 1500)	oc	Southern Sami	sma	Wu Chinese	wuu
Chechen	ce	Hiligaynon	hil	Limburgan	li	Old English (ca. 450-1100)	ang	Southern Sotho	st	Xhosa	xh
Cherokee	chr	Hindi	hi	Lingala	ln	Old French (842-ca. 1400)	fro	Southwestern Dinka	dik	Yakut	sah
Chhattisgarhi	hne	Hiri Motu	ho	Lingua Franca Nova	lfn	Old Frisian	ofs	Spanish	es	Yaqui	yaq
Chinese	zh	Hmong Daw	mww	Literary Chinese	lzh	Old Norse	non	Standard Malay	zsm	Yiddish	yi
Choctaw	cho	Ho	hoc	Lithuanian	lt	Old Russian	orv	Standard Moroccan Tamazight	zgh	Yoruba	yo
Church Slavic	cu	Huastec	hus	Liv	liv	Old Spanish	osp	Sumerian	sux	Zarma	dje
Chuvash	cv	Hungarian	hu	Lojban	jbo	Oriya (macrolanguage)	or	Sundanese	su	Zaza	zza
Coptic	cop	Hunsrik	hrx	Lombard	lmo	Orizaba Nahuatl	nlv	Swabian	swg	Zulu	zu
Cornish	kw	Hupa	hup	Low German	nds	Oromo	om	Swahili (individual language)	swh		

2) Annotation method: To better evaluate the quality of large-scale translation, we adopted a translation and back-translation method in our human evaluation. For instance, we presented a Chinese input text to the models and asked them to produce a translated text and a back-translated Chinese text. The annotators assessed the degree of information overlap between the input text and the back-translated Chinese text.

3) Annotation process: To ensure inter-annotator agreement, we assigned each sample to two distinct annotators at a cost of $0.028 per datum. The resulting evaluation scores ranged from 0 to 5. A score of 0 meant that the language was not supported or could not be translated at all. A score of 5 implied that not only was the content preserved, but the expression was also very smooth. The average inter-annotator agreement score was 0.79, indicating good evaluation quality.

Among the overlapping languages, LegoMT2 had an average translation score of 3.12, while Google Translator had an average score of 3.64. Among the non-overlapping languages, LegoMT2's average score was 3.03, while Baidu Translator's average score was 2.55.

E LANGUAGE GROUP BY KMEANS.

In this study, we categorize languages based on the magnitude of language-specific data and partition them into distinct groups of equivalent size. This partitioning method was chosen due to our observation that balanced training flows among different clients facilitate multilingual machine translation. Furthermore, language clustering is commonly performed based on similarity. While it is possible to utilize existing linguistic knowledge for classification, this approach becomes labor-intensive when dealing with more than 400 languages. As such, we employ similarity clustering

Table 9: Statistics of the constructed dataset.

code	sentence pairs	code	sentence pairs	code	sentence pairs	code	sentence pairs	code	sentence pairs	code	sentence pairs
aa	25190	cni	366213	he	768039586	lo	2934940	pag	41	swg	1485
ab	24734	co	5679	hi	218864052	lt	467441039	pam	1897	swh	767
ace	55744	cop	392871	hif	30	ltg	25791	pap	16428	syr	393273
acm	38	cr	128	hil	2044	luo	91	pau	28	sz	10
acu	275510	crh	583965	hne	3624732	lut	61	pcd	238	szl	45989
ady	10	crp	1698290	ho	51	luy	105	pck	1722862	ta	90971643
ae	139	cs	1457869889	hoc	517	lv	355693685	pdc	63	tc	2831
af	55335682	csb	1087185	hr	737162068	lzh	540	pes	1744278	te	20088988
afb	77	cu	1996	hrx	558	mad	947	phn	30	tet	12255
afh	73	cv	24927	hsb	662844	mai	1969608	pi	2306	tg	11994239
agr	296459	cx	2852903	ht	12715844	mam	358606	pl	1650606708	th	111068105
ain	306	cy	15839521	hu	1254849755	max	345	plt	1715974	thv	41
ak	13593	cycl	43	hup	287	mfe	8944	pms	6128	ti	98816
ake	278088	da	1024948205	hus	81	mg	18564176	pmy	5324	tk	237791
akl	23	de	2564377381	hy	19095048	mgm	27	pnb	154	tl	62019683
aln	23	dik	290563	ia	243295	mh	188	pot	163018	tlh	22430
am	12065296	din	2457	iba	42	mhr	150906	ppk	363985	tly	38
amu	375783	dje	1728497	id	697068570	mi	5753968	ppl	27	tmh	166643
an	457768	djk	354595	ie	19196	mic	10	prg	407	tmp	19110
ang	151166	dng	22	ig	4802381	mik	15	prs	14123	tmr	380
aoz	20	dop	381489	ik	393	min	84	ps	7700300	tn	488012
apc	35	drt	46	ike	32	miq	8506	pt	2812386990	to	1479
ar	1079338710	dsb	7157	ilo	891090	mk	177474445	qa	521	toki	37627
arq	50647	dtp	1911	inh	17366	ml	57004885	qd	1896	tpi	81
ary	155	dws	56	io	149762	mn	11603195	qu	31780	tpw	72
arz	78593	dz	161086	iro	8	mo	31	quc	358962	tr	1193231266
as	2307772	ee	376963	is	104661362	moh	72	quw	391236	trv	1535
ase	6084	efi	4358	it	2093054002	mos	1864	quz	20	ts	51109
ast	12083731	egl	322	iu	6120	mr	31855664	qya	171	tt	1501339
av	7398	el	1258104866	izh	9	ms	149607728	rap	22	tvl	13
avk	1757	en	5781922682	ja	434118540	mt	82700941	rif	60	tw	479
awa	225	enm	741	jak	368614	mus	9229	rm	10037	ty	17
ay	43034	eo	71211656	jam	29	mvv	8	rn	6358	tz	55
az	22317802	es	3911731697	jbo	53616	mwl	36153	ro	1335221001	tzl	1415
azb	6270	et	647382971	jiv	278960	mww	65	rom	391669	udm	53
ba	414706	eu	79865761	jv	12235804	my	9517618	ru	1460007489	ug	915049
bal	2285	evn	64	ka	23136675	myv	22	rue	175	uk	280561930
bar	75324	ext	57	kab	469669	na	16	rup	2965	umb	54
be	41361204	fa	383151473	kam	8	nah	160	rw	1271784	ur	47703807
bem	19058	ff	329791	kbh	407244	nan	9666	ry	5054	usp	368078
ber	192407	fi	1081684445	kek	1674772	nap	3093	sa	93931	uz	3381954
bg	1130459221	fil	1091348	kg	131420	nb	27802066	sah	835	ve	8057
bh	2613	fj	3443	kha	1282	nch	75	sat	114	vec	26482
bho	1263	fkv	498	kik	267	nds	6525803	sc	55166	vi	500458007
bi	6112	fo	228021	kj	5446	ne	36233624	scn	7790	vls	430
bjn	16	fr	3412558369	kjh	15	ngt	15	sco	44793	vo	4484
bm	5993	frm	827	kk	16875999	ngu	31	sd	2816050	wa	2659876
bn	156924699	fro	44	kl	33411	nhg	376653	sdh	28	wae	74267
bnt	1534	frp	82087	km	11875237	niu	24	se	1912829	wal	374085
bo	108249	frr	402	kmr	714	nl	1777745084	sg	10	war	1230
bom	39	fur	328314	kn	5999187	nlv	12	sgn	688	wo	983607
br	4839927	fuv	2482	ko	285583000	nn	6036066	sgs	40	wuu	10993
brx	2126	fy	6208767	koi	12	no	698491446	sh	22711333	xal	3583
bs	221212239	ga	21763185	kr	11412	nog	79	shi	378312	xh	8640822
bsn	325256	gan	12	krl	314	non	16	shn	40453	xmf	36
bua	1948	gbi	350547	ks	64356	nov	919	shs	20833	yaq	81
bug	1659	gbm	33	ksh	2892	npi	93	shy	15	yi	1038001
bvy	21	gcf	1009	ku	6566496	nr	874	si	52111630	yo	5433688
bzt	1196	gd	833984	kv	59	ns	103879	sjn	293	zam	1379
ca	303844363	gil	12	kw	82917	nso	427594	sk	809520471	ze	25667080
cak	355513	gl	110969736	ky	7814500	nst	644	sl	834996012	zgh	97
cb	354133	gn	10158	kzj	1543	nus	2496	sm	73	zh	660697725
cbk	2141	gom	49256	la	6202902	nv	358	sma	39	zhs	37264
cdo	20	gos	3382	lad	4634	ny	4130938	sml	1711	zht	39547
ce	13338	got	234	lb	13159469	oc	8708362	sn	4557031	zhtrad	143676341
ceb	3534028	gr	5607	ldn	163	ofs	8	so	9082662	zlm	92
ch	356694	grc	1105	lfn	13823	ojb	299926	sq	203389893	zsm	2719
cho	309	gsw	247	lg	248315	om	203313	sr	825444520	zu	3516139
chq	356343	gu	7015993	li	365187	ood	21	ss	672164	zz	44
chr	392260	gv	537765	lij	1673	or	1005953	st	10364	zza	27246
cjp	389090	ha	8504550	liv	27	orv	1348	stq	128		
ckb	78358	hai	1866	lkt	25	os	61302	su	10421463		
cku	571	hak	16	lld	10268	osp	10	sux	153		
cmn	16159	haw	385	lmo	13318	ota	880	sv	1297167012		
cnh	1784	hbo	101	ln	171241	pa	7181860	sw	87842873		

to establish a baseline. Utilizing a single multilingual model, we obtain language id embeddings and apply KMeans clustering to them. The results of this clustering are depicted in Figure 7, which clearly illustrates the variation in the number of languages across different clusters. We also conduct an experiment in which language groups are randomly split. Our findings, indicate that a severely unbalanced distribution of clients negatively impacts system performance.

A comparison is made between the performance of ChatGPT and LegoMT2 using the first 100 samples extracted from the *Flores-101* devtest. The effects of both X→En and En→X are tested. For the sys-

Table 10: Language groups. We sort languages based on the size of language-centric data and split them into 8 equal-size chunks.

Family	435 Languages
Family-1	fr, es, en
Family-2	nl, tr, pl, it, de, pt
Family-3	bg, ar, ru, fa, el, hu, ro, cs
Family-4	sk, da, uk, sl, he, fi, id, sv, vi
Family-5	ko, sq, hr, mk, sr, zh, no, bs, hi
Family-6	eo, mt, eu, sw, is, lv, ca, th, ms, zhtrad, bn, lt, et
Family-7	ig, km, ky, ps, tg, gv, nb, br, ss, sh, ze, zu, nn, pa, so, sn, kk, cy, mg, am, xh, az, gu , hy, kn, te, ga, gl, be, mr, ne, si, af, ml, tl
Family-8	iro, kam, mvv, ofs, izh, ady, mic, osp, sg, sz, gan, gil, koi, nlv, tvl, kjh, mik, ngt, shy, bjn, hak, na, non, ty, aoz, cdo, quz, bvy, ood, dng, myv, rap, akl, aln, niu, lkt, liv, mgm, ppl, pau, sdh, jam, hif, phn, mo, ngu, ike, gbm, apc, xmf, acm, tly, bom, sma, sgs, pag, thv, iba, cycl, fro, zz, drt, ho, udm, umb, tz, dws, ext, kv, rif, lut, pdc, evn, mww, moh, tpw, afh, sm, nch, afb, nog, hus, tpi, yaq, min, luo, zlm, npi, zgh, hbo, luy, sat, cr, stq, ae, sux, pnb, ary, nah, ldn, qya, rue, mh, awa, got, pcd, gsw, kik, hup, sjn, ain, cho, krl, egl, max, nv, tmr, haw, ik, frr, prg, vls, tw, fkv, hoc, qa, lzh, hrx, cku, nst, sgn, kmr, enm, swh, frm, sah, nr, ota, nov, mad, gcf, grc, bzt, war, bho, kha, orv, que, zam, tzl, to, swg, bnt, trv, kzj, bug, lij, sml, avk, cnh, mos, hai, qd, pam, dtp, bua, cu, hil, brx, cbk, zhyue, bal, pi, din, fuv, nus, bh, zsm, tc, ksh, rup, nap, gos, fj, xal, efi, vo, lad, ry, pmy, kj, gr, co, bm, ase, bi, iu, pms, azb, rn, hbs, dsb, av, scn, ve, miq, mfe, mus, mwl, nan, rm, gn, lld, st, wuu, kr, tet, lmo, ce, ak, lfn, prs, cmn, pap, ber, inh, bem, tmp, ie, toki, shs, tlh, ab, cv, aa, ltg, zhs, vec, zza, zht, qu, kl, ilo, bar, shn, ay, sco, szl, arz, gom, arq, ts, jbo, sc, ace, os, ks, wae, ckb, frp, kw, zhtw, ti, sa, ns, bo, kg, ba, fo, io, dz, mhr, ang, ln, pot, tmh, om, fil, ia, lg, tk, csb, yi, acu, ake, cb, jiv, se, dik, an, tn, agr, tt, kek, ojb, crp, pck, plt, dje, pes, lb, gbi, djk, cak, mai, bsn, chq, quc, mam, ch, fur, ppk, cni, usp, jak, wal, amu, ee, lo, rw, nhg, shi, dop, wa, cx, li, cjp, rom, quw, chr, cop, syr, ug, su, kab, hsb, kbh, hne, uz, nso, fy, ht, wo, crh, la, ny, or, gd, oc, jv, nds, mn, as, ast

Figure 6: Pre-training is negatively impacted by low-resource language groups. Two experiments were conducted to determine the effects of including or excluding Family-7 and Family-8. The Y-axis displays the performance improvements from pre-training.

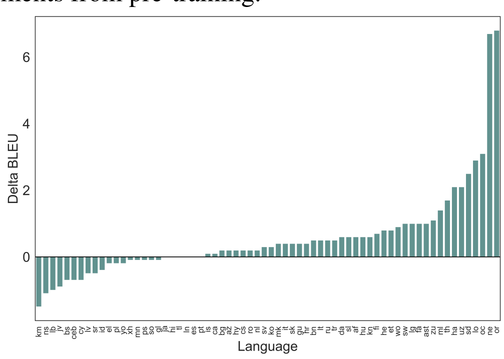
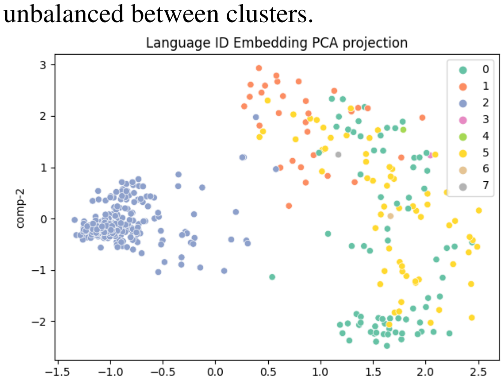


Figure 7: Language clustering results. After obtaining the model through single-model fine-tuning, we extract embedding vectors corresponding to all language IDs. Then perform K-means clustering on this embedding matrix and visualize the clustering results using PCA. The results show that the clustering quantity is unbalanced between clusters.



tem, the given prompt for ChatGPT is: “You are a helpful assistant that translates {SOURCE_LANG} to {TARGET_LANG}.” For the sentences that needed to be translated, the given prompt is: “Translate the following {SOURCE_LANG} text to {TARGET_LANG}: {SOURCE_TEXT}.” Both zero-shot and eight-shot results are tested, with the eight-shot samples being randomly extracted from the *Flores-101* dev.

Table 11: Human evaluation result on Zh→X direction. Manually comparing the performance of LegoMT2 with NLLB-200-1.3B, Google, and Baidu translators, respectively. Based on the results of human evaluation, it has been found that LegoMT2's performance surpasses that of Baidu by a substantial margin and is on par with Google's performance.

Translator	**En**	**Es**	**Fr**	**Pt**	**De**	**It**	**Nl**	**Pl**	**Ru**	**Da**	**Kn**	**Mr**	**Ka**	**Ja**	**Fa**
LegoMT2	3.96	2.99	3.34	3.74	3.61	3.53	2.94	3.58	3.64	3.63	3.29	3.57	2.78	3.63	2.90
NLLB-200-1.3B	2.52	2.16	2.31	2.44	2.43	2.10	1.86	2.10	2.39	2.16	2.52	2.57	1.87	2.30	2.32
Google	4.32	3.33	3.46	3.95	3.88	3.96	3.32	3.82	3.84	4.25	3.80	3.96	3.81	3.66	3.10
Baidu	4.32	3.18	3.51	3.94	3.87	3.93	3.30	3.72	3.80	4.02	1.95	2.70	1.95	4.14	2.79
Correlation	0.70	0.44	0.41	0.68	0.62	0.79	0.72	0.69	0.7	0.71	0.83	0.51	0.83	0.76	0.27

Translator	**Sr**	**Sk**	**He**	**Hr**	**No**	**Id**	**Et**	**Vi**	**Lt**	**Ms**	**Yo**	**Te**	**Hy**	**Ca**	**Ko**
LegoMT2	3.23	3.28	3.54	3.47	2.70	3.76	2.87	3.95	3.69	3.41	3.18	3.46	3.48	3.45	3.24
NLLB-200-1.3B	2.27	1.88	1.88	1.86	2.03	2.49	2.02	2.70	2.33	2.34	2.44	2.32	2.12	2.47	2.35
Google	3.74	3.72	3.90	3.70	3.32	3.87	3.16	4.23	4.06	4.00	3.74	4.01	3.59	3.72	3.69
Baidu	3.26	3.29	3.39	3.55	2.62	3.73	3.15	4.10	3.77	3.63	1.67	1.87	3.29	3.48	4.20
Correlation	0.62	0.60	0.72	0.7	0.66	0.64	0.45	0.63	0.65	0.6	0.74	0.76	0.71	0.56	0.76

Translator	**Th**	**Gl**	**Is**	**Mt**	**Tl**	**Ml**	**Af**	**Ur**	**Be**	**Tg**	**Ig**	**Kk**	**Cy**	**Uk**	**Bs**
LegoMT2	3.49	2.80	3.28	3.44	3.40	3.58	3.39	3.13	1.60	3.51	3.29	3.30	3.14	3.55	3.32
NLLB-200-1.3B	2.18	2.08	1.92	2.54	2.36	2.72	1.71	2.72	1.91	2.37	2.20	2.16	2.20	2.31	2.08
Google	3.75	2.94	4.09	4.14	3.94	4.05	3.63	3.99	3.26	3.94	3.42	3.73	3.43	3.91	3.79
Baidu	3.91	2.93	3.12	3.82	3.25	2.77	3.03	2.81	2.89	2.54	2.23	0.00	3.05	3.45	3.59
Correlation	0.66	0.47	0.77	0.61	0.65	0.68	0.6	0.63	0.69	0.65	0.69	0.94	0.61	0.66	0.74

Translator	**Km**	**My**	**So**	**Oc**	**Xh**	**Ha**	**Ky**	**Pa**	**Gu**	**Ln**	**Sn**	**Jv**	**Ast**	**Hi**	**Mk**
LegoMT2	2.92	2.83	2.75	2.82	3.52	2.98	3.19	3.37	3.49	3.21	2.85	3.26	2.41	3.37	3.71
NLLB-200-1.3B	2.15	1.86	2.10	2.55	2.61	2.40	1.98	2.73	2.60	2.45	2.20	2.40	1.36	2.55	2.59
Google	3.43	3.20	3.12	0.00	3.83	3.44	3.83	3.92	3.74	3.88	3.22	3.70	0.00	3.73	4.15
Baidu	1.75	1.90	1.99	2.67	2.85	1.89	2.31	1.91	2.13	1.09	1.83	1.12	3.29	2.48	3.84
Correlation	0.83	0.74	0.45	0.92	0.58	0.6	0.78	0.72	0.71	0.82	0.53	0.88	0.85	0.63	0.67

Translator	**Cs**	**Ro**	**Sv**	**El**	**Hu**	**Tr**	**Bg**	**Fi**	**Ar**	**Lg**	**Ny**	**Am**	**Lo**	**Bn**	**As**
LegoMT2	3.50	3.41	3.42	3.64	3.72	3.84	3.06	2.97	3.18	2.24	2.86	3.07	3.60	3.42	2.64
NLLB-200-1.3B	2.09	2.40	2.15	2.24	2.03	2.21	1.55	2.16	1.62	1.98	2.34	1.99	2.84	2.42	2.00
Google	3.75	3.80	3.99	3.94	3.80	4.04	3.34	3.24	3.45	3.66	3.08	3.30	3.97	3.68	3.41
Baidu	3.75	1.93	3.85	3.78	3.76	3.44	3.27	3.13	2.93	2.20	1.01	1.74	1.73	2.59	1.72
Correlation	0.72	0.72	0.64	0.61	0.69	0.59	0.59	0.28	0.54	0.83	0.83	0.49	0.59	0.68	0.63

Table 12: Comparison of ChatGPT and LegoMT2: While ChatGPT outperforms LegoMT2 for some language pairs, LegoMT2 has an absolute advantage for the vast majority. On average, ChatGPT lags behind LegoMT2 in both the En→X and X→En directions by more than 6 points.

X→En	**ChatGPT**	**LegoMT2**	**X→En**	**ChatGPT**	**LegoMT2**	**X→En**	**ChatGPT**	**LegoMT2**	**X→En**	**ChatGPT**	**LegoMT2**
af	54.9	58.9	gu	20.0	39.1	lo	9.8	37.3	ru	32.6	36.8
am	2.7	32.4	ha	13.4	31.3	lt	30.9	35.4	sd	13.0	22.0
ar	33.7	41.6	he	32.6	41.5	luo	8.1	27.5	sk	35.5	41.6
as	12.9	31.1	hi	33.9	47.1	lv	30.5	35.7	sl	33.7	36.7
ast	38.3	33.3	hr	36.9	39.5	mi	19.4	30.0	sn	13.2	30.5
az	18.7	27.7	hu	32.6	35.6	mk	37.6	43.0	so	14.3	32.5
be	19.2	19.9	hy	14.5	39.0	ml	18.5	41.0	sr	35.2	40.7
bg	37.1	41.4	id	40.1	45.0	mn	11.1	30.2	sv	46.3	49.4
bn	21.2	38.5	ig	8.7	28.4	mr	20.4	39.6	sw	40.4	47.0
bs	41.3	44.6	is	28.9	35.0	ms	43.8	47.6	ta	13.6	32.5
ca	43.1	46.3	it	34.4	35.5	mt	42.8	60.5	te	18.6	42.1
ceb	37.5	45.0	ja	26.5	30.5	my	2.8	30.2	tg	13.4	32.9
cs	38.2	43.7	jv	27.4	45.1	ne	21.2	40.5	th	21.9	33.6
cy	44.0	54.6	ka	12.1	27.6	nl	34.8	36.2	tl	41.9	51.4
da	47.6	51.3	kam	9.8	19.6	no	41.3	45.7	tr	36.0	39.0
de	41.4	44.4	kea	33.7	51.2	ns	13.9	43.2	uk	37.2	41.5
el	33.9	39.1	kk	18.6	35.6	ny	15.1	32.4	umb	5.0	14.8
es	29.9	31.4	km	13.6	36.8	oc	45.3	56.8	ur	24.6	38.5
et	35.9	38.7	kn	20.0	35.1	om	4.9	22.6	uz	19.3	34.6
fa	30.4	37.2	ko	26.1	28.3	or	14.0	36.3	vi	33.3	42.0
ff	7.3	12.0	ku	9.6	35.7	pa	24.0	44.2	wo	8.5	21.5
fi	31.5	33.9	ky	10.7	26.9	pl	29.9	33.6	xh	17.1	39.6
fr	43.9	46.9	lb	39.6	45.5	ps	10.6	35.6	yo	9.8	26.0
ga	33.2	43.3	lg	11.1	23.1	pt	47.5	50.5	zh	28.3	30.5
gl	39.2	40.5	ln	10.6	28.7	ro	42.7	48.1	zu	18.0	41.5
EN→X	**ChatGPT**	**LegoMT2**	**EN→X**	**ChatGPT**	**LegoMT2**	**EN→X**	**ChatGPT**	**LegoMT2**	**EN→X**	**ChatGPT**	**LegoMT2**
af	44.3	45.3	gu	19.0	34.8	lo	4.0	28.9	ru	36.0	39.0
am	2.9	26.9	ha	8.1	26.9	lt	27.2	33.5	sd	8.4	33.3
ar	31.6	36.1	he	27.0	37.2	luo	4.2	18.3	sk	34.5	38.9
as	7.3	24.6	hi	29.2	46.6	lv	27.9	23.2	sl	32.5	37.1
ast	29.8	30.3	hr	34.4	35.7	mi	16.0	19.8	sn	5.8	19.5
az	11.8	20.4	hu	27.2	34.9	mk	33.1	43.4	so	6.4	18.2
be	16.4	23.4	hy	10.5	33.1	ml	12.0	38.0	sr	1.5	29.3
bg	38.7	49.3	id	45.4	46.6	mn	5.5	18.8	sv	46.5	46.6
bn	18.4	33.7	ig	6.2	19.9	mr	10.4	27.4	sw	37.5	40.1
bs	34.0	35.1	is	22.0	30.2	ms	39.2	47.2	ta	10.2	20.8
ca	46.8	48.9	it	35.8	36.5	mt	31.6	64.4	te	13.2	41.6
ceb	24.5	18.9	ja	29.7	33.5	my	2.5	15.5	tg	11.0	32.5
cs	36.7	40.5	jv	15.6	30.3	ne	15.0	26.4	th	22.1	21.1
cy	44.0	43.8	ka	11.1	23.0	nl	31.7	31.9	tl	31.2	34.9
da	45.4	45.5	kam	4.9	7.4	no	36.6	37.2	tr	34.5	36.4
de	40.3	41.7	kea	11.5	17.5	ns	6.6	26.8	uk	33.3	40.1
el	30.9	34.5	kk	11.1	33.7	ny	6.3	23.8	umb	2.8	2.9
es	32.3	30.7	km	4.4	15.9	oc	28.2	44.0	ur	16.8	27.4
et	33.6	34.4	kn	14.3	31.6	om	1.7	10.8	uz	15.8	27.3
fa	25.4	35.0	ko	25.0	26.0	or	11.3	32.3	vi	38.7	43.2
ff	3.0	0.1	ku	5.0	3.5	pa	20.3	36.1	wo	5.1	6.3
fi	33.3	31.2	ky	7.2	24.4	pl	29.3	31.9	xh	6.4	28.9
fr	53.2	56.8	lb	24.2	1.1	ps	3.4	22.0	yo	3.4	4.2
ga	26.9	3.7	lg	3.6	12.5	pt	54.6	55.4	zh	30.7	27.1
gl	36.3	38.2	ln	5.8	26.0	ro	44.4	48.2	zu	6.6	32.2

Table 13: Comparison between ChatGPT and LegoMT2. Both in the En→X and X→En direction, ChatGPT falls behind LegoMT2 even with eight-shot.

Model	**X→En**	**En→X**	**AVG.**
ChatGPT zero-shot	27.9	23.9	25.9
ChatGPT eight-shot	31.9	24.7	28.3
LegoMT2	**38.3**	**31.6**	**35.0**

The detailed results are shown in the table below Table 13. For some language pairs, the performance of ChatGPT is better than that of LegoMT2, such as En→Zh, where ChatGPT scores 30.7 versus LegoMT2 's 27.1. However, for the vast majority of language pairs, LegoMT2 has an absolute advantage. On average, ChatGPT lags behind LegoMT2 in both the En→X and X→En directions by more than 6 points.

Comparison between ChatGPT with LegoMT2 A comparative analysis between ChatGPT (GPT 3.5) and LegoMT2 on 100 samples in *Flores-101*, as shown in Table 13, reveals that in zero-shot and eight-shot performance, ChatGPT lags behind LegoMT2 in the En→X and X→En direction more than 6 points. The prompts utilized for ChatGPT are "You are a helpful assistant that translates {*SOURCE_LANG*} to {*TARGET_LANG*}." for the system and "Translate the following {*SOURCE_LANG*} text to {*TARGET_LANG*}: {*SOURCE_TEXT*}." for the user.