Towards Making the Most of Multilingual Pretraining for Zero-Shot Neural Machine Translation

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Abstract

This paper demonstrates that multilingual pretraining, a proper fine-tuning method and a large-scale parallel dataset from multiple auxiliary languages are all critical for zero-shot translation, where the NMT model is tested on source languages unseen during supervised training. Following this idea, we present SixT++, a strong many-to-English NMT model that supports 100 source languages but is trained once with a parallel dataset from only six source languages. SixT++ initializes the decoder embedding and the full encoder with XLM-R large, and then trains the encoder and decoder layers with a simple two-stage training strategy. SixT++ achieves impressive performance on many-to-English translation. It significantly outperforms CRISS and m2m-100, two strong multilingual NMT systems, with an average gain of 7.2 and 5.0 BLEU respectively. Additionally, SixT++ offers a set of model parameters that can be further fine-tuned to develop unsupervised NMT models for low-resource languages. With back-translation on monolingual data of low-resource language, it outperforms all current state-of-the-art unsupervised methods on Nepali and Sinhal for both translating into and from English.

1 Introduction

Neural machine translation systems (Sutskever et al., 2014; Bahdanau et al., 2015; Vaswani et al., 2017) have demonstrated state-of-the-art results on resource-rich language pairs such as French-English and German-English. However, due to the large parameter space, the NMT model still works poorly when the available training examples are limited. Previous researches show that NMT system underperforms phrase-based statistical machine translation (Koehn and Knowles, 2017; Lample et al., 2018b) or requires careful hyper-parameter tuning (Sennrich and Zhang, 2019) in the low-data conditions.

As a result, research on low-resource language translation, in which no direct parallel corpora are available, is drawing increasing attention, and it has been found promising to utilize parallel datasets from other auxiliary languages. Prior works build multilingual NMT and conduct zero-shot translations between unseen language pairs (Johnson et al., 2017; Gu et al., 2019; Zhang et al., 2020). Both languages in the zero-shot translation pair have some parallel data with other languages under this setting. As such, the system can learn to process both languages. However, these approaches may be infeasible for rare languages where the parallel dataset of any kind is hard to collect. Some works address this by initializing with a multilingual pretrained language model (MulPLM) or/and introducing additional training objective with monolingual dataset of the language pair (Guzmán et al., 2019; Ko et al., 2021; Garcia et al., 2021; Liu et al., 2020b). However, these methods are either computational costly or fail to fully utilize the multilingual knowledge learned in the MulPLM. Recently, Chen et al. (2021) propose SixT, a transferability-enhanced fine-tuning method that better adapts XLM-R (Conneau et al., 2020) for translating unseen source languages. Although obtaining promising results, they focus on developing the fine-tuning approach by conducting experiments on a parallel dataset of one auxiliary language. Such setting limits the model’s performance on unseen languages, as adding more parallel data and more auxiliary languages are reported to improve performance for unsupervised NMT (García et al., 2020; Bai et al., 2020; García et al., 2021).

In this paper, we present SixT++, a strong many-to-English NMT model that is trained with a parallel dataset from only six source languages. It can translate 100 source languages which are supported by the XLM-R model. SixT++ is trained with a
much larger supervised dataset than SixT, with 110 million English-centric sentence pairs across six languages from different language families. Therefore, to better fit the large-scale dataset, SixT++ improves over SixT by removing the positional disentangled encoder and keeping the decoder embeddings frozen during the whole training process, which simplifies the model, reduces the model size and speeds up the training. Specifically, we first initialize the encoder and embeddings of SixT++ with XLM-R large and then train SixT++ with a simple two-stage training method. At the first stage, we only train the decoder layers, while at the second stage, all model parameters except the embeddings are jointly optimized. When combined with back-translation, SixT++ can be further fine-tuned for the unsupervised NMT systems that translate the low-resource languages both into and from English.

Extensive experiments demonstrate that SixT++ works remarkably well. For zero-shot translation, SixT++ significantly outperforms all the baselines across 17 languages, including CRISS and m2m-100, the strong unsupervised and supervised multilingual NMT models trained with a much larger dataset. Furthermore, when combining with back-translation, SixT++ achieves state-of-the-art performance for the unsupervised low-resource language translation for both translating into and out of English. It outperforms various explicitly designed unsupervised NMT models for low-resource language with an average gain over 1.2 BLEU.

2 SixT++

In this section, we present a simple and strong many-to-English NMT model: SixT++. Different from SixT which explores a better fine-tuning method for utilizing XLM-R (Conneau et al., 2020) for cross-lingual transfer in NMT task, SixT++ aims at building a strong many-to-English NMT model. We argue that multilingual pretraining, a proper fine-tuning method and a large-scale parallel dataset from multiple auxiliary languages are all critical for zero-shot translation. Therefore, we initialize the NMT model with XLM-R large and train SixT++ with a simple two-stage fine-tuning method on large-scale parallel data from six auxiliary languages.

2.1 Data: AUX6 corpus

Datasets To build a strong many-to-English translation model, we utilize De, Es, Fi, Hi, Ru, and Zh as the auxiliary source languages, which are high-resource languages from different language families. We do not add more auxiliary languages to limit the computation cost and the training data size. The training data is from the WMT and CCAigned dataset, consisting of 110 million sentence pairs. We concatenate the validation sets of auxiliary languages to select the best model. We use AUX6 to denote our dataset. The dataset details are in the appendix. Following Conneau and Lample (2019), sentences of the $i$th language pair are sampled according to the multinomial distribution calculated as follows:

$$q_i = \frac{p_i^\alpha}{\sum_j p_j^\alpha}$$

where $p_j$ is the percentage of each language in the training dataset and we set the hyper-parameter $\alpha$ to be 0.2.

Preprocessing Since our model initializes the encoder and embeddings with XLM-R, we tokenize all datasets with the same tokenizer as XLM-R, which is a sentencepiece model (Kudo, 2018, SPM) learned on the full Common Crawl data that includes 250k subword tokens. We do not apply additional preprocessing, such as truecasing or normalizing punctuation/characters. Following XLM-R, we add the [BOS] and [EOS] tokens at the head and tail of the input sentence, respectively.

2.2 Model

Architecture The SixT++ is a Transformer-based NMT model with $\sim0.7$B model parameters. To initialize the encoder with XLM-R large, our encoder has the same configuration as XLM-R large, with 24 encoder layers, hidden state dimension of 1024, feed-forward dimension of 4096, and head number of 16. For the decoder, we follow the suggestion in Chen et al. (2021) and use a deeper decoder than the standard Transformer to digest the large-scale training dataset. It has 12 decoder layers, hidden dimension of 1024, feed-forward dimension of 3072 and head number of 16. We use the same vocabulary as XLM-R and tie the encoder embeddings, decoder embeddings and decoder output projection to reduce the model size.

Learning We first initialize the encoder and embeddings with XLM-R large, and then fine-tune the model on auxiliary parallel dataset. Compared with fine-tuning XLM-R for NLU tasks like text
classification, the prediction space for SixT++ is much larger and it has to learn much more randomly initialized parameters. Directly fine-tuning all parameters may degrade the cross-lingual transferability that is learned in XLM-R. Therefore inspired by Chen et al. (2021), we train SixT++ with a two-stage training framework.

**Stage 1: Decoder Training** To preserve the cross-lingual transferability of XLM-R, we first train the decoder by keeping the encoder frozen:

\[
L_{\theta_{\text{dec}}} = \sum_{D_i \in D} \log P(y|x; \theta_{\text{dec}}),
\]

where \(D = \{D_1; ...; D_K\}\) is a collection of parallel dataset in \(K\) auxiliary languages, \(\langle x, y \rangle\) is a parallel sentence pair with source language \(i\) and \(\theta_{\text{dec}}\) is the set of parameters of the decoder layers.

**Stage 2: Fine-tuning** Freezing the encoder parameters may limit the capacity of the NMT model, especially when the training data goes large. Therefore, we jointly train the full model in another stage:

\[
L_{\theta} = \sum_{D_i \in D} \sum_{\langle x, y \rangle \in D_i} \log P(y|x; \theta),
\]

where \(\theta\) is the set of parameters of the full NMT model. Since the decoder has been well adapted to the encoder at the first stage, we expect the model can be fine-tuned for better performance on the supervised translation directions while preserving the transferability of the encoder.

Different from SixT which fine-tunes the decoder embedding, we keep the embeddings fixed during the whole training process. Our preliminary experiments find that this strategy leads to higher computational efficiency without obviously degrading the performance. Besides, we remove the positional disentangled encoder in SixT to make our model simpler, as this technique does not show clear performance improvement when the training dataset goes large (See Section 3.3).

**Optimization** SixT++ is trained on 128 Nvidia V100 GPUs (32GB) with 100K and 10K steps for the first and second training stage. The batch size is 4096 for each GPU. We use the Adam optimizer (Kingma and Ba, 2015) with \(\beta_1 = 0.9\) and \(\beta_2 = 0.98\). At the first stage, the learning rate is 0.0005, and the warmup step is 4000, while at the second stage, we set the learning rate as 0.0001 and do not use warmup. The dropout probabilities are set to be 0.1. All experiments are done with the fairseq toolkit (Ott et al., 2019).

### 3 Zero-Shot Neural Machine Translation

#### 3.1 Experiment Settings

We evaluate the translation performance of SixT++ on the test sets of 23 language pairs from 9 various language groups: German group (De, Nl), Romance group (Es, Ro, It), Uralic and Baltic group (Fi, Lv, Et), Slavic group (Ru, Pl), Arabic group (Ar, Ps), Indo-Aryan group (Hi, Ne, Si, Gu), Turkic (Tr, Kk), East Asian (Zh, Ja, Ko) and Khmer (My, Km). The dataset details are in the appendix. For decoding, we use beam-search with beam size 5 for all translation directions and do not tune length penalty. We report detokenized BLEU for all directions using sacrebleu.

We compare SixT++ with SixT and four other baselines. Among the four baselines, XLM-R-FT and mBART-FT use the same training data as SixT++, while CRISS and m2m-100 are strong multilingual unsupervised and supervised NMT models, which use a much larger training dataset than SixT++. As SixT++, CRISS and m2m-100 have different model size, support different number of languages and are trained with different training dataset, the comparisons are not completely fair, but the results can demonstrate the strong performance of SixT++.

- **CRISS** (Tran et al., 2020). This model is the SOTA unsupervised many-to-many multilingual NMT model. It is initialized with the mBART model and fine-tuned on 180 language directions (90 language pairs) from CCMatrix. It only supports 25 input languages.
- **m2m-100** (Fan et al., 2020). This model is a strong supervised many-to-many multilingual NMT model. It is a large Transformer trained on huge parallel data across 2200 language directions and with 7.5B parallel sentences from CCMatrix and CCAligned as well as additional back-translations. We evaluate the official version with 1.2B model parameters for comparison.
- **SixT** (Chen et al., 2021). This model is what motivates SixT++. We compare with the best performing SixT model in Chen et al. (2021), which is a

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1We refer to the language group information in Table 1 of Fan et al. (2020).

2BLEU+case,mixed+numrefs.1+smooth.exp+tok.13a+version.1.5.0
Table 1: BLEU comparison with baselines on many-to-English test sets. ‘# Sent’ is the number of sentences in the training set. ‘Param.’ is the number of model parameters. ‘−’ indicates the source language is not supported by CRISS. ‘Avg.’ is the average BLEU across all test directions. Since CRISS does not support Pl, Ps and Km, we report a second column (†) of average BLEU that does not include these directions to compare with CRISS. The best BLEU is bold and underlined.

| Model           | # Sent | Param. | German | Romance | Slavic | Arabic |
|-----------------|--------|--------|--------|---------|--------|--------|
|                 | De     | Ni     | Es     | Ro      | It     | Fi     | Lv     | Et     | Ru     | Pl     | Ar     | Ps     |
| CRISS           | 1.8B   | 0.7B   | 28.8   | 47.0    | 32.2   | 35.4   | 48.9   | 23.9   | 18.6   | 23.5   | 21.2   | −      | −      |
| m2m-100         | 7.5B   | 1.2B   | 31.9   | 54.0    | 32.8   | 38.3   | 55.9   | 29.0   | 23.0   | 30.7   | 24.2   | 29.9   | 28.4   | 10.9   |
| SixT            | 0.04B  | 0.7B   | 33.8   | 54.7    | 30.1   | 33.9   | 43.0   | 26.3   | 19.7   | 25.7   | 20.4   | 23.9   | 25.1   | 11.4   |
| mBART-FT        | 0.11B  | 0.6B   | 32.2   | 50.6    | 33.0   | 34.0   | 53.3   | 28.7   | 17.9   | 22.0   | 21.7   | 15.0   | 19.2   | 0.9    |
| XLM-R-FT        | 0.11B  | 0.7B   | 32.8   | 37.7    | 34.4   | 32.5   | 37.2   | 29.5   | 17.9   | 23.7   | 23.4   | 19.6   | 22.3   | 8.5    |
| SixT++ (1st)    | 0.11B  | 0.7B   | 35.2   | 52.5    | 34.1   | 36.8   | 49.4   | 30.0   | 21.4   | 27.4   | 23.5   | 19.6   | 22.3   | 8.5    |
| SixT++          |        |        | 35.2   | 52.5    | 34.1   | 36.8   | 49.4   | 30.0   | 21.4   | 27.4   | 23.5   | 19.6   | 22.3   | 8.5    |

Table 1: BLEU comparison with baselines on many-to-English test sets. ‘# Sent’ is the number of sentences in the training set. ‘Param.’ is the number of model parameters. ‘−’ indicates the source language is not supported by CRISS. ‘Avg.’ is the average BLEU across all test directions. Since CRISS does not support Pl, Ps and Km, we report a second column (†) of average BLEU that does not include these directions to compare with CRISS. The best BLEU is bold and underlined. Note that mBART-FT, XLM-R-FT, SixT++ (1st, i.e. first training stage) and SixT++ are trained with the same parallel dataset, and the last three of them utilize the same MulPLM (XLM-R large) but with a different fine-tuning method.

3The comparison is between the average BLEU across the same language pairs supported by CRIS.
Table 2: BLEU comparison of our many-to-many NMT model (ours m2m) with m2m-100 on zero-shot translations. We use a target-language-aware linear projection layer to generate different target languages for the SixT++ (m2m) model. Ours (m2En) is the many-to-English SixT++ model trained with the AUX6 dataset. The best average BLEU for each target language is bold and underlined.

| Tgt | Model         | NL | Ro | Sr | Lv | Pl | Ne | Ja | Mr | Kk | Km | Tr | Avg |
|-----|---------------|----|----|----|----|----|----|----|----|----|----|----|-----|
| → En | m2m-100       | 29.7 | 40.7 | 39.6 | 33.1 | 27.1 | 13.2 | 1.7 | 23 | 22.3 | 5.2 | 14.0 | 33.0 | 23.6 |
|     | Ours (m2En)   | 29.6 | 39.1 | 37.9 | 31.3 | 26.1 | 35.3 | 33.5 | 21.3 | 29.9 | 27.2 | 21.4 | 33.1 | 30.5 |
|     | Ours (m2m)    | 29.0 | 37.9 | 37.0 | 30.6 | 25.3 | 34.5 | 32.1 | 20.2 | 29.4 | 27.0 | 21.7 | 32.3 | 29.8 |
| → De | m2m-100       | 21.8 | 28.1 | 27.7 | 14.8 | 19.8 | 17.5 | 16.0 | 15.1 | 11.9 | 14.5 | 14.8 | 11.8 | 18.7 |
|     | Ours (m2m)    | 20.1 | 24.5 | 24.1 | 19.8 | 17.5 | 16.0 | 15.1 | 11.9 | 14.5 | 14.8 | 11.8 | 18.7 | 17.4 |
| → Es | m2m-100       | 18.9 | 24.1 | 22.6 | 20.7 | 19.8 | 8.6 | 1.8 | 15.8 | 13.0 | 6.3 | 10.4 | 19.8 | 15.2 |
|     | Ours (m2m)    | 16.5 | 21.7 | 19.3 | 16.3 | 16.6 | 14.4 | 12.5 | 12.2 | 13.1 | 14.1 | 10.4 | 16.2 | 15.3 |
| → Fi | m2m-100       | 14.4 | 18.0 | 17.6 | 17.4 | 14.6 | 6.2 | 1.1 | 11.5 | 9.1 | 4.4 | 7.0 | 14.3 | 11.3 |
|     | Ours (m2m)    | 11.6 | 13.8 | 12.7 | 12.4 | 11.1 | 10.0 | 8.7 | 7.4 | 8.3 | 9.0 | 7.3 | 10.0 | 10.2 |
| → Hi | m2m-100       | 16.1 | 20.7 | 20.6 | 18.8 | 16.1 | 11.1 | 1.4 | 14.8 | 18.2 | 3.7 | 8.0 | 19.1 | 14.1 |
|     | Ours (m2m)    | 14.5 | 18.2 | 18.3 | 15.3 | 13.4 | 20.0 | 20.0 | 10.8 | 17.7 | 13.3 | 10.7 | 14.2 | 15.5 |
| → Ru | m2m-100       | 17.2 | 24.4 | 25.0 | 19.1 | 18.6 | 7.4 | 1.0 | 14.4 | 12.5 | 4.8 | 8.5 | 18.5 | 14.3 |
|     | Ours (m2m)    | 13.9 | 19.4 | 20.6 | 19.4 | 16.0 | 13.0 | 12.7 | 9.9 | 12.0 | 14.5 | 9.8 | 14.5 | 14.6 |
| → Zh | m2m-100       | 25.7 | 29.4 | 29.2 | 22.6 | 25.5 | 12.8 | 0.7 | 26.9 | 19.5 | 7.3 | 12.4 | 26.7 | 19.9 |
|     | Ours (m2m)    | 26.3 | 29.6 | 28.7 | 27.1 | 25.2 | 24.6 | 22.5 | 24.7 | 23.1 | 23.9 | 20.3 | 26.0 | 25.2 |

Table 2: BLEU comparison of our many-to-many NMT model (ours m2m) with m2m-100 on zero-shot translations. We use a target-language-aware linear projection layer to generate different target languages for the SixT++ (m2m) model. Ours (m2En) is the many-to-English SixT++ model trained with the AUX6 dataset. The best average BLEU for each target language is bold and underlined.

3.3 Analysis

Many-to-Many Translations SixT++ shows impressive performance on zero-shot many-to-

English translation. The method can also be used to build a many-to-one NMT model for other target language or a many-to-many NMT model that can support multiple target languages. In this experiment, we examine the performance of our method on many-to-many multilingual NMT. Following Zhang et al. (2020), we switch between different target languages by using a target-language-aware linear projection layer between the encoder and the decoder. The linear layers are trained in both training stages. We learn the model with the same AUX6 dataset and initialization/training framework as SixT++, but additionally include the En→{De,Es,Fi,Ru,Zh} translation directions during supervised training and validation. We evaluate the performance on Flores 101 testset (Goyal et al., 2021), which is a multilingual aligned benchmark that covers 101 different languages. We re-

| Data  | Size | De-En | Hi | Ne | Si | Gu | Avg. |
|-------|------|-------|----|----|----|----|------|
| Diverse | 8M   | 20.9 | 16.6 | 15.1 | 20.9 | 18.4 |
Table 4: The BLEU comparison between SixT++ with and without positional disentangled encoder (denoted as ‘ResDrop’). The best average BLEU for each training dataset is bold and underlined.

| Dataset       | #Sent | Config.               | De  | Nl  | Ro  | Lv  | Et  | Ne  | Si  | Gu  | Ja  | Ko  | Avg. |
|---------------|-------|-----------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|
| Europarl      | 1.9M  | Ours                  | 29.1| 44.2| 27.2| 39.0| 15.3| 20.5| 10.1| 8.8 | 12.6| 7.1 | 20.1 | 20.5 |
|               |       | Ours + ResDrop        | 28.7| 44.7| 28.3| 39.2| 16.0| 21.4| 11.0| 10.0| 12.8| 8.0 | 23.5 | **21.5** |
| WMT19         | 41M   | Ours                  | 34.1| 54.9| 33.5| 43.5| 19.7| 25.5| 14.1| 12.0| 17.0| 10.3| 30.2 | 26.1 |
|               |       | Ours + ResDrop        | 33.8| 54.7| 33.9| 43.0| 19.7| 25.7| 14.4| 12.2| 17.3| 10.7| 31.2 | **26.3** |
| AUX6          | 110M  | Ours                  | 35.2| 58.5| 39.0| 61.1| 23.2| 30.1| 23.6| 17.4| 27.2| 13.7| 32.5 | 32.6 |
|               |       | Ours + ResDrop        | 35.3| 58.5| 38.6| 60.9| 23.3| 30.5| 23.7| 17.5| 27.5| 13.1| 33.3 | **32.7** |

Effect of the Multilinguality of Auxiliary Languages

Previous studies report that adding more parallel data and more auxiliary languages improves performance for unsupervised NMT (García et al., 2020; Bai et al., 2020; Garcia et al., 2021). In this experiment, we examine whether increasing multilinguality under a fixed data budget improves the zero-shot performance of SixT++. We fix the amount of auxiliary parallel sentence pairs to 8 million and vary the number of auxiliary languages. We report the results in Table 3. It is observed that the model trained with four auxiliary languages (De, Es, Fi, Ru) outperforms that of one auxiliary language (De), with an average gain of 3.7 BLEU. Note that for both cases, we use auxiliary languages not in the Indo-Aryan group to alleviate the impact of language similarity. This observation demonstrates the necessity of utilizing multiple auxiliary languages in the training dataset.

Effect of Positional Disentangled Encoder

In this experiment, we include positional disentangled encoder as a comparison since it is reported to improve zero-shot translation (Liu et al., 2020a; Chen et al., 2021). Specifically, we remove the residual connection at the 23th (penultimate) encoder layer at the second training stage as suggested by Chen et al. (2021). We denote this technique as ResDrop. It reduces the strong positional correspondence between the input text and the output encoder representation brought by residual connections, thus facilitating the cross-lingual transfer. We refer the readers to Liu et al. (2020a); Chen et al. (2021) for more details.

Table 4 presents the results. We find that on the small-scale Europarl dataset, ResDrop improves the zero-shot performance with an average gain of 1.0 BLEU. However, when the training data goes large, the gain decreases (see results on WMT19 and AUX6). Considering that the model without ResDrop is simpler and usually performs better in the supervised translation direction, we do not utilize it in our proposed SixT++. However, for cases where the training data is small, we recommend ResDrop at the second training stage.

Similarity Search

We assume the strong performance of SixT++ is brought by the language-agnostic encoder representation it learns. To verify the assumption, we conduct a set of similarity search experiments to compare different fine-tuning methods. Similarity search aims at...
finding the nearest neighbor of each sentence in another language according to the cosine similarity of sentence representations. We conduct the similarity search following the method in the XTREME benchmark (Hu et al., 2020) which uses the average-pooled encoder output as the sentence representation and reports accuracy as a quantitative indicator of how language-agnostic the encoder representations are. We select two auxiliary languages De, Hi and two unseen languages Gu, Ne, which are in the same language group with Hi but not with De. Then we conduct the similarity search between each auxiliary language and each unseen language, as SixT++ transfers from auxiliary languages to unseen source languages. We also include the accuracy on Hi and De to better understand our model. We use Flores 101 as the test set for each language pair, as shown in Table 5. Note that the results of SixT++ (1st) are the same as XLM-R large, as the encoder is kept fixed in this model.

First, SixT++ gets the highest accuracy in all auxiliary-unseen language pairs regardless whether they are in the same language group, demonstrating its ability to learn language-agnostic representation that benefits cross-lingual transfer. Moreover, we observe that SixT++ gets higher accuracy than SixT++ (1st) for all language pairs. The results show that SixT++ even learns a more language-agnostic encoder than XLM-R large, as the encoder is kept fixed in this model.

| Models          | Hi-De | Ne-Hi | Gu-Hi | Ne-De | Gu-De | Avg. |
|-----------------|-------|-------|-------|-------|-------|------|
| XLM-R FT-all    | 99.5  | 97.7  | 59.9  | 98.1  | 69.0  | 84.8 |
| SixT++ (1st)    | 86.5  | 84.7  | 88.6  | 83.2  | 77.3  | 84.1 |
| SixT++          | 99.3  | **98.4** | **97.7** | **99.1** | **97.8** | **98.5** |

Table 5: Accuracy comparison of different models on the similarity search task. Hi and De are among the auxiliary languages while the rests are not. The highest accuracy for each language pair is bold and underlined.

4 Neural Machine Translation for Low-Resource Languages

SixT++ provides a promising solution for translating low-resource language to English, where direct parallel corpus could be unavailable. However, the reverse NMT model that translates from English to a low-resource language is also useful in real scenarios. Therefore, we follow the common practice in unsupervised NMT and utilize back-translation (Sennrich et al., 2016) to build the reverse unsupervised NMT system. Specifically, we first generate synthetic parallel corpus with SixT++ and monolingual dataset in the low-resource language using offline back-translation. Then we train the En→X model using the same training framework as SixT++, but with the synthetic parallel dataset as the training dataset. To save computation cost, we do not apply other unsupervised NMT techniques that are reported to be useful, such as iterative back-translation (Lample et al., 2018b; Garcia et al., 2021; Ko et al., 2021), cross-translation (Xia et al., 2019; Garcia et al., 2021) or iterative mining of parallel sentence pairs (Tran et al., 2020).

Experimental Settings We evaluate our method on Ne and Si, two commonly used benchmark languages for evaluating low-resource language translation. The monolingual dataset of Ne and Si consists of 7 million sentences that are sampled from CC100 and CCNet datasets. The validation and test set are from the Flores dataset (Guzmán et al., 2019). We set the beam size to 5 during the offline back-translation. Note that different from common unsupervised NMT (Lample et al., 2018b), we do not need any monolingual dataset from English during NMT training. In addition to CRISS and m2m-100, we compare with the state-of-the-art unsupervised and supervised baselines from the literature on these two languages. Most of these additional baselines are not multilingual and are explicitly designed for low-resource language translation.

- Unsupervised baselines. We include the results of three unsupervised methods. Guzmán et al. (2019) utilize Hi as auxiliary language and train with auxiliary supervised translation and iterative back-translation. Garcia et al. (2021) utilize six languages as auxiliary languages and present a three-stage method with various loss functions, including auxiliary supervised translation, iterative back-translation, denoising autoencoding and cross-translation. Ko et al. (2021) fine-tune mBART on the parallel dataset from Hi and monolingual data in an iterative manner with auxiliary supervised translation, back-translation, denoising autoencod-
Table 6: BLEU comparison of different models on the low-resource language translation. † denotes the results are quoted from the original paper. The best unsupervised method for each translation direction is bold, while the best supervised method is underlined.

Results The results are illustrated in Table 6. Our model outperforms all unsupervised baselines for all translation directions, improving the best performing unsupervised baseline with an average gain of 1.2 BLEU. In addition, it even outperforms all supervised baselines and achieves new state-of-the-art performance on Ne→En and En→Ne translations. Our method is also computationally efficient. For translating into English, SixT++ can be trained once to support various low-resource languages. For translating out of English, we run back-translation only once for one low-resource language. For cases when the sizes of monolingual dataset of English and low-resource language are similar, our computation cost on back-translation is around 25% of the commonly used two iterations of back-translation (Garcia et al., 2021; Liu et al., 2020b). Our method may be further improved with iterative back-translation and cross-translation, we leave more in-depth study as further work.

5 Related Work

5.1 Multilingual Neural Machine Translation

Early works on multilingual NMT show its zero-shot translation capability, where the tested translation direction is unseen during supervised training (Johnson et al., 2017; Ha et al., 2016). To further improve the zero-shot performance, one direction is to learn language-agnostic encoder representations and make the most of cross-lingual transfer. Some approaches introduce auxiliary training objectives to encourage similarity between the representations of different languages (Arivazhagan et al., 2019; Al-Shedivat and Parikh, 2019; Pham et al., 2019; Pan et al., 2021). For example, Pan et al. (2021) utilize contrastive loss to explicitly align representations of a bilingual sentence pair. Some other works modify the encoder architecture to facilitate language-independent representations. Lu et al. (2018) incorporate an explicit neural interlingua after the encoder. Liu et al. (2020a); Chen et al. (2021) remove the residual connection at one of the encoder layers to relax the positional correspondence. Other studies encourage cross-lingual transfer by initializing the model with a multilingual pretrained language model or combining the denoising training objective on a monolingual dataset during NMT training (Gu et al., 2019; Ji et al., 2020; Liu et al., 2020b; Chen et al., 2021; Garcia et al., 2021). Our work follows the last line but improves over them by making the most of MulPLM with a simple yet effective fine-tuning method and large-scale parallel dataset from auxiliary languages.

5.2 Zero-shot Translation with Multilingual Pretrained Language Model

For natural language generation such as neural machine translation, most work leverage multilingual pretrained seq2seq language models such as mBART (Liu et al., 2020b), mT5 (Xue et al., 2020) and ProphetNet-X (Qi et al., 2021) for cross-lingual transfer. For example, Liu et al. (2020b) fine-tune mBART with the parallel dataset of one language pair and test on unseen source languages. Considering the great success of multilingual pretrained encoder (MulPE) such as XLM-R (Conneau et al., 2020) and mBART (Wu and Dredze, 2019) in zero-shot cross-lingual transfer for NLU tasks (Liang et al., 2020), the use of it for cross-lingual transfer...
in NLG tasks is still under-explored. One of such studies (Wei et al., 2021) fine-tunes their proposed MulPE with a two-stage training method to conduct zero-shot translation. However, they mainly focus on building better MulPE instead of better zero-shot NMT. Our work is most similar to SixT (Chen et al., 2021), which propose a two-stage fine-tuning method to utilize XLM-R for zero-shot NMT and further improve zero-shot performance with positional disentangled encoder. However, since SixT focuses on designing novel fine-tuning method, it conducts experiments with one auxiliary language, which limits the model’s performance. In contrast, SixT++ aims at building a strong zero-shot NMT model, especially for low-resource languages. It extends SixT to large-scale multilingual fine-tuning and improves over SixT with a simpler architecture, smaller model size, and more efficient training method.

6 Conclusion

In this paper, we introduce SixT++, a strong many-to-English NMT model that supports 100 source languages but is trained once with parallel dataset from only six source languages. Our model makes the most of multilingual pretraining for zero-shot NMT by fine-tuning on large-scale parallel corpora from six auxiliary source languages with a simple yet effective two-stage fine-tuning method. Extensive experiments demonstrate that SixT++ outperforms all baselines on many-to-English translation. When combining with back-translation, our model achieves new state-of-the-art performance among unsupervised models for both translating low-resource language from and into English.

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A Dataset

A.1 Machine Translation Dataset

The dataset is from WMT translation task, CCAligned corpus,\(^5\) WAT21 translation task,\(^6\) Flores Testset\(^7\) and Tatoeba test sets.\(^8\) We use the first 20M sentence pairs of the CCAligned corpus for Es-En and Ru-En language pairs as training data. All texts are tokenized by the same XLM-R sentencepiece (Kudo, 2018) model. The source sentence length is limited within 512, which is the maximum source sentence length supported by XLM-R. More details are shown in Table 7 and Table 8.

B Language Code

We refer to the language information in Table 1 of Fan et al. (2020).

\(^5\)http://www.statmt.org/cc-aligned/

\(^6\)http://lotus.kuee.kyoto-u.ac.jp/WAT/indic-multilingual/indic_wat_2021.tar.gz

\(^7\)https://github.com/facebookresearch/flores/raw/master/data/flores_test_sets.tgz

\(^8\)https://object.pouta.csc.fi/Tatoeba-Challenge/test-v2020-07-28.tar

| Type       | Lang | Source   | # Sent |
|------------|------|----------|--------|
| Training set | De-En | Europarl v7 | 1.9M   |
| Training set | De-En | WMT19    | 41M    |
| Training set | Es-En | CCAligned | 20M    |
| Training set | Fi-En | CCAligned | 9.2M   |
| Training set | Hi-En | CCAligned | 7.4M   |
| Training set | Ru-En | CCAligned | 20M    |
| Training set | Zh-En | WMT18    | 22.6M  |

| Valid set   | Lang     | Source   | # Sent |
|-------------|-----------|----------|--------|
| Valid set   | De-En     | Newstest 16 | 2999   |
| Valid set   | Es-En     | Newstest 10 | 2489   |
| Valid set   | Fi-En     | Newstest 19 | 1996   |
| Valid set   | Hi-En     | Newsdev 14 | 520    |
| Valid set   | Ne-En     | Flores    | 2559   |
| Valid set   | Ru-En     | Newstest 16 | 2998   |
| Valid set   | Si-En     | Flores    | 2898   |
| Valid set   | Zh-En     | Newstest 17 | 2001   |

Table 7: Training and valid set for any-to-English translation. ‘# Sent’ is the number of parallel sentences in the dataset.

| Lang | Source   | Lang | Source   |
|------|----------|------|----------|
| Ar-En  | IWSLT 17 | Lv-En  | Newstest 17 |
| De-En  | Newstest 14 | My-En  | WAT21     |
| Es-En  | Newstest 13 | Ne-En  | Flores    |
| Et-En  | Newstest 18 | Ni-En  | Tatoeba   |
| Fi-En  | Newstest 16 | Pi-En  | Newstest 20 |
| Gu-En  | Newstest 19 | Ps-En  | Newstest 20 |
| Hi-En  | Newstest 14 | Ro-En  | Newstest 16 |
| It-En  | Tatoeba   | Ru-En  | Newstest 20 |
| Ja-En  | Newstest 20 | Si-En  | Flores    |
| Kk-En  | Newstest 19 | Tr-En  | Newstest 16 |
| Km-En  | Newstest 20 | Zh-En  | Newstest 18 |
| Ko-En  | Tatoeba   |       |          |

Table 8: Test sets for any-to-English translation.
## Table 9: Languages used in this paper.

| ISO | Language | Family  | ISO | Language | Family   |
|-----|----------|---------|-----|----------|----------|
| ar  | Arabic   | Arabic  | ko  | Korean   | Koreanic |
| cs  | Czech    | Slavic  | lv  | Latvian  | Baltic   |
| de  | German   | Germanic| my  | Burmese  | Sino-Tibetan |
| en  | English  | Germanic| ne  | Nepali   | Indo-Aryan |
| es  | Spanish  | Romance | nl  | Dutch    | Germanic |
| et  | Estonian | Uralic  | pl  | Polish   | Slavic   |
| fi  | Finnish  | Uralic  | ps  | Pashto   | Iranian  |
| fr  | French   | Romance | ro  | Romanian | Romance  |
| gu  | Gujarati | Indo-Aryan| ru | Russian  | Slavic   |
| hi  | Hindi    | Indo-Aryan| si | Sinhala  | Indo-Aryan |
| it  | Italian  | Romance | ta  | Tamil    | Dravidian |
| ja  | Japanese | Japonic | tr  | Turkish  | Turkic   |
| kk  | Kazakh   | Turkic  | vi  | Vietnamese| Vietic   |
| km  | Khmer    | Khmer   | zh  | Chinese  | Chinese  |