The LMU Munich System for the WMT 2021 Large-Scale Multilingual Machine Translation Shared Task

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Abstract

This paper describes the submission of LMU Munich to the WMT 2021 multilingual machine translation task for small track #1, which studies translation between 6 languages (Croatian, Hungarian, Estonian, Serbian, Macedonian, English) in 30 directions. We investigate the extent to which bilingual translation systems can influence multilingual translation systems. More specifically, we trained 30 bilingual translation systems, covering all language pairs, and used data augmentation techniques such as back-translation and knowledge distillation to improve the multilingual translation systems. Our best translation system scores 5 to 6 BLEU higher than a strong baseline system provided by the organizers (Goyal et al., 2021). As seen in the Dynalab leaderboard, our submission is the only fully constrained submission that uses only the corpus provided by the organizers and does not use any pre-trained models.

1 Introduction

Neural Machine Translation (NMT) (Vaswani et al., 2017) has been shown to be effective with rich and in-domain bilingual parallel corpora. Although the NMT model obtained promising performances for high resource language pairs, it is hardly feasible to train translation models for all directions of the language pairs since the training progress is time- and resource-consuming. Recent work has shown the effectiveness of multilingual neural machine translation (MNMT), which aims to handle the translation from multiple source languages into multiple target languages with a single unified model (Johnson et al., 2017; Aharoni et al., 2019; Arivazhagan et al., 2019; Zhang et al., 2020; Fan et al., 2021; Goyal et al., 2021).

The MNMT model dramatically reduces training and serving costs. It is faster to train a MNMT model than to train bilingual models for all language pairs in both directions, and MNMT significantly simplifies deployment in production systems (Johnson et al., 2017; Arivazhagan et al., 2019). Further, parameter sharing across different languages encourages knowledge transfer, which improves low-resource translation directions and potentially enables zero-shot translation (i.e., direct translation of a language pair not seen during training) (Ha et al., 2017; Gu et al., 2019; Ji et al., 2020; Zhang et al., 2020).

We participate in the WMT 2021 multilingual machine translation task for small track #1. The task aims to train a multilingual model to translate 5 Central/East European languages (Croatian, Hungarian, Estonian, Serbian, Macedonian) and English in 30 directions. The multilingual systems presented in this paper are based on the standard paradigm of MNMT proposed by Johnson et al. (2017), which prefixes the source sentence with a special token to indicate the desired target language and does not change the target sentence at all. Language tags are typically used in MNMT to identify the language to translate to. A language code, in the form of a two- or three-character identification such as en for English, is the main constituent of a language tag and is provided by the ISO 639 standard (International Organization for Standardization, nd). Following ISO 639 standard, en indicates English, mk indicates Macedonian, sr indicates Serbian, et indicates Estonian, hr indicates Croatian, and hu indicates Hungarian in this paper.

Compared with the other three submissions to the task, our submissions have the following advantages:

• Our submissions are fully constrained, which means we use the data only provided by the organizer, and do not use models pre-trained on extra data.

• Our model only has 313M parameters, which

1https://en.wikipedia.org/wiki/ISO_639
Table 1: Number of sentences in bitext datasets (total in 15 directions) for different filtering schemes. Whole denotes the use of all data provided by the organizers, Select denotes the use of data selection.

| Filtering Scheme                | Whole | Select |
|---------------------------------|-------|--------|
| No filter                       | 387M  | 71M    |
| + punctuation filter            | 384M  | 71M    |
| + deduplicated filter           | 304M  | 44M    |
| + langid filter                 | 302M  | 43M    |
| + length filter                 | 274M  | 42M    |

is smaller than the other submissions.

2 Data

The training data provided by the organizers come from the public available Opus repository (Tiedemann, 2012), which contains data of mixed quality from a variety of domains (WMT-News, TED, QED, OpenSubtitles, etc.). In addition to the bilingual parallel corpora, in-domain Wikipedia monolingual data for each language is provided. The validation and test sets are obtained from the Flores 101 evaluation benchmark (Goyal et al., 2021), which consists of 3001 sentences extracted from English Wikipedia covering a variety of different topics and domains. See Table 1 for details on data used for training our systems.

2.1 Data Preprocessing

To prepare the data for training, we used the following steps to process all of the corpora:

1. The datasets were truecased and the punctuation was normalized with standard scripts from the Moses toolkit\(^2\) (Koehn et al., 2007).
2. Sentences containing 50% punctuation are removed.
3. Duplicate sentences are removed.
4. We used a language detection tool\(^3\) (langid) to filter out sentences with mixed language.
5. SentencePiece\(^4\) (Kudo and Richardson, 2018) was used to produce subword units. We trained a model with 0.9995 character coverage to have sufficient coverage of character-based languages.
6. The length filtering removes sentences that are too long (more than 250 subwords after segmentation with Sentencepiece), sentences with a mismatched length ratio (more than 3.0) between source and target language are removed.

2.2 Data Selection

Data selection (Moore and Lewis, 2010; Axelrod et al., 2011; Gascó et al., 2012), aims to select the most relevant sentences from the out-of-domain corpora, which improved the in-domain translation performance. The training data provided by the organizers is large scale and contains multiple domains. Therefore, the data selection becomes a key factor affecting the performance of MNMT. Preliminary experiments (see in Table 1 model #3 and model #4) showed that the performance of using all corpora provided by the organizer was poor. Following the original paper (Goyal et al., 2021), we selected three data sources (CCAligned, MultiCCAligned, WikiMatrix) for further experimentation.

3 Method Description

We first trained bilingual translation models with 30 directions for all language pairs. Next, we trained a single multilingual model that can translate all language pairs. Finally, we use back-translation and knowledge distillation technologies to further improve the performance of the multilingual translation system. The details of these components are outlined next.

3.1 Bilingual NMT Model

We use Transformer (Vaswani et al., 2017) architecture for all bilingual models. To achieve the best BLEU score on the validation dataset, random search was used to select the hyperparameters since the datasets are in different sizes. We segment the data into subword units using SentencePiece jointly learned for all languages. The details of selected hyper-parameters are listed in Section 4.1.

3.2 Multilingual NMT Model

The multilingual model architecture is identical to the bilingual NMT model. To train multilingual models, we used a simple modification to the
source sentence proposed by Johnson et al. (2017) which introduce an artificial token at the begin-
ing of the source sentence indicating the target
language (Johnson et al., 2017). For instance, for
the English-Macedonian (en→mk) translation di-
rection, we insert a token like <2mk> at the begin-
ing of all English sentences and do not change the
Macedonian sentences.

3.3 Back Translation
Back-translation (BT) (Sennrich et al., 2016) is a
simple and effective data augmentation technique,
which makes use of monolingual corpora and has
proven to be effective. Back-translation first trains
a target-to-source system that is used to translate
monolingual target data into source sentences, re-
sulting in a pseudo-parallel corpus. Then we mix
the pseudo-parallel corpus with the authentic par-
allel data and train the the desired source-to-target
translation system. Zhang et al. (2020) has shown
how BT can be useful for multilingual MT.

After generating the pseudo parallel corpus, we
tag our BT data by adding an artificial token <BT>
at the beginning of the source sentence (Caswell
et al., 2019), which indicates that the data is gener-
ated by back-translation.

3.4 Knowledge Distillation
Knowledge Distillation (KD) is a commonly used
technique to improve model performance. The stan-
dard KD training (Kim and Rush, 2016) derives a
student model from a teacher model by training the
student model to mimic the outputs of the teacher.
We follow a recent approach to KD proposed by
Wang et al. (2021), which uses selection at the
batch level and at the global level to choose suit-
able samples for distillation.

4 Experiments
4.1 Training Details
We use the Transformer architecture (Vaswani et al.,
2017) as implemented in fairseq\footnote{https://github.com/pytorch/fairseq} (Ott et al., 2019).
For training NMT and MNMT systems, we use the
Transformer-Big architecture (hidden state
1024, feed-forward layer 4096, 16 attention heads,
6 encoder layers, 6 decoder layers). For optimization,
we follow the default settings from the original
paper (Vaswani et al., 2017) and used the Adam
optimizer with a learning rate of 0.0003. To pre-
vent overfitting, we applied a dropout of 0.3 on all
layers. At the time of inference, a beam search
of size 5 is used to balance the decoding time and
accuracy of the search. The number of warm-up
steps was set to 4000 and the vocabulary size is
133k. In addition, we set a length penalty factor of
1.7 to maintain a balance between long and short
sentences. The batch size is set to 128 during de-
coding. We trained our models for approximately 3
weeks on one machine with 8 NVIDIA GTX 2080
Ti 11GB GPUs.

Because of the problems of the international tok-
enization in the standard BLEU score, the organiz-
ers used sentence-piece BLEU (spBLEU)\footnote{https://github.com/ngoyal2707/sacrebleu/tree/adding_spm_tokenized_bleu} (Goyal
et al., 2021) as the official evaluation metric which
operates on strings segmented using a Sentence-
Piece model. Recently, the BLEU score was crit-
icized as an unreliable automatic metric (Mathur
et al., 2020; Kocmi et al., 2021). Therefore, we also
evaluate our models using chrF (Popović, 2015)
and BERTScore (Zhang et al., 2019).

4.2 Systems
All of our systems described in Section 3.2 are
listed as follows:
Flores. As a baseline system, we use the pre-
trained models public available by Flores teams. We use flores101_mm100_615M tested on the
devtest datasets as our baseline.
Bilingual. We trained the bilingual models using
standard Transformer-Big architecture for 6
languages in 30 directions. The hyperparameters
used are discussed in Section 4.1.
Multilingual. We trained the multilingual transla-
tion model using standard Transformer-Big
architecture and a specific language token to indi-
cate the desired translation target language.
Tagged BT. We augment the training data by
exploring the monolingual corpus using back-
translation proposed by Caswell et al. (2019), with
tagged back-translated source sentences with an
extra token <BT>.
Selective KD. We focused on selective knowledge
distillation proposed by Wang et al. (2021), which
uses batch-level and global-level selections to pick
suitable samples for distillation.

4.3 Results
The results of our systems on the devtest dataset are
presented in Table 2. For models 1–4, we observed
Table 2: The automatic evaluation metrics on devtest data. spBLEU, chrF, BERTScore denotes the average scores of spBLEU, chrF and BERTScore respectively, BEST BLEU denotes the language pair with the best BLEU score. Systems with subscript whole denote the use of all data provided by the organizers, and systems with subscript select denote the use of data selection. Model #6 is our primary system submitted to the Dynalab leaderboard. Systems 7* and 8* were trained after the shared task and were not used for the final submission.

| #     | Systems                              | spBLEU | chrF | BERTScore | BEST BLEU |
|-------|--------------------------------------|--------|------|-----------|-----------|
| 0     | Flores                               | 28.0   | 0.528| 0.867     | sr-mk (36.0) |
| 1     | Bilingual,whole                      | 21.1   | 0.477| 0.831     | en-mk (31.3) |
| 2     | Bilingual,select                     | 28.4   | 0.533| 0.863     | sr-en (40.6) |
| 3     | Multilingual,whole                   | 16.7   | 0.431| 0.827     | sr-en (26.1) |
| 4     | Multilingual,select                  | 30.9   | 0.555| 0.874     | sr-en (40.0) |
| 5     | Multilingual,select + TaggedBT(Multilingual,select) | 30.7   | 0.548| 0.873     | sr-en (40.5) |
| 6     | Multilingual,select + TaggedBT(Bilingual,select) | 32.3   | 0.562| 0.879     | sr-en (41.5) |
| 7*    | Multilingual,select + TaggedBT(Bilingual,select) + KD_batch | 33.2   | 0.572| 0.883     | sr-en (42.0) |
| 8*    | Multilingual,select + TaggedBT(Bilingual,select) + KD_global | 33.9   | 0.576| 0.887     | sr-en (42.4) |

Figure 1: spBLEU scores on devtest data in 30 directions

that the amount of training data is not proportional to the performance of the model for the bilingual or multilingual translation model. The training data provided by the organizers contains multiple domains and does not match the dev/devtest/test data domain. Therefore, we apply the data selection methods to select data-relevant data from the training dataset to do the following experiments. Our multilingual model (#4) performs competitively with the Flores strong baseline (Model #0).

After these initial experiments, we explored how the bilingual models can be used to improve the multilingual model. More specifically, we use the Bilingual,select model (#2) and Multilingual,select model (#4) to back-translate the relevant monolingual corpora, and then we use the back-translations to train a new multilingual model. Although the overall performance of the Multilingual model (#4) is better than the Bilingual model (#2), back-

translation using the Bilingual model (model #6) is better than back-translation using the Multilingual model (model #5). The possible reason is that the multilingual BT is in fact a form of self-training, but bilingual BT uses separate models, which means the knowledge obtained from bilingual BT models is more independent of the knowledge already learned by the baseline multilingual BT model.

Knowledge Distillation further improves performance slightly (Model # 7* and Model # 8*). Based on Model # 6, selective KD (Wang et al., 2021) is added to further improve the performance of the multilingual system.

Our best systems were outperformed by two other shared task submissions, which however used models pre-trained on additional data sources.

The performance grid of our best system (Model # 8*) is presented in Figure 1. We see from the results that the sr-en language pair produced the best results in terms of spBLEU score while the hu-hr language pair scored the lowest.

5 Conclusions

In this paper, we presented the LMU Munich system for the WMT 2021 Large-scale Multilingual Translation shared task for small track #1. The task evaluates translation between five central/eastern European languages and English, in total 30 translation directions. The system we submitted was fully constrained, using only the data provided by the organizers and not using any pre-trained model. The experiments show that back-translation and knowledge distillation techniques are effective for training multilingual machine translation systems.
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