DFKI-NMT Submission to the WMT19 News Translation Task

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Abstract
This paper describes the DFKI-NMT submission to the WMT19 News translation task. We participated in both English-to-German and German-to-English directions. We trained standard Transformer models and adopted various techniques for effectively training our models, including data selection, back-translation, in-domain fine-tuning and model ensemble. We show that these training techniques improved the performance of our Transformer models up to 5 BLEU points. We give a detailed analysis of the performance of our system.

1 Introduction
This paper describes the DFKI-NMT submission to the WMT19 News translation task. We participated in both English-to-German and German-to-English directions. We trained Transformer models (Vaswani et al., 2017) using Sockeye\textsuperscript{1} (Hieber et al., 2017). Compared to RNN-based translation models (Bahdanau et al., 2014), Transformer models can be trained very fast due to parallelizable self-attention networks. We applied several very useful techniques for effectively training our models.

Data Selection The parallel training data provided for German-English is quite large (38M sentence pairs). Most of the parallel data is crawled from the Internet and is not in News domain. Out-of-domain training data can hurt the translation performance on News test sets (Wang et al., 2017) and also significantly increase training time. Therefore, we trained neural language models on a large monolingual News corpus to perform data selection (Schamper et al., 2018).

Back-translation Large monolingual data in the News domain is provided for both German and English, which can be back-translated as additional parallel training data for our system (Sennrich et al., 2016a; Fadaee and Monz, 2018). The back-translated parallel data is in the News domain, which is a big advantage compared to out-of-domain parallel training data provided for the News task.

In-domain Fine-tuning The Transformer models were finally fine-tuned using the small in-domain parallel data provided for the News task (Luong and Manning, 2015; Schamper et al., 2018). Note that the large back-translated parallel data is also in-domain, but it has relatively low quality due to translation errors.

Model Ensemble We trained two Transformer models with different sizes, Transformer-base and Transformer-big. Our final submission is an ensemble of both models (Schamper et al., 2018). The ensemble of both models outperformed a single base or big model most likely because the two models can capture somewhat different features for the translation task.

2 System Details

2.1 Data Selection
The parallel data provided for the German-to-English and English-to-German tasks includes Europarl v9, ParaCrawl v3, Common Crawl corpus, News Commentary v14, Wiki Titles v1 and Document-split Rapid corpus. We also used old test sets (newstest2008 to newstest2017) for training our systems. We consider News Commentary v14 and old test sets as in-domain data and the rest as out-of-domain data. Compared to the in-domain data (356k sentence pairs), the size of the out-of-domain data (38M sentence pairs) is quite large, which makes the training process relatively slow and may also hurt the translation per-
performance due to domain mismatch. Therefore, we performed data selection on out-of-domain data.

Inspired by Schamper et al. (2018)’s work which used KenLM (Heafield, 2011) for data selection, we trained two neural language models based on self-attention networks using the 2018 part of the large monolingual News crawl corpus for English and German, respectively. Because these neural language models are trained on the News domain, we can use them to score out-of-domain data. Sentences with higher probabilities are more likely to be in News domain. Equation 1 is used to score each sentence pair in the out-of-domain corpus. In Equation 1, $P_s$ is the language model probability of the source sentence; $N_s$ is the length of the source sentence; $P_t$ is the language model probability of the target sentence; $N_t$ is the length of the target sentence. We selected the top 15M scored sentence pairs from out-of-domain data for training our systems.

$$\frac{\log P_s}{N_s} + \frac{\log P_t}{N_t}$$  \hspace{1cm} (1)

The neural language models trained for data selection in our experiments are based on self-attention networks which can be trained very fast. Figure 1 (a) shows the structure of the standard Transformer translation model (Vaswani et al., 2017) and we removed the encoder and the attention layer in the decoder from the Transformer translation model to create our Transformer language model as shown in Figure 1 (b). For training efficiency, we used byte pair encoding (Sennrich et al., 2016b) to learn a vocabulary of 50k for English and German respectively.

### 2.2 Back-translation

We back-translated the 2018 part of the large monolingual in-domain News crawl data as additional training data for our translation systems. Fadaee and Monz (2018) showed that it is more beneficial to back-translate sentences that contain difficult words. In our experiments, we consider words which occur less than 1000 times in the bilingual training data as difficult words. Then we randomly selected 10M sentences which contain difficult words for back-translation. The mod-
Table 1: Training data used in different training stages.

| Stage  | in-domain | out-of-domain | back-translated |
|--------|-----------|---------------|-----------------|
| 1      | ✓         | ✓             |                 |
| 2      | ✓         | ✓             | ✓               |
| 3      | ✓         |               |                 |

Table 2: Training epochs for different training stages.

| Stage  | en-de base | en-de big | de-en base | de-en big |
|--------|------------|-----------|------------|-----------|
| 1      | 7.3        | 7.6       | 6.6        | 6.8       |
| 2      | 0.3        | 0.4       | 0.8        | 1.4       |
| 3      | 18.5       | 18.5      | 12.4       | 12.4      |

Table 3: Case-insensitive BLEU scores on newstest2018. “Ensemble” means ensemble both Transformer-base and Transformer-big after Stage 3.

| Stage  | en-de base | en-de big | de-en base | de-en big |
|--------|------------|-----------|------------|-----------|
| 1      | 44.24      | 45.03     | 45.34      | 45.75     |
| 2      | 46.42      | 47.10     | 47.84      | 48.65     |
| 3      | 47.80      | 48.83     | 48.65      | 49.33     |
| Ensemble | 49.45    |           | 49.75      |           |

We trained two Transformer models for each translation task as Transformer-base and Transformer-big. The settings of Transformer-base is the same as the baseline Transformer in Vaswani et al. (2017)’s work. For Transformer-big, we changed word embedding size into 1024 and kept other parameters unchanged. A joint vocabulary of 50k for German and English is learned by byte pair encoding (BPE) (Sennrich et al., 2016b).

We set dropout to 0.1 for both Transformer-base and Transformer-big. We used adam (Kingma and Ba, 2014) for optimization. We used newstest2018 as the validation set for model training. The training processes for both Transformer-base and Transformer-big consist of three stages.

**Stage 1** We first trained the Transformers using bilingual training data, including all in-domain data and selected out-of-domain data as described in section 2.1. Note that the back-translated data was not used in this stage. Each training batch contains 8192 words and the validation frequency is 2000 batches. We set the initial learning rate to be 2.00e-04. We reduced the learning rate by a factor of 0.70 whenever the validation score does not improve 8 times. We stopped the training process after 5 times of learning rate reduction.

**Stage 2** We used all bilingual training data used in the first training stage together with the back-translated monolingual data to continue training the models which had converged in the first training stage. We kept the batch size to be 8192 words and changed the validation frequency to 1000 batches. We set the initial learning rate to be 1.00e-05 and stopped the training process when the validation score does not improve 8 times.

**Stage 3** For fine-tuning, we used the small parallel in-domain data as described in section 2.1 to continue training the models which had converged in the second training stage. We changed batch size to be 1024 words and validation frequency to be 100 batches. We set the initial learning rate to be 1.00e-06 and stopped the training process when the validation score does not improve 8 times.

Table 1 shows training data used in different training stages. The models trained in the first training stage were used to back-translate monolingual data as described in section 2.2. In Stage 2, we continued training the models which had converged in Stage 1 instead of training models with random initialization in order to reduce the training time of Stage 2.

**2.4 Results and Analysis**

Table 2 shows the numbers of training epochs for different training stages and Table 3 shows the performance of our systems after different training stages. As we can see, back-translation (Stage 2) and in-domain fine-tuning (Stage 3) both improved the translation quality on a significant level. An ensemble of Stage 3 Transformer-base and Transformer-big achieved further improvements. We also tried to ensemble different checkpoints of Transformer-big, but achieved little improvement, likely because different checkpoints of
the same model are very similar.

In addition, we give some translation examples in Table 4 to analyze when and why our translation system makes mistakes. The translations in Table 4 are produced by our best system, i.e., ensemble of Transformer-base and Transformer-big after training stage 3. In Example 1, “wei@@ dez@@ aun@@ projekt” (pasture fence project) is wrongly translated into “electric sound project”, likely because “weidezaun-projekt” is an unknown word and does not occur in the training data. Although BPE can help to relieve data sparsity by using smaller and more frequent sub-word units, the automatic BPE segmentation “wei@@ dez@@ aun@@ projekt” is a bad segmentation with linguistically meaningless sub-word pieces. A better segmentation “weide@@ (pasture) zaun@@ (fence) projekt” may help to reduce data sparsity and get better translation. Example 2 does not contain rare words, but “nimmt vor” is still wrongly translated into “takes”. This is likely because “nimmt vor” has different translations in the training data and the correct translation here “targeting” is relatively uncommon. We find many translation mistakes of our system are caused by rare words or uncommon usages of words as shown in Table 4, which we will work on in the future.

Table 4: Translation examples. “@@” means segmented by byte pair encoding.

| Example 1       | Src   | Ref                                      | Ours                                      |
|-----------------|-------|------------------------------------------|-------------------------------------------|
|                 | wei@@ dez@@ aun@@ projekt ist element@@ ar | past@@ ure fence project is fundamental   | electric sound project is elementary       |
|                 |       |                                          |                                           |
|                 | Jetzt nimmt sich das weiße haus von trump die freiheits@@ statue vor | now trump ‘s white house is targeting the statue of liberty | now trump ‘s white house takes the statue of liberty |

Acknowledgments

This work is supported by the German Federal Ministry of Education and Research (BMBF) under the funding code 01IW17001 (Deeplee). Responsibility for the content of this publication is with the authors.

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