NoahNMT at WMT 2021: Dual Transfer for Very Low Resource Supervised Machine Translation

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Abstract

This paper describes the NoahNMT system submitted to the WMT 2021 shared task of Very Low Resource Supervised Machine Translation. The system is a standard Transformer model equipped with our recent technique of dual transfer. It also employs widely used techniques that are known to be helpful for neural machine translation, including iterative back-translation, selected finetuning, and ensemble. The final submission achieves the top BLEU for three translation directions.

1 Introduction

In this paper, we describe the NoahNMT system submitted to one of the WMT 2021 shared tasks. The shared task features both unsupervised machine translation and very low resource supervised machine translation. As our core technique is mainly suitable for low resource supervised machine translation, we participated in four translation directions between Chuvash-Russian (chv-ru) and Upper Sorbian-German (hsb-de).

Our core technique is called dual transfer (Zhang et al., 2021), which belongs to the family of transfer learning. It transfers from both high resource neural machine translation model and pretrained language model to improve the quality of low resource machine translation. As discussed in the original paper, it is possible to use shared target transfer (B=Q) or shared source transfer (A=P). Taking chv→ru as an example, we can choose en→ru as the high resource translation direction, resulting in an instance of shared target transfer. In this shared task, when training the high resource translation model, we always initialize the shared language side with the pretrained language model BERT (Devlin et al., 2019).

2 Approach

In this section, we describe the techniques used in our system. Interested readers are encouraged to check out the original papers for further details.

2.1 Dual Transfer

We reproduced the illustration of dual transfer from the original paper (Zhang et al., 2021), as shown in Figure 1. This illustration shows the case of general transfer, where the high resource translation direction is A→B, and the low resource translation direction is P→Q. As discussed in the original paper, in many cases, it is possible to use shared target transfer (B=Q) or shared source transfer (A=P). Taking chv→ru as an example, we can choose en→ru as the high resource translation direction.

2.2 Iterative Back-Translation

Iterative back-translation (Hoang et al., 2018) is an extension of back-translation (Sennrich et al., 2016a). It can exploit both sides of monolingual data of a language pair, and produces translation models for both directions, which is suitable for this shared task.

The initial models for generating synthetic parallel data are produced by using dual transfer with low resource authentic parallel data. In each iteration of iterative back-translation, we use the latest model to greedily decode a disjoint subset of 4m monolingual sentences\textsuperscript{1} to generate synthetic parallel data. Then a new model is trained on a mixture of authentic and synthetic parallel data. With the use of dual transfer, model training can start from

\textsuperscript{1}For chv and hsb, all monolingual sentences are used in each iteration.
the initial parameters as shown in Step (4) of Figure 1. This has the additional benefit of reducing training time, because convergence is faster than training from random initialization.

### 2.3 Selected Finetuning

Selected finetuning aims to deal with the domain difference that may exist between the test set and the training set. Given the source side of the test set, we try to select similar source sentences from the training set, and then finetune the translation model on the selected subset of training sentence pairs.

We use BM25 (Robertson and Zaragoza, 2009) to calculate the similarity between two sentences for retrieval. The BM25 score between a query sentence $Q$ and a sentence $D$ in the corpus for retrieval $C$ is given by

$$s(D, Q) = \sum_{i=1}^{L_Q} \frac{\text{IDF}(q_i) \cdot (k + 1) \cdot \text{TF}(q_i, D)}{k \cdot \left(1 - b + b \cdot \frac{L_D}{L_{\text{avg}}} \right) + \text{TF}(q_i, D)},$$

where the query sentence $Q$ is a sequence of $L_Q$ subwords $\{q_i\}_{i=1}^{L_Q}$. IDF($q_i$) is the Inverse Document Frequency for $q_i$ in the corpus $C$, TF($q_i, D$) is the Term Frequency for $q_i$ in the sentence $D$, $L_D$ is the length of the sentence $D$, $L_{\text{avg}}$ is the average length of the corpus $C$, $k$ and $b$ are hyperparameters, which are set as 1.5 and 0.75, respectively.

Based on the BM25 score, we calculate the similarity between a source test sentence (as the query sentence) and the source sentences in the training set to obtain the top 500 sentences. After performing the selection for all the source test sentences, we merge them and remove duplicates to obtain the set for finetuning.

| language code | # sentence (pair) |
|---------------|-------------------|
| cs-de         | 15m               |
| hsb-de        | 0.1m              |
| kk-ru         | 3.9m              |
| en-ru         | 17m               |
| chv-ru        | 0.7m              |
| cs            | 90m               |
| de            | 100m              |
| hsb           | 0.8m              |
| kk            | 17m               |
| en            | 54m               |
| ru            | 110m              |
| chv           | 3m                |

Table 1: Training data statistics.

| parent language | chv→ru BLEU |
|-----------------|-------------|
| kk              | 18.47       |
| en              | 18.61       |

Table 2: Test set BLEU for chv→ru, when the parent language is either kk or en (i.e. the parent translation direction is either kk→ru or en→ru). The translation model is Transformer base.
Table 3: Test set BLEU for the four translation directions, using either Transformer base or Transformer big for dual transfer. *: The parent translation direction is \textit{ru→kk}, and we did not train a Transformer base with \textit{ru→en} as the parent, though the resulting \textit{ru→chv} BLEU scores should be close based on the experiment in Section 4.1.

| model               | \textit{chv→ru} | \textit{ru→chv} | \textit{hsb→de} | \textit{de→hsb} |
|---------------------|-----------------|-----------------|-----------------|-----------------|
| Transformer base    | 18.61           | 16.18*          | 55.60           | 55.98           |
| Transformer big     | 19.24           | 17.12           | 56.10           | 57.12           |

Table 4: Runtime of each step in dual transfer for \textit{NMT\textsubscript{chv→ru}} with Transformer big.

| model     | runtime (hours) |
|-----------|-----------------|
| BERT\textsubscript{en} | 143             |
| BERT\textsubscript{chv}  | 54              |
| NMT\textsubscript{en→ru} | 52              |
| NMT\textsubscript{chv→ru} | 14              |

3 Experimental Setup

3.1 Data

We collected allowed data for the involved languages and followed the same preprocessing pipeline of punctuation normalization and tokenization, using scripts from Moses\textsuperscript{2}. The English monolingual data came from the English original side of \textit{ru-en} back-translated news\textsuperscript{3}, but its automatic translation to Russian was discarded. The provided Chuvash-Russian dictionary was not used. Each language was encoded with byte pair encoding (BPE) (Sennrich et al., 2016b). The BPE codes and vocabularies were learned on each language’s monolingual data, and then used to segment parallel data. We used 32k merge operations for all languages. After BPE segmentation, we discarded sentences with more than 128 subwords, and cleaned parallel data with length ratio 1.5. Training data statistics is provided in Table 1. Note that we experimented with Kazakh (\textit{kk}) data (Section 4.1), but did not use it for our final submission. Evaluation on test sets is given by SacreBLEU\textsuperscript{4} (Post, 2018), after BPE removal and detokenization.

3.2 Hyperparameters

We use Transformer (Vaswani et al., 2017) as our translation model, but with slight modifications that follow the implementation of BERT\textsuperscript{5}. The absolute position embeddings are also learned as in BERT. The encoder and decoder embeddings are independent because each language manages its own vocabulary, but we tie the decoder input and output embeddings (Press and Wolf, 2017). We apply dropout with probability 0.1. We use LazyAdam as the optimizer. Learning rate warms up for 16,000 steps and then follows inverse square root decay. The peak learning rate is $5 \times 10^{-4}$ for parent translation models, and $1 \times 10^{-4}$ for child translation models. Early stopping occurs when the validation BLEU does not improve for 10 checkpoints. We set checkpoint frequency to 2,000 updates for parent translation models and 1,000 updates for child translation models. The batch size is 6,144 tokens per GPU and 8 NVIDIA V100 GPUs are used.

Hyperparameters for BERT are the same as in the original paper (Zhang et al., 2021). For selected finetuning, we use stochastic gradient descent as the optimizer, and the learning rate is $1 \times 10^{-5}$. We finetune for 10,000 updates, and save a checkpoint every 100 updates. The checkpoint with the highest validation BLEU is kept.

4 Results

4.1 The Choice of Parent Language

In our preliminary experiments, we found it beneficial to use a closely related language as the parent language. It is clear that there are several factors that should be taken into account, such as the degree of closeness, and the amount of resource for training the parent model. For Upper Sorbian, Czech (\textit{cs}) is closely related to it, and Czech-German has a good amount of parallel data, so we directly choose Czech as the parent language.

Chuvash, however, is a rather isolated language in the Turkic family. The closest language with usable data is Kazakh (\textit{kk}), but the amount of parallel data for Kazakh-Russian is relatively small, and we found it to be quite noisy. Therefore, we considered

\textsuperscript{2}https://github.com/moses-smt/mosesdecoder
\textsuperscript{3}http://data.statmt.org/wmt20/translation-task/back-translation
\textsuperscript{4}SacreBLEU signature: BLEU+case.mixed+numrefs.1+smooth.exp+tok.13a+version.1.4.12.
\textsuperscript{5}https://github.com/google-research/bert
| iteration | chv→ru | ru→chv | hsb→de | de→hsb |
|-----------|--------|--------|--------|--------|
| 0         | 19.24  | 17.12  | 56.10  | 57.12  |
| 1         | 19.73  | 17.45  | 57.23  | 56.81  |
| 2         | **20.42** | 17.69  | 57.12  | 56.79  |
| 3         | 19.85  | **17.81** | **57.72** | **57.47** |
| 4         | 19.57  | 17.78  | 57.40  | 57.33  |
| 5         | 19.60  | 17.48  | 57.66  | 57.07  |

Table 5: Test set BLEU for the four translation directions with iterative back-translation. Iteration 0 is the Transformer big model in Table 3. Best BLEU scores are in bold.

| method              | chv→ru | ru→chv |
|---------------------|--------|--------|
| before selected finetuning | 20.42  | 17.69  |
| after selected finetuning   | 20.55  | 18.03  |

Table 6: Test set BLEU to show the effect of selected finetuning.

| model     | hsb→de | de→hsb |
|-----------|--------|--------|
| best single | 57.72  | 57.47  |
| ensemble  | 58.54  | 58.28  |

Table 7: Test set BLEU to show the effect of ensemble.

4.2 The Effect of Transformer Big

The original paper (Zhang et al., 2021) evaluated dual transfer only with Transformer base. In this shared task, we scale up to Transformer big. We also face a more realistic setting where the monolingual data for the low resource languages (chv and hsb) are quite scarce. Therefore it is worth testing the effect of scaling up. Results in Table 3 show that Transformer big brings consistent improvements. We also report the runtime of each step in dual transfer for NMT$_{chv→ru}$ with Transformer big in Table 4 for reference, but the numbers can vary depending on implementation and data size. In the following experiments and our final submission, we use Transformer big models.

4.3 Iterative Back-Translation

We ran five iterations of iterative back-translation. Results are shown in Table 5. The best BLEU scores are attained with two or three iterations. Another observation is that iterative back-translation brings larger improvements for chv→ru and hsb→de than ru→chv and de→hsb. This is probably because the monolingual data for chv and hsb are small in quantity.

4.4 Selected Finetuning

We only use selected finetuning for the chv→ru pair because parallel data for hsb→de is scarce. In order to test the effect of selected finetuning, we start from the models of Iteration 2 in Table 5. Results in Table 6 indicate that selected finetuning gives modest improvements.

4.5 Ensemble

We validate the effectiveness of ensemble on hsb→de and de→hsb, by performing ensemble decoding from the five models from iterative back-translation. Results in Table 7 demonstrate that ensemble gives BLEU improvements of about 0.8.

4.6 Final Submission

For chv→ru and ru→chv, we perform selected finetuning starting from the best models from iterative back-translation (Iteration 2 for chv→ru, Iteration 3 for ru→chv). Note that the selected training subsets are different from those in Section 4.4 because the selection is based on the source side of the blind test sets. We finetune five times
with different random seeds for model ensemble. For hsb→de and de→hsb, we ensemble the five models from iterative back-translation.

5 Conclusion

In this paper, we describe a series of experiments that contribute to our submission to the WMT 2021 shared task of Very Low Resource Supervised Machine Translation. These experiments, as well as the good results of the final submission, show that dual transfer can work in synergy with several widely used techniques in realistic scenarios.

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