Transfer Learning across Languages from Someone Else’s NMT Model

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Abstract
Neural machine translation is demanding in terms of training time, hardware resources, size, and quantity of parallel sentences. We propose a simple transfer learning method to recycle already trained models for different language pairs with no need for modifications in model architecture, hyper-parameters, or vocabulary. We achieve better translation quality and shorter convergence times than when training from random initialization. To show the applicability of our method, we recycle a Transformer model trained by different researchers for translating English-to-Czech and used it to seed models for seven language pairs. Our translation models are significantly better even when the re-used model’s language pair is not linguistically related to the child language pair, especially for low-resource languages. Our approach needs only one pre-trained model for all transferring to all various languages pairs. Additionally, we improve this approach with a simple vocabulary transformation. We analyze the behavior of transfer learning to understand the gains from unrelated languages.

1 Introduction
Neural machine translation (NMT), the current prevalent approach to automatic translation, is known to require large amounts of parallel training sentences and an extensive amount of training time on dedicated hardware. This complicates training of strong baselines and quick prototyping, especially when experimenting with various language pairs.

A large body of research has been already invested into both the design of NMT model architectures, promoting self-attentive (Vaswani et al., 2017) or convolutional (Gehring et al., 2017) over recurrent ones (Bahdanau et al., 2014), as well as to the implementation of heavily optimized toolkits (Junczys-Dowmunt et al., 2018) to cut down on the long training time.

The need for sizable training data has been addressed by methods of transfer learning when data from a related task are used to improve the accuracy of the main task in question (Tan et al., 2018). Transfer learning in NMT is usually used in low-resource conditions: we start by training a parent model for a high-resource language pair until convergence and follow with the training of the child model for the investigated language pair (Zoph et al., 2016; Neubig and Hu, 2018). Initially, the languages in the parent and child model were supposed to be linguistically related, but Kocmi and Bojar (2018) showed, that the relatedness of languages is not essential for transfer learning to work, at least for the Transformer NMT model (Vaswani et al., 2017). The most critical parameter is the size of the parent training dataset.

Most works on transfer learning have relied on a shared vocabulary between parent and child models. In this paper, we propose a novel view on re-using already trained models without the need to prepare shared vocabulary in advance. Our approach leads to better performance and faster convergence speed compared to training the model from scratch. The method does not need any changes to training hyper-parameters or vocabulary. More interestingly, it is useful even for language pairs with both different languages than the parent model’s language pair.

Contrary to transfer learning approaches, we show that our method helps even for high-resource languages, not only low-resource ones as expected. We also show that a simple vocabulary transformation can make the improvements better, especially for languages using an alphabet different from the re-used (parent) model.

The paper is organized as follows: Section 2
describes our method of direct transfer learning, including the improvement of vocabulary transformation. Section 3 presents the model, training data, and our experimental setup. Section 4 describes the results of our methods followed by the analysis in Section 5. Related work is summarized in Section 6 and we conclude the discussion in Section 7.

2 Proposed Method

We build upon the work of Kocmi and Bojar (2018) who extended the applicability of transfer learning to unrelated language pairs and simplified the approach. In line with the standard practice, Kocmi and Bojar (2018) train NMT models on subword units (Sennrich et al., 2016b; Wu et al., 2016) because vocabulary sizes of realistic datasets exceed the memory limits for NMT models. Kocmi and Bojar (2018) have focused on a straightforward approach to transfer learning: train on one language pair (the parent) until convergence and then switch to the desired language pair (the child). This lead to a better performing system than the child data alone would allow. The main result is that the Transformer model benefits from this approach whenever the parent data are larger than the child data and that the original languages or their relatedness are not particularly important.

The only requirement, and also the main disadvantage of the method, is that the vocabulary has to be shared and constructed for all considered languages jointly. It substantially increases the overall training time needed to obtain the desired MT system for the child language pair. In practice, their method consists of three steps: (1) construct the vocabulary from both the parent and child corpora, (2) train the parent model with the shared vocabulary until convergence, and (3) continue training on the child data.

Neubig and Hu (2018) define this approach as a warm-start, where we have to know the child language pair in advance of parent training. In this work, we focus on a cold-start scenario, where the parent model is trained without a need to know the language pair in advance, and we cannot make any modifications of the parent training to better handle the child language pair.

### Algorithm 1: Transforming parent vocabulary to contain child subwords and match positions for subwords common for both language pairs.

| Input: Parent vocabulary (an ordered list of parent subwords) and the training corpus for the child language pair. Generate custom child vocabulary with the maximum number of subwords equal to the parent vocabulary size; |
|---|
| for subword S in parent vocabulary do |
| if S in child vocabulary then |
| continue; |
| else |
| Replace position of S in the parent vocabulary with the first unused child subword not contained in the parent; |
| end |
| Result: Transformed parent vocabulary |

2.1 Direct Transfer

Our proposed method is a further simplification of Kocmi and Bojar (2018). We ignore the specifics of the child vocabulary and train the child model using the same vocabulary as the parent model. This allows using any model as the parent, even if it was trained by someone else and we cannot access its original training data.

We take an already trained model and use it as initialization for a different (child) language pair. We continue the training process without any change to the vocabulary or hyper-parameters. This applies even to the training parameters, such as the learning rate or moments.

This method of continued training on different data while preserving hyper-parameters was used in the past under the name “continued training” or “fine-tuning”, but it was always limited to a given language pair or specially prepared parent. We show that it can also be used for different and linguistically unrelated language pairs. Moreover, thanks to the simplicity, the technique is easy to put into practice.

2.2 Vocabulary Transformation

Our direct transfer relies on the fact that we use subword units. The subword construction methods are designed to handle unseen words or even
unseen characters, breaking the input into shorter units, possibly down to individual bytes. This property ensures that the parent vocabulary can, in principle, serve for any child language pair, but it can be highly suboptimal, segmenting child words into too many subwords. As expected, this is most noticeable for languages using different scripts (see the statistics in Section 3.3).

We propose a vocabulary transformation method that changes the original parent word-piece vocabulary more towards the needs of the child language pair, but conservatively the unrelated parent model can still be reused.

NMT models associate each vocabulary item with its distributed representation (embedding). When moving from the parent to the child, we decide which subwords should keep their embedding as trained in the parent model and which embeddings should be remapped to different subwords needed by the child and not contained in the parent vocabulary.

Our vocabulary transformation starts by constructing the optimal subword vocabulary for only the child language pair with size equal to the parent vocabulary size because the parent model has a fixed number of embeddings.

Algorithm 1 transforms the parent vocabulary for the child training corpus. The algorithm generates an ordered list of child subwords, where subwords known to the parent vocabulary are on the same positions as they were in the parent vocabulary and other subwords are assigned arbitrarily to places where parent-only subwords were stored.

We noticed that the vocabulary is structured in stages roughly based on the frequency of subwords in the corpora. This is due to the vocabulary creation that adds less frequent subwords in stages until reaching the requested size of the vocabulary. For most of the experiments, we are using this technique.

In contrast to frequency, we can assign tokens at random. Other option is the assignment of subwords based on some distance. We select the Levenshtein distance, which measures the number of edits between two strings. The vocabulary created by this technique assigns subwords iterative by increasing the allowed distance for assignment. In other words, it starts by assigning all matching subwords (distance 0), then subwords that have a distance of one edit, then two edits and so on.

Also, there is still plenty of space for experiments with more advanced techniques of vocabulary and embedding mapping, e.g. utilizing multilingual embeddings like Multivec (Brard et al., 2016). We leave this for future work and focus more on the analysis.

3 Experiments

In this section, we first provide the details of the NMT model used in our experiments and the used set of language pairs. We then discuss the convergence and a stopping criterion and finally present the results of our method for recycling the NMT model as well as improvements thanks to the vocabulary transformation.

3.1 Parent Model and its Training Data

In order to document that our method is general, not restricted to our laboratory setting and that it is replicable, we do not train the parent model by ourselves. Instead, we recycle a system not trained by us, namely the winning model of WMT 2018 English-to-Czech and Czech-to-English News Translation Task (Popel, 2018). The parent and child model always match the English side, e.g. English-to-Russian child has English-to-Czech as a parent.

We decided to use this model for several reasons. It is trained to translate into Czech, a high-resource language that is dissimilar from any of the languages used in this work. Lastly, it is trained using the state-of-the-art Transformer architecture as implemented in the popular Tensor2Tensor framework (Vaswani et al., 2018).

Table 1: Corpora statistics. Word counts are from the original corpus, tokenized only at whitespace and preserving the case.

| Language pair          | Sent. pairs | Words src lang. | Words trg lang. |
|------------------------|-------------|-----------------|-----------------|
| Eng. - Odia            | 27k         | 706k            | 604k            |
| Eng. - Estonian        | 0.8M        | 20M             | 14M             |
| Eng. - Finnish         | 2.8M        | 64M             | 44M             |
| Eng. - German          | 3.5M        | 77M             | 73M             |
| Eng. - Russian         | 12.6M       | 321M            | 297M            |
| Eng. - French          | 34.3M       | 912M            | 1044M           |
| Fre. - Spanish         | 10.0M       | 228M            | 297M            |

1Of our target language selection (see Table 1 linguistically closest language is Russian, but we do not transliterate Cyrillic into Latin script. Therefore the system cannot associate similar Russian and Czech words based on appearance.

https://github.com/tensorflow/tensor2tensor
Table 2: Corpora used for each language pair. The names specify the corpora from WMT News Task data.

| Language pair      | Training set                        | Development set | Test set  |
|--------------------|-------------------------------------|-----------------|-----------|
| English - Odia     | Parida et al. (2018)                | Parida et al. (2018) | Parida et al. (2018) |
| English - Estonian | Europarl, Rapid                     | WMT dev 2018    | WMT 2018  |
| English - Finnish  | Europarl, Paracrawl, Rapid          | WMT 2015        | WMT 2018  |
| English - German   | Europarl, News commentary, Rapid    | WMT 2017        | WMT 2018  |
| English - Russian  | News Commentary, Yandex, and UN Corpus | WMT 2012   | WMT 2018  |
| English - French   | Commoncrawl, Europarl, Giga FREN, News commentary, UN corpus | WMT 2013 | WMT dis. 2015 |
| French - Spanish   | UN corpus                           | WMT 2011        | WMT 2013  |

3.2 Studied Language Pairs

We use several child language pairs to show that our approach is useful for various sizes of corpora, language pairs, and scripts. As an outlier, we also experiment with a language pair with both languages different from the parent model. To cover this range of situations, we select languages in Table 1.

Another decision behind selecting these language pairs is to include language pairs reaching various levels of translation quality. This is indicated by automatic scores of the baseline setups ranging from 3.54 BLEU (English-to-Odia) to 36 BLEU (English-to-German), see Table 4.

The sizes of corpora and their word counts are in Table 1. The smallest language pair is English-Odia, which uses the Brahmic writing script and contains only 27 thousands training pairs. The biggest is the high-resource English-French language pair.

For most of the language pairs, we use training data from WMT (Bojar et al., 2018). We use the training data without any preprocessing, not even tokenization. See Table 2 for the list of used corpora for each language pair.

Based on our previous experiments, we exclude the noisiest corpus, i.e. web crawled ParaCrawl or Commoncrawl. Only for English-French where we want the child model to be very high-resourced, we keep all WMT18 corpora and perform a quick cleaning using language detection by Langid.py (Lui and Baldwin, 2012). We drop all sentences that are not recognized as the correct language. This cleaning removes 6.5M sentence pairs from the English-French training corpora.

For English-Estonian, we use only the Rapid corpus, instead of all available corpora, in order to have one language pair with training data at the magnitude of 100 thousand sentence pairs.

3.3 Parent Vocabulary Effect

Most of the current NMT system use either byte-pair-encoding (Sennrich et al., 2016b) or word-piece tokenization (Wu et al., 2016). Which take the training corpus and apply a deterministic ap-

3The systems submitted to WMT 2018 for English-to-German translation have better performance than our baseline due to the fact, that we decided not to use Commoncrawl, which artificially made English-German parallel data less resourceful. See Table 2 for the list of used corpora for each language pair.

4 While the recommended best practice in past WMT evaluations was to use Moses tokenizer. It is not recommended for Tensor2Tensor with its build-in tokenizer any more.
Table 3: Average number of tokens per sentence (column “Sent.”) and average number of tokens per word (column “Word”). “Custom vocab” represents the effect of using vocabulary customized for examined language pair. “EN-CS” corresponds to the use of English-Czech vocabulary (Popel, 2018).

Table 3: Average number of tokens per sentence (column “Sent.”) and average number of tokens per word (column “Word”). “Custom vocab” represents the effect of using vocabulary customized for examined language pair. “EN-CS” corresponds to the use of English-Czech vocabulary (Popel, 2018).

3.4 Convergence and Stopping Criterion

Training of NMT models is complicated by the fact, that the learning curves, showing the performance of the model over the learning period, usually never fully flatten or start decreasing on reasonably big datasets. Signs of overfitting are noticeable in low-resource settings only. On the biggest parallel corpora, we can get some improvements, usually around tenths of a BLEU point, even after several weeks of training and the model will not start overfitting on the training data and we usually wait for flattening out of the learning curve.

The common practice in machine learning is to use some stopping criterion. We can set either the maximum number of training steps or evaluate the model every X updates (or minutes) on a development set and stop the training whenever the last N updates did not improve the performance by at least some delta.

The former approach is based on an intuition of how long approximately will be enough to train a model. The latter approach is sensitive to the number of updates (or duration) between individual evaluations: if the evaluations are too close to each other, the training can stop too early, and when they are too far apart the training would not stop in a reasonable time.

In our paper, we compare low-resource language pairs that converge within 50k steps and high-resource pairs which improve even after 1000k steps. We define a more general convergence criterion. We stop the training whenever there was no improvement bigger than 0.5% of maximal reached BLEU over the past 50% of evaluations. Once the training stops, we take the best performing model on the development set and report its training time.

This criterion is comparable to stopping after X batch updates without any improvement, and it is less sensitive to the number of steps between evaluations.

4 Results

All reported results are calculated on the test data and evaluated with SacreBLEU (Post, 2018). The results are in Table 4. We discuss the training time separately, automatically assessed transla-
Table 4: Translation quality and training time. “Baseline” is trained from scratch with its own vocabulary. “Direct transfer” is initialized with parent model using the parent vocabulary and continues training. “Transformed vocab” has the same initialization but merges the parent and child vocabulary as described in Section 2.2. Best score and lowest training time in each row in bold.

| Parent model       | Language pair             | Baseline BLEU | Baseline Steps | Direct transfer BLEU | Direct transfer Steps | Transformed vocab BLEU | Transformed vocab Steps |
|--------------------|---------------------------|---------------|---------------|----------------------|----------------------|------------------------|------------------------|
| English-to-Czech   | English-to-Odia           | 3.54          | 45k           | 0.26                 | 47k                  | 6.38                   | 38k                    |
|                    | English-to-Estonian       | 16.03         | 95k           | **20.75**            | **75k**              | 20.27                  | **75k**                |
|                    | English-to-Finnish        | 14.42         | 420k          | 16.12                | **255k**             | 16.73                  | 270k                   |
|                    | English-to-German         | 36.72         | 270k          | 38.58                | 190k                 | **39.28**              | **110k**               |
|                    | English-to-Russian        | 27.81         | 1090k         | 27.04                | 630k                 | **28.65**              | **450k**               |
|                    | English-to-French         | 33.72         | 820k          | 34.41                | **660k**             | 34.46                  | 720k                   |
|                    | French-to-Spanish         | 31.10         | 390k          | 31.55                | 435k                 | **31.67**              | **375k**               |
| Czech-to-English   | Estonian-to-English       | 21.07         | 70k           | 24.36                | **30k**              | 24.64                  | 60k                    |
| Czech-to-English   | Russian-to-English        | 30.31         | 980k          | 23.41                | **420k**             | **31.38**              | **700k**               |

4.1 Training Time

First, let us consider the number of training steps. Both of our methods converged in a similar or lower number of steps than the baseline. The reduction in the number of steps is most visible in German and Russian, where we got to less than half of the total number of steps. When target language is aligned with the parent target language, the transfer learning takes fewer steps compared to reverse direction when English is on the source side. It is important to note that the number of steps is not precisely proportional to training time, as the duration of computing one step fluctuates during training. However, the actual training time in our experiments correlates with the number of steps.

4.2 Direct Transfer Learning

By comparing the performance score, we see that direct transfer learning without transforming vocabulary is better than the baseline in both translation direction in all cases except for Odia and Russian, which we will discuss later. All the improvements over the baseline are significant according to paired bootstrap resampling against the baseline setup (1000 samples, confidence level 0.05; Koehn, 2004). We get improvements for various language types, as discussed in Section 3.2. The biggest improvement is of 4.72 BLEU for the low-resource language of Estonian as well as 0.69 BLEU for the high-resource French. We get an improvement of 0.45 BLEU for the language pair with no language in common with the parent model.

The results are even more surprising when we take into account the fact that the model uses the parent vocabulary and thus segmenting words into considerably more subwords. This suggests that the transformer architecture generalizes very well to short subwords.

The worse performance of English-Odia and English-Russian is due to the different writing script. The Odia script is not contained in the parent vocabulary at all, leading to segmenting of each word into individual bytes, the only common units with the parent vocabulary. Furthermore, for these two languages, we increased the filtering of long sentences (see Section 3) from 100 to 500 subwords.

4.3 Results with Transformed Vocabulary

As the results in Table 4 confirm, our method described in Section 2.2 successfully tackles the problem when child language uses a different writing script. We see “Transformed vocab” delivering the best performance for all language pairs except English-to-Estonian, significantly improving over “Direct transfer” in most cases. The only exceptions are English-to-Estonian and English-to-French, where neither of the systems is significantly better than the other. However, both of them are significantly better than the baseline.

4.4 Various Vocabulary Transformations

Our Transformed vocabulary technique assigns unmatched subwords mostly at random. However,
there are many other variants. We propose several of them and evaluate them in this section. The approach used in previous experiments is called “Frequency-based”.

We can assign tokens at random. Either all of them or only unmatching tokens. We call the former approach “Everything random”. It is when all subword tokens are first shuffled and then assigned at random. This approach does not match any tokens. Therefore the NMT needs to learn even tokens that have been used by the parent model. The latter approach is called “Unmatched random”. It first assigns subwords that are in parent and child vocabulary. Then it assigns the remaining child tokens at random.

The results of comparing various approaches to replacing tokens in parent vocabulary are in Table 5. All approaches reach comparable performance except assignment of everything by random. Thus we found no significant differences in the performance as long as subwords common to both the parent and child keep their embeddings, i.e. are mapped to the same index in the vocabulary. The subwords unique to the child vocabulary can be assigned randomly to the unused parent embeddings.

4.5 Comparison to Kocmi and Bojar (2018)

We replicated the experiments of Kocmi and Bojar (2018) in order to compare their method to ours. We train four models, two English-to-Czech and two Czech-to-English on the same parent training data as in the original paper. All vocabularies contain 32k subwords.

Comparing the results in Table 6 we see that the method by Kocmi and Bojar (2018) reaches better performance in most language pairs, which is understandable since the parent model is already trained with prepared vocabulary. However, when we compare the total number of steps needed to reach the performance, our method is significantly faster. This is because the method by Kocmi and Bojar (2018) first needs to train the parent model, while our method can directly use any of the already trained models. This makes our method applicable to the current training workflow, where without any modifications of architecture, we can improve the performance and shorten the training time. However, if the training time is not relevant criterion Kocmi and Bojar (2018) method performs better.

In conclusion, our approach performs worse than Kocmi and Bojar (2018), but it converges faster. Furthermore, we need to take into account that separate parent had to be trained for each of the Trivial transfer language pairs. Thus total training time increases significantly. In contrast, our method uses two models for all language pairs that we have not trained at all. Therefore, our method can be used especially for prototyping of new experiments or language pairs when the training speed is more important than performance.

5 Analysis by Freezing Parameters

In order to analyze which transferred parameters are the most helpful for the child model and which need to be updated the most, we follow the strategy applied to model adaptation by Thompson et al. (2018). We continue the training of the child model but freeze various parts. The analysis has been carried out on the English-to-Finnish (En-Fi) and Estonian-to-English (Et-En) child models.

Based on the internal layout of Transformer model parameters in the Tensor2Tensor, we divided the model into four parts. (i) Word embeddings map each subword unit to a dense vector
representation. The same embeddings are shared between the encoder and decoder. (ii) The encoder part includes all the six feed-forward layers converting input sequence to the deeper representation. (iii) The decoder part is again six feed-forward layers preparing the choice of the next output subword unit. (iv) The multi-head attention is used throughout encoding as well as decoding, as self-attention layers interleaved with the feed-forward layers. It is unfortunately not easy to separate the self-attention layers used in the encoder or decoder. Therefore when freezing encoder (resp. decoder for Et-En) or attention is not that critical as a frozen decoder (resp. encoder). The bad result of the encoder (resp. decoder) being the only non-frozen part in Table 8 shows that it is not capable of providing all the needed capacity for the new language, unlike the self-attention where the loss is not that large.

The results for transformed vocabulary are straightforward: freezing anything except the embeddings behaves similarly to Direct transfer, however freezing embeddings hurts the performance significantly. This is due to the arbitrary assignment of child subwords to the original word embeddings. On the other hand, trainable embeddings alone are not sufficient.

In Table 8, it is surprising that the model is more dependent on embeddings when the shared English is on the target side: the best score for Et-En (22.92) was obtained when only embeddings were trainable, unlike En-Fi where training Decoder or Attention was more important. This goes against the intuition that the English embeddings should be already trained from the parent model.

All in all, these experiments illustrate the robustness of the Transformer model in that it is able to train and reasonably well utilize pre-trained weights even when they are severely crippled.

6 Related Work

This paper focuses on reusing an existing NMT model in order to improve the performance in terms of training time and/or translation quality.
without any need to modify the model or pretrained weights.

The use of other language pairs for improving results for the language pair of interest has been approached from various angles. One option is to build multi-lingual models, ideally so that they are capable of zero-shot, i.e. translating in a translation direction that was never part of the training data. Johnson et al. (2017) and Lu et al. (2018) achieve this with a unique language tag that specifies the desired target language. The training data includes sentence pairs from multiple language pairs, and the model implicitly learns translation between many languages. In some cases, it can even translate between languages never seen together. Gu et al. (2018) tackled the problem by creating universal embedding space across multiple languages and training many to one language translation system. Firat et al. (2016) propose multi-way multi-lingual systems. Their goal is to reduce the total number of parameters needed to train multiple source and target models. In all cases, the methods are dependent on a special training schedule.

Lakew et al. (2018) presented two model modifications for multilingual machine translation and showed that one could train the parent model followed by dynamically updating embeddings for the vocabulary of a second target language improving the performance on the latter language. The lack of parallel data can also be tackled by unsupervised translation (Artetxe et al., 2018; Lample et al., 2018). The general idea is to train monolingual autoencoders for both source and target languages separately, followed by mapping both embeddings to the same space and training simultaneously two models, each translating in a different direction. In an iterative training, this pair of MT systems is further refined, each system providing training data for the other one by back-translating monolingual data (Sennrich et al., 2016a).

For very closely related language pairs, transliteration can be used to generate training data from a high-resourced pair to support the low-resourced one as described in Karakanta et al. (2018).

7 Conclusion

In this paper, we proposed a method of recycling Transformer NMT models and reusing them unchanged for any “child” language pair regardless of the original “parent” training languages. The technique is simple, effective, and applicable to models trained by others, which makes it more likely that our experimental results will be replicated in practice. Additionally, we proposed a simple way of transforming the parent vocabulary and showed that despite the random assignment of subwords, the transformed vocabulary improves the performance of the child translation system.

We showed that the cold-start scenario of transfer learning could be used instead of random initialization without any performance or speed losses. We see our approach as an exciting option for improving the reproducibility of NMT experiments. Instead of training from randomly-initialized models, NMT papers could start from a published well-known baselines.

We showed that this approach to transfer learning is not restricted to low-resource languages; we analyzed the gains documenting that most improvements are due to the shared English source. Interestingly, we observe improvements even on language pairs not using English, such as French-to-Spanish. Finally, we confirmed the robustness of the Transformer architecture and its ability to achieve good results in adverse conditions like very fragmented subword units or parts of the network frozen.

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