Training Multilingual Machine Translation by
Alternately Freezing Language-Specific Encoders-Decoders

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Abstract

We propose a modular architecture of language-specific encoder-decoders that constitutes a multilingual machine translation system that can be incrementally extended to new languages without the need for retraining the existing system when adding new languages. Differently from previous works, we simultaneously train $N$ languages in all translation directions by alternately freezing encoder or decoder modules, which indirectly forces the system to train in a common intermediate representation for all languages.

Experimental results from multilingual machine translation show that we can successfully train this modular architecture improving on the initial languages, while falling slightly behind when adding new languages or doing zero-shot translation. Additional comparison of the quality of sentence representation in the task of natural language inference shows that the alternately freezing training is also beneficial in this direction.

1 Introduction

Multilingual machine translation generates translations automatically across a number of languages. In the last years, the neural encoder-decoder machine translation architecture (Bahdanau et al., 2014) has allowed for radical improvements in this area.

Multilingual neural machine translation can refer to translating from one-to-many languages (Dong et al., 2015), from many-to-one (Zoph and Knight, 2016) and many-to-many (Johnson et al., 2017). Within the many-to-many paradigm, existing approaches can be further divided into shared or language-specific encoder-decoders. The latter approaches vary from sharing parameters (Firat et al., 2016b; Firat et al., 2016a; Lu et al., 2018) to no sharing at all (Escolano et al., 2019a; Escolano et al., 2019b; Escolano et al., 2020).

Previous research on language-specific encoders-decoders (Escolano et al., 2019a; Escolano et al., 2019b) without sharing any parameters shows that the proposed multilingual system performs quite poorly when new languages are added in the system compared to when languages were jointly trained in the system. One of the main reasons is that the new language module is trained with a frozen module, whereas the initial languages are not trained in such conditions. With respect to the initial architecture, we propose a variation that is specifically designed to add new languages into the system.

In particular, we propose a new framework that extends previous approach that does not share parameters at all (Escolano et al., 2020). As opposed to any proposal that shares parameters, new languages are naturally added to the system by training a new module coupled with any of the existing ones, while new data can be easily added by retraining only the module for the corresponding language. Our proposal (§3) follows (Escolano et al., 2020) and it is based on language-specific encoders and decoders that rely on a common intermediate representation space. For that purpose, we also simultaneously train the initial $N$ languages in all translation directions (§2). However, and differently from (Escolano et al., 2020), we propose to alternately freezing the corresponding encoders and decoders. This condition goes beyond teaching each encoder and decoder module to be compatible with the other modules (Escolano et al., 2020). In our new alternately freezing training framework, we are accounting by design that a single model can be improved and extended to new languages as new data become available.
We evaluate our proposal on three experimental configurations: translation for the initial languages, translation when adding a new language, and zero-shot translation. Our results show that the proposed method is competitive in the first configuration, while still under-performing in the other two conditions. So as to better understand the nature of the learned representations, we run additional experiments on natural language inference, where the alternately freezing outperform in terms of accuracy.

2 Background

In this section, we present the baseline system from which our proposed approach follows the idea of training a separate encoder and decoder for each of the $N$ languages available.

2.1 Definitions

We next define the notation that we will be using throughout the paper. We denote the encoder and the decoder for the $i$th language in the system as $e_i$ and $d_i$, respectively. For language-specific scenarios, both the encoder and decoder are considered independent modules that can be freely interchanged to work in all translation directions. To refer to the freezing schedules employed in the language-specific models, each source-target language pair will be described as $f-n$, $n-f$, or $n-n$, where $f$ denotes a frozen language and $n$ a normally trained one.

2.2 Basic Procedure

In what follows, we describe the basic procedure presented in $\text{(Escolano et al., 2020)}$ in two steps: joint training and adding new languages.

**Joint Training** The straightforward approach is to train independent encoders and decoders for each language. The main difference from standard pairwise training is that, in this case, there is only one encoder and one decoder for each language, which will be used for all translation directions involving that language.

**Adding New Languages** Once we have our jointly trained model for $N$ languages, the next step is to add new languages. Since parameters are not shared between the independent encoders and decoders, the basic joint training enables the addition of new languages without the need to retrain the existing modules. Let us say we want to add language $N+1$. To do so, we must have parallel data between $N+1$ and any language in the system. For illustration, let us assume that we have $L_{N+1}$-parallel data. Then, we can set up a new bilingual system with language $L_{N+1}$ as source and language $L_i$ as target. To ensure that the representation produced by this new pair is compatible with the previously jointly trained system, we use the previous $L_i$ decoder ($d_{L_i}$) as the decoder of the new $L_{N+1}$-$L_i$ system and we freeze it. During training, we optimize the cross-entropy between the generated tokens and $L_i$ reference data but update only the parameters of to the $L_{N+1}$ encoder ($e_{L_{N+1}}$). Following the same principles, the $L_{N+1}$ decoder can also be trained.

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Algorithm 1: Multilingual training step

1: procedure **MULTILINGUALTRAININGSTEP**
2: $N \leftarrow$ Number of languages in the system
3: $S = \{s_{0,0}, ..., s_{N,N}\} \leftarrow \{(e_i, d_j) \text{ if } i \neq j\}$
4: $E = \{e_0, ..., e_N\} \leftarrow$ Language-specific encs.
5: $D = \{d_0, ..., d_N\} \leftarrow$ Language-specific decs.
6: for $i \leftarrow 0$ to $N$ do
7: for $j \leftarrow 0$ to $N$ do
8: if $s_{i,j} \in S$ then
9: $l_i, l_j = \text{get\_parallel\_batch}(i, j)$
10: train($s_{i,j}(e_i, d_j), l_i, l_j)$

For each translation direction $s_{i,j}$ in the training schedule $S$ with language $i$ as source and language $j$ as target, the system is trained using the language-specific encoder $e_i$ and decoder $d_j$.
As argued in (Escolano et al., 2020), this approach, even if not sharing parameters at all, does not suffer from the attention mismatch problem (Firat et al., 2016b; Lu et al., 2018) because, within an initial set of \( N \) languages, the system is trained using pair-wise corpus in all translation directions (without requiring multi-parallel corpus as previous works (Escolano et al., 2019a)). Due to the joint training, once the initial system is trained, only \( N \) encoders and \( N \) decoders (\( 2 \times N \)) are required.

3 Proposed method: Frozen Procedure

As discussed in the previous section, new languages are added into the system by learning a new encoder \( e \) (or decoder \( d \)) with a frozen decoder \( f(d) \) (or frozen encoder \( f(e) \)) already in the system. To simulate this condition from the very beginning, we propose modifying the joint training by alternately training encoders and decoders while systematically freezing modules. Thanks to this, we are enabling the independent modules to encode and decode using a common representation. For that purpose, we modify Algorithm 1 by adding new training schedules, so line 3 becomes the following:

\[
3: \ S = \{ s_{0,0}, ..., s_{N,N} \} \leftarrow \{ (e_i, f(d_j)), (f(e_i), d_j), (e_i, d_j) \}
\]

Note that we are still training all possible translation combinations among the \( N \) languages (avoiding autoencoding and alternating batches in each direction).

We freeze the encoder or decoder for a subset of the combinations. When freezing \( f(d_j) \), we effectively force the representation of \( e_i \) to be as compatible as possible with the representations of the rest of the encoders. This holds true because, if \( e_i \) generated an incompatible representation, \( f(d_j) \) would be unable to adapt to it given that it is frozen, which would increase their corresponding loss. Similarly, freezing \( f(e_i) \) allows \( d_j \) to be more robust to a representation that has not been explicitly adapted to it. See Figure 1 for an illustration of this with 4 languages for one training schedule.

![Figure 1: Alternate training of frozen encoders and decoders for 4 languages for particular training schedules: (left) gradient flow, (right) specific freezing modules.](image)

Given a set of \( N \) languages, we can define a directed graph where each language is a node and each edge is a training translation direction. Figure 1 (left) shows the gradient flow between the different languages: \( l \) means language; \( 0...3 \) are four different languages in the system; \( f() \) means frozen and \( n() \) non-frozen, dotted lines means frozen language pairs, continuous lines means non-frozen language pairs. Let’s interpret the dotted arrow from box \( l_0 \) to \( l_1 \) with the scheme \( f(l_0), n(l_1) \). When training the translation direction from language 0 (\( l_0 \)) to language 1 (\( l_1 \)), we will freeze the \( l_0 \) encoder and only update the parameters of the \( l_1 \) decoder. For the opposite translation direction, we will freeze the \( l_0 \) decoder and only update the parameters of the \( l_1 \) encoder. This can be extended to translation pairs: \((l_1,l_2); (l_2,l_3)\) and \( (l_0,l_2) \). For pairs \((l_1,l_2)\) and \((l_0,l_3)\) no language is frozen and therefore, there are continuous arrows in two directions because the gradient flows both ways.

Note that the proposed schedule ensures that for any pair of languages there are two different paths from which information can flow during the training process. This training procedure enables different freezing schedules, which we explore in section 1. Figure 1 (right) explicitly shows the encoders and decoders that are frozen and non-frozen for 4 languages and the gradient flow represented in the Figure 1 (left).
For $N$ languages, our proposed freezing schedule allows $N/2$ pairs to be fully trained, while for the rest of the pairs one direction is frozen. The frozen directions (discontinuous lines in Figure 1 (left)) forms an Eulerian cycle between all these languages where one learns from another language and lets another one learning from it. This is a trade-off between freezing and non-freezing that induces the system to jointly learn an intermediate representation.

This approach is directly extensible to new languages as explained in the previous section for the basic procedure. We can add a new language $N+1$ by training $e_{(N+1)}$ with $f(d_j)$. Once it is trained, this new $e_{(N+1)}$ should be compatible with any $d_j$.

4 Experiments in Multilingual Machine Translation

In this section we report machine translation experiments in different settings.

4.1 Data and Implementation

We used 2 million sentences from the EuroParl corpus (Koehn, 2005) in German, French, Spanish and English as training data, with parallel sentences among all combinations of these four languages. For Russian-English, we used 1 million training sentences from the Yandex corpus. As validation and test set, we used newstest2012 and newstest2013 from WMT which is multi-parallel across all the above languages. Note that we require multi-parallel corpus in inference (not in training), but only for the specific purpose of evaluating under the condition of zero-shot translation. All data were preprocessed using standard Moses scripts (Koehn et al., 2007).

We evaluate our approach in 3 different settings: (i) the initial training, covering all combinations of German, French, Spanish and English; (ii) adding new languages, tested with Russian-English in both directions; and (iii) zero-shot translation, covering all combinations between Russian and the rest of the languages.

Experiments were done using the Transformer implementation provided by Fairseq. We used 6 layers, each with 8 attention heads, an embedding size of 512 dimensions, and a vocabulary size of 32k subword tokens with Byte Pair Encoding (Sennrich et al., 2016) (per pair). Dropout was 0.3 and trained with an effective batch size of 32k tokens for approximately 200k updates, using the validation loss for early stopping. In all cases, we used Adam (Kingma and Ba, 2014) as the optimizer, with learning rate of 0.001 and 4000 warmup steps. All experiments were performed on an NVIDIA Titan X GPU with 12 GB of memory.

4.2 Basic vs Frozen

We used multiple configurations for the case of frozen. The main difference in these configurations is which languages and modules are frozen.

Basically, we followed the criterion of linguistic families. We assumed that languages that belong to the same linguistic family are closer than those that are not.

Based on this, English/German-French/Spanish are candidates to be farthest language pairs. To decide which of Spanish and French is the farthest from English, we follow the criterion of language distance proposed by Gamallo et al. (2017): We used an English-Spanish distance of 18 which is higher than the English-French distance (16). Therefore, we chose as more distant pairs of languages English-Spanish and German-French. The reason to choose German-French is so that the same language will not be frozen in several pairs, otherwise, we risk that this language will not able to train well for all translation directions. English-German and French-Spanish are chosen as the closest language pairs.

We could either train without freezing the farthest pairs (far) or train without freezing the closest pairs of modules (close). The order of the modules to be frozen is given in Table 1.

We found the option of freezing in all cases to perform poorly in our preliminary experiments. Finally, and inspired by curriculum learning techniques (Bengio et al., 2009), we can use an adaptive scheme
Table 1: Initial training. In bold, best global results.

|            | Basic | Frozen |
|------------|-------|--------|
|            | Far   | Close  | Adapt |
| de-en      | 22.04 | 23.25  | n-f   |
| de-es      | 22.38 | 24.25  | n-f   |
| de-fr      | 25.08 | 23.47  | n-n   |
| en-de      | 19.44 | 20.88  | f-n   |
| en-es      | 26.79 | 27.42  | n-f   |
| en-fr      | 27.72 | 28.03  | f-n   |
| es-de      | 17.7  | 18.21  | f-n   |
| es-en      | 24.9  | 27.06  | n-n   |
| es-fr      | 27.31 | 29.34  | f-n   |
| fr-de      | 16.88 | 19.22  | n-n   |
| fr-en      | 23.5  | 25.11  | n-f   |
| fr-es      | 26.78 | 28.14  | n-n   |

Ru-en 25.52 25.08
En-ru 21.44 21.33

Table 2: Adding a new language translation.

|            | Basic | Frozen |
|------------|-------|--------|
|            |       |        |
| ru-de      | 12.73 | 11.85  |
| ru-es      | 18.71 | 15.31  |
| ru-fr      | 18.05 | 15.46  |
| de-ru      | 14.39 | 14.99  |
| es-ru      | 15.93 | 14.85  |
| fr-ru      | 15.1  | 14.99  |

Table 3: Zero-shot translation.

(adapt) which basically after each epoch computes a new training schedule based on the average validation loss. Two pairs with higher loss are not frozen, and then, the rest of the languages are frozen composing the Eulerian cicle as explained in section 3.

Initial Training Table 1 shows a comparison between training language-specific encoders and decoders using either the basic or the frozen procedure. The frozen procedure clearly outperforms the basic one for all language pairs. When comparing different training schedules for the frozen procedure (far vs close), the results show that the far configuration in the frozen procedure is the best one, except in 4 (out of 12) language directions. When comparing far with adapt, the former is again the best one, except in 4 (out of 12) language directions. Adapting the training schedule based on the loss ends up as a pre-defined one. What we observed in the adaptive schedule is that we start from the far configuration and the system moves to the close configuration in one iteration and does not change anymore. When using the loss as a criteria, we are introducing external factors, so this criteria does not seem flexible enough. Given these results, the rest of the experiments were performed using the far training schedule.

Adding New Languages As shown in Table 2, the basic procedure performs slightly better than the frozen one when adding a new language into the system.

Zero-shot As shown in Table 3 the basic procedure also outperforms the frozen procedure in zero-shot translation for 6 (out of 7) translation directions.

4.3 Discussion

Surprisingly, we are obtaining improvements in the condition that we did not expect (the initial one). The very first motivation of the frozen procedure is to simulate the conditions of adding a new language which consists in training with a frozen module. So, we were expecting the frozen procedure to improve over the basic one when adding new languages and performing zero-shot translation. Under these two conditions, the frozen procedure is slightly worse than the basic procedure.

However, and proven by the nice improvements reported under the initial condition, we believe that the alternatively freezing scheme that we are proposing has a big potential to be exploited in investigating alternative training schedules, e.g. employing more advanced techniques of curriculum learning (Bengio et al., 2009).

Taking a closer look at the results, we can find different behaviors between languages pairs frozen during training and those that not. Starting by the initial condition, non-frozen pairs (German-French, Spanish-English) are the best performing systems and further outperform the basic procedure by an average of 2.21 BLEU points, while frozen ones (German-English, German-Spanish, French-English)
reduce those gains to 1.19 points. Those results show that the additional information available to not frozen language-pairs is beneficial in the initial task. The additional information comes from the fact that both encoder and decoder are updated during training in the case of German-French and Spanish-English.

On the other hand, this behaviour is reversed when looking at zero-shot results. In the case of zero-shot, Spanish that was not frozen to English is the worst performing language in the zero-shot task. Whereas languages (French, German) that were frozen to English are closer to the baseline performance (even better in the German-to-Russian case). The additional information in training, which was beneficial for the initial task, seems to be detrimental for zero-shot translation. Previous works (Lu et al., 2018; Gu et al., 2019) reported similar conclusions, showing that language-specific information (or spurious correlation) harms the model’s generalization to other languages as the task of zero-shot requires.

To further understand the performance of the frozen procedure, we are exploring its performance in the task of natural language inference in the next section.

5 Experiments in Cross-lingual Natural Language Inference

Given two sentences, a reference and a hypothesis, the natural language inference (NLI) task consists in deciding whether the relationship between them is entailment, contradiction or neutral. This task has been addressed as a classification problem using the relatedness of the representation of sentences. Following the procedure of (Conneau et al., 2018) a model is trained to classify a classifier to task. In the original work, the model consisted of a bidirectional recurrent encoder and as classifier, two fully connected layers with ReLU and Softmax activation respectively. The classifier is fed with the following combination of the encoding of both reference and hypothesis:

\[ h = [u, v, |u - v|, u * v] \]

where \( u \) is the reference encoding, \( v \) is the hypothesis encoding and \( * \) is the element multiplication of both vector representations. In that work, encoders were trained specifically on the task of natural language inference, independently for each language and representations were forced to share representation space by means of additional loss terms. For our task, we want to study the shared space already trained by the different configurations of multilingual machine translation systems from section 4.1. For each of them, a classifier is trained using its English encoder, which is frozen to help the classifier learn from the current shared space. To keep the encoding as described in equation [1] while using a Transformer encoder, the contextual embeddings are averaged to create a fixed-sized sentence representation. This approach was previously proposed by (Arivazhagan et al., 2019), where pooling was employed and allows the representation size to be fixed while not adding extra padding to the data; at the cost of producing an information bottleneck for the classification because all sentence information has to be condensed into a single fixed-size vector, independently of the sentence’s length.

Given that all language pairs in both language-specific architectures were trained to share sentence representations, we can evaluate the classifier’s performance compared with that of all the other languages in the multilingual system without any extra adaptation.

5.1 Data and implementation

For this task, we use the MultiNLI corpus[^4] for training, which contains approximately 430k entries. We use the XNLI validation and test set (Conneau et al., 2018) for cross-lingual results, which contain 2.5k and 5k segments, respectively, for each language.

We use the exact same encoders trained for the machine translation experiments (§ 4.1), which are not further retrained or fine-tuned for this task. A classifier with 128 hidden units is exclusively trained on top of the English encoder, which is the only language for which we have training data. Note that the basic and frozen language-specific encoder-decoders, each language has its own encoder, and both vocabulary and parameters are fully independent.

[^4]: [https://cims.nyu.edu/~sbowman/multinli/](https://cims.nyu.edu/~sbowman/multinli/)
5.2 Results

Table 4 shows the results for the XNLI task using either basic or frozen language-specific encoder-decoders. Note that our goal is not to improve the state-of-the-art in this task, but rather to analyze the nature and quality of the cross-lingual representations arising in the different multilingual architectures.

**Basic vs Frozen** The frozen procedure outperforms the basic one for all cases. This shows that the frozen procedure helps in creating a coherent intermediate representation.

6 Visualization

![Figure 3: Visualization of words embeddings for the basic (left) and frozen (right) approaches.](image)

In what follows, we use a tool (Escolano et al., 2019b) freely available[^5] that allows us to visualize intermediate sentence representations. The tool uses the encoder’s output fixed-representations as input data and performs a dimensionality reduction in these data using UMAP (McInnes et al., 2018). Additionally, we are also adding a comparison of words embeddings. In both cases, we make the comparison for the two architectures (basic and frozen) from the paper.

[^5]: https://github.com/elorala/interlingua-visualization
Figure 4: Visualization of sentence representations for the basic (left) and frozen (right) approaches.

Figure 4 shows the intermediate representation of 100 sentences in each languages (German, English, Spanish, French and Russian) of the sentence since 2011 a dozen States have adopted laws requiring voters to prove they are American citizens and the corresponding translations.

Note that, although all the points seems to be mixed together, the representation of the same sentence in different languages is not placed exactly in the same point in the space. For the example, representation seems closer between sentences for the frozen architecture than in the basic case. In the case of the basic architecture, the sentence representations of Russian, which is the language that is added later, seem to be quite far from those of the others languages. The frozen training schedule, while forcing the language-specific modules to adapt to the representations already learned from other languages may help producing a more general language representation, as already shown in the downstream task experiments.

While sentence representation are not fully shared between languages, our next question is if that difference in the representation is also present in the multilingual word representations. Figure 3 shows a two-dimensional representation of the words embeddings of each architecture; obtained using UMAP dimensionality reduction, as done for sentences in Figure 4.

Visualizations shows similar representations for word embeddings, in the sense that each language has its own cluster, which indicates that each of the modules has learnt its individual word representation. This finding shows that while a shared word embedding space might not be mandatory for the task it would be interesting to explore its impact in future work. Table 5 shows how for the sentence the new election laws require voters to show a photo ID card and proof of US citizenship, the basic architectures wrongly translate photo ID while the frozen architecture is able to keep the original term.

Note that the visualization and the example shown in here only pretends to provide a small qualitative and interpretable analysis of the proposed models.

7 Conclusions

In this paper, we present a novel training methodology language-specific encoders-decoders specifically designed to perform well when incrementally adding new languages into the system without having to retrain it. We believe that this approach can be particularly useful for situations in which a rapid extension of an existing machine translation system is critical (e.g. aiding in a disaster crisis where international help is required in small region, or developing a translation system for a client).

We provide a comparison of the language-specific procedure for the previously proposed basic procedure (Escolano et al., 2020) and our current proposal of alternatively freezing encoders-decoders during training. Comparison is done for the task of machine translation in the situation of initial language training, adding new languages and zero-shot translation. Performance of the frozen procedure is better in the first situation and slightly worse in the other two. Additional experiments in natural language inference
| System | Languages | Sentence |
|--------|-----------|----------|
| Reference | DE | the new electoral laws require the voters to present a beacon and proof of US citizenship |
| | ES | the new electoral laws require the voters to submit an identity card with a photograph as well as a test of American citizenship |
| | FR | the new electoral laws require the voters to present an identity card with a photograph and proof of American citizenship |
| | RU | the new electoral laws require the voter to have a photo ID and proof of the existence of American citizenship |
| Basic | DE | the new electoral laws require voters to present a ray of light and evidence of US citizenship |
| | ES | the new electoral laws require voters to present an identity document with a photograph, as well as a test of American citizenship |
| | FR | the new electoral laws require voters to present an identity card with evidence of American citizenship |
| | RU | the new electoral laws require the voter to have a photograph card and proof of American citizenship |
| Frozen | DE | the new electoral laws require the voters to produce a beacon and proof of US citizenship |
| | ES | the new electoral laws require the voters to submit an identity card with a photograph as well as a test of American citizenship |
| | FR | the new electoral laws require the voters to present an identity card with a photograph and proof of American citizenship |
| | RU | the new electoral laws require the voters to have a photo ID and proof of the existence of American citizenship |

Table 5: Translation examples for each of the tested architectures: basic and frozen.

show that the accuracy of classification when using the sentence representation of the language-specific encoders is higher in the current proposed frozen procedure.

While we obtained improvement in the machine translation condition that we did not expect (the initial one instead of the adding new languages for which we trained for), we believe that the alternatively freezing scheme has further potential to be exploited in investigating alternative training schedules.

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