Multilingual Unsupervised NMT using Shared Encoder and Language-Specific Decoders

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Abstract
In this paper, we propose a multilingual unsupervised NMT scheme which jointly trains multiple languages with a shared encoder and multiple decoders. Our approach is based on denoising autoencoding of each language and back-translating between English and multiple non-English languages. This results in a universal encoder which can encode any language participating in training into an interlingual representation, and language-specific decoders. Our experiments using only monolingual corpora show that multilingual unsupervised model performs better than the separately trained bilingual models achieving improvement of up to 1.48 BLEU points on WMT test sets. We also observe that even if we do not train the network for all possible translation directions, the network is still able to translate in a many-to-many fashion leveraging encoder’s ability to generate interlingual representation.

1 Introduction
Neural machine translation (NMT) (Kalchbrenner and Blunsom, 2013; Cho et al., 2014; Sutskever et al., 2014; Bahdanau et al., 2015) has become a dominant paradigm for machine translation achieving state-of-the-art results on publicly available benchmark datasets. An effective NMT system requires supervision of a huge amount of high-quality parallel data which is not easily available for many language pairs. In absence of such huge amount of parallel data, NMT systems tend to perform poorly (Koehn and Knowles, 2017). However, NMT without using any parallel data such as bilingual translations, bilingual dictionary or comparable translations, has recently become reality and opened up exciting opportunities for future research (Lample et al., 2018; Artetxe et al., 2018; Yang et al., 2018). It completely eliminates the need of any kind of parallel data and depends heavily on cross-lingual embeddings and iterative back-translations (Sennrich et al., 2016) between the source and target language using monolingual corpora. On the architectural point of view, the approaches combine one encoder and one (Lample et al., 2018) or two (Artetxe et al., 2018) decoders. In supervised NMT settings, combining multiple languages to jointly train an NMT system has been found to be successful in improving the performance (Dong et al., 2015; Firat et al., 2016; Johnson et al., 2017). However, to the best of our knowledge, this is the very first attempt which aims at combining multiple languages in an unsupervised NMT training.

To translate between many languages using bilingual version of unsupervised NMT, we require an encoder and one (Lample et al., 2018) or two (Artetxe et al., 2018) decoders for each pair of languages. However, we may not need separate decoders depending on the source language. We can train source-independent, target-specific decoders, wherein each decoder will take an intermediate representation of a source sentence obtained from the shared encoder to translate into their corresponding language. Also, to translate in many-to-many direction for \( n \) languages using bilingual unsupervised NMT (Artetxe et al., 2018), we may need \( n \) autoencodings and \( n \times (n - 1) \) back-translations in each iteration during training.

In this work, we propose to combine multiple languages in an unsupervised NMT training using a shared-encoder and language-specific decoders through one source to many targets and many targets to one source translations. Our proposed approach needs only \( 2 \times (n - 1) \) back-translations in each iteration during training. Specifically, we train an NMT system, using only monolingual corpora, for 6 translation directions using 4 languages (English, French, German and Spanish) to perform translation in 12 directions. We take En-
lish as the anchor language and map three non-English languages’ embeddings into the English embedding space. We train the network to denoise all the four languages and back-translate between English and non-English languages. We evaluate on newstest13 and newstest14 using BLEU (Papineni et al., 2002) score. We find that the multilingual model outperforms the bilingual models by up to 1.48 BLEU points. We also find that the network learns to translate between the non-English (French, German and Spanish) language pairs as well even though it does not explicitly see these pairs during training. To translate between a non-English language pair, no modification to the network is required at inference time. We also evaluate the performance of the non-English language pairs and achieve a maximum BLEU score of 13.92.

The key contributions of our current work are as follows: (i) we propose a strategy to train multilingual unsupervised NMT for one source to many targets and many targets to one source translations; (ii) we empirically show that jointly training multiple languages improves separately trained bilingual models; and (iii) we also show that without training the network for many-to-many translations, the network can translate between all the languages participating in the training.

3 Background

In this section, we briefly describe the basic unsupervised NMT model as proposed in Artetxe et al. (2018). The architecture has one shared encoder and two language specific decoders, and uses following two strategies to train the NMT system in an unsupervised manner:

Denoising Autoencoding: The shared encoder takes a noisy (noise through random swaps between two adjacent words) sentence in a given language, initialized with cross-lingual embeddings, encodes into an intermediate representations, and the decoder of that specific language reconstructs the original sentence from that intermediate representations.

Back-translation: Training strategy with denoising involves one language at a time, thus it is nothing more than a copying task. In order to perform actual translation without violating the constraint of using nothing but monolingual corpora, back-translation approach is adapted to generate synthetic parallel sentences. At first, for a given sentence in one language, authors (Artetxe et al., 2018) use the system in inference mode to translate it in another language using greedy decoding. Then, the system is trained to predict the original sentence from this synthetic sentence.

4 Proposed Approach

Our proposed approach comprises mainly two steps: in the first step, we map multiple languages into a shared latent space through cross-lingual embedding mapping, and in the second step, using the shared representation we train NMT using only monolingual corpora with the help of a shared encoder and language-specific decoders through denoising and back-translation.

4.1 Cross-lingual Embedding

For creating cross-lingual embedding, we follow the work by Conneau et al. (2018), which is a fully unsupervised approach to aligning monolingual word embeddings and is based on the existing work of Mikolov et al. (2013). At first, two monolingual embedding spaces $X$ and $Y$ are learned. Then using adversarial training (Ganin et al., 2016), a translation matrix $W$ is learned to map $X$ into $Y$. A discriminator is trained to discriminate between $WX$ and $Y$, while $W$ is trained.
to prevent the discriminator from doing so by making $WX$ and $Y$ as similar as possible. Using $W$, a small bilingual dictionary of frequent words is learned. A new translation matrix $W$ that translates between $X$ and $Y$ space is induced by solving the Orthogonal Procrustes problem:

$$W^* = \arg\min_W \|WX - Y\|_F = UV^T$$

subject to $WW^T = I, U\Sigma V^T = SVD(YX^T)$

This step can be iterated multiple times by using new $W$ to extract new translation pairs. New translation pairs between the two languages are produced using cross-domain similarity local scaling (CSLS) (Conneau et al., 2018).

### 4.2 Multilingual Embeddings

In general, for $n$ languages, we choose one language $L_1$ as anchor to map other $n - 1$ languages into its embedding space. To do so, we first train monolingual word embeddings for each of $n$ languages. Then one by one, we map each of $n - 1$ languages’ embedding into embedding space of $L_1$. In our experiments, we consider 4 languages, namely English, French, Spanish and German. We create three cross-lingual embeddings for French, Spanish, and German by keeping English embedding fixed.

#### 4.3 Multilingual NMT Training

NMT systems are ideally trained to predict a target sentence given a source sentence. However, in case of unsupervised version of NMT training, we only have monolingual corpora. In absence of a true source-target pair, we depend on synthetic source-target pair having a authentic monolingual sentence at the target side and synthetic equivalent of target at the source side.

Our proposed multilingual unsupervised NMT training strategy is inspired by a recent work of Artetxe et al. (2018), which has mainly two steps, viz. (i) denoising autoencoding of the sentences of source and target; and (ii) back-translation between source and target. For $n$ languages $L_1, L_2, ..., L_n$, in each iteration, we perform denoising of $n$ languages, back-translation from $L_1$ to the other $n - 1$ languages, and back-translation of $n - 1$ languages to $L_1$. Figure 1 shows the block-diagrammatic representation. In our experimental setting, we have 4 languages and $L_1$ is English. In denoising autoencoding step, sentences in one language are corrupted by some random shuffle of words and the decoder is trained to predict the original sentences. In back-translation step, to train the system for a source-to-target direction, first a target sentence is translated to a source sentence using the system in inference mode (using the shared encoder and the source language decoder) to generate pseudo source-target parallel sentence and then this pseudo parallel sentence is used to train the network for source-to-target direction. Similarly for a target-to-source training, the process is analogous to the above approach.

![Figure 1: Block diagrammatic view of the proposed network. The shared encoder and decoders of each language are 2-layered bidirectional GRUs. In each iteration of the training: 1. we denoise all languages $L_1, L_2, L_3, ..., L_n$; 2. back-translate from each $L_i$ to $L_1$ as shown using red arrows; 3. back-translate from $L_1$ to each $L_i$ as shown using blue arrows, where $i \in \{2, 3, ..., n\}$.](image-url)

### 5 Datasets and Experimental Setup

#### 5.1 Datasets

We use monolingual English, French, and German news corpora from WMT 2014\(^1\) (Bojar et al., 2014) and Spanish from WMT 2013\(^2\) (Bojar et al., 2013) for the experiments. The number of tokens for English, German, French and Spanish are 495.5, 622.6, 224.3 and 122.9 millions, respectively. For English-{French, German}, we use newstest2013 and newstest2014, and for English-Spanish, we use newstest2013. We do not use any parallel data to train, or development set to tune a model. We tokenize and truecase the data using Moses tokenizer\(^3\) and truecaser scripts.

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\(^1\)http://www.statmt.org/wmt14/translation-task.html

\(^2\)http://www.statmt.org/wmt13/translation-task.html

\(^3\)https://github.com/moses- smt/mosesdecoder/blob/RELEASE-3.0/scripts/tokenizer/tokenizer.perl
5.2 Experimental Setup

Monolingual embeddings are trained using fastText\(^4\) using the skip-gram model with vector dimension of 300. For other hyperparameters, we keep default values of fastText (Bojanowski et al., 2017). After getting monolingual embedding for each language, we map every non-English embedding into the embedding space of English using the cross-lingual embedding mapping code MUSE\(^5\) by Conneau et al. (2018). For mapping, we use no bilingual data. We implement the proposed multilingual NMT architecture using PyTorch\(^6\), and is based on the implementation of Artetxe et al. (2018). The encoder and decoders are 2-layered bidirectional gated recurrent units (Cho et al., 2014). We keep the maximum sentence length to 50 tokens. For training, we keep embedding dimension of 300 and hidden dimension of 600, vocabulary size 50K, learning rate 0.0002 with Adam optimizer (Kingma and Ba, 2015). As we do not use any development set, we run all the models (bilingual as well as multilingual) for 200k iterations keeping batch size of 50 sentences, and take the final models for evaluation.

6 Results and Analysis

We train bilingual models for English↔\{French, German, Spanish\} as the baselines following Artetxe et al. (2018). We present the BLEU score for each translation direction using bilingual and multilingual models in Table 1. From Table 1, we observe that proposed multilingual model outperforms the separately trained bilingual models for all translation directions on both test sets with a maximum improvement of 1.48 BLEU points for Spanish to English on newstest2013. As the parameters are shared at only encoder side and a separate decoder is used for each target language, multilingual training provides an improved performance for all the language pairs without loosing their own linguistic characteristics.

Table 1: BLEU scores on newstest2013 and newstest2014. ▲ shows improvements over bilingual models. Spanish (Es) is not part of the newstest2014 test set. Base: Baseline. Multi: Multilingual

| System | newstest2013 | newstest2014 |
|--------|--------------|--------------|
|        | Base | Multi ▲ | Base | Multi ▲ |
| Fr→En  | 13.81 | 14.47 | +0.66 | 14.98 | 15.76 | +0.78 |
| Es→En  | 13.97 | 15.45 | +1.48 | - | - | - |
| En→Fr  | 13.28 | 13.71 | +0.43 | 14.57 | 14.69 | +0.12 |
| En→Es  | 14.01 | 14.82 | +0.81 | - | - | - |
| De→En  | 11.30 | 11.94 | +0.64 | 10.48 | 11.21 | +0.73 |
| En→De  | 7.24 | 8.09 | +0.85 | 6.24 | 6.77 | +0.53 |

Table 1: BLEU scores on newstest2013 and newstest2014. ▲ shows improvements over bilingual models. Spanish (Es) is not part of the newstest2014 test set. Base: Baseline. Multi: Multilingual

6.1 Translation between Unseen Language Pairs

In Table 2, we show the results of the language pairs never seen explicitly during training. During training, we only back-translate between English and non-English (Spanish, French, German) languages, but the network learns to translate between the non-English language pairs as well. For example, to translate from Spanish to French, we encode a Spanish sentence and the encoded output of the encoder is decoded by the French decoder. For evaluation, we use the newstest2013\(^7\) test set for Spanish-French, Spanish-German, and French-German language pairs. From Table 2, we see translations between French and Spanish achieve very encouraging BLEU scores of 13.87 and 13.92, and pairs involving German achieve

\(^4\)https://github.com/facebookresearch/fastText
\(^5\)https://github.com/facebookresearch/MUSE
\(^6\)https://pytorch.org
\(^7\)It is a multilingual test set.
moderate BLEU score of up to 7.40 considering the fact that the network is not trained for these pairs. For sample outputs, refer to Table 4 in Appendix A.

|   | Es  | Fr  | De  |
|---|-----|-----|-----|
| Es | -   | 13.92 | 4.78 |
| Fr | 13.87 | -   | 4.59 |
| De | 7.40 | 6.78 | -   |

Table 2: BLEU scores of translation between non-English languages on newstest2013. Consider rows are source and columns are target. The network is not trained for these language pairs and still it is possible to translate between these pairs by using the shared encoder and language specific decoders.

### 6.2 Interlingual Representations

Though the network is not trained for many-to-many translation direction, it is still able to translate in all directions. In multilingual training, the encoder is shared by all the languages while each language has a separate decoder. The hidden vectors generated by the shared encoder is consumed by a language-specific decoder to generate the translation in that specific language. The network learns to translate between the non-English languages as well, though the network is not trained to do so. It may happen that the encoder generates an interlingual representation from which a language-specific decoder is able to generate the translation. To see if the encoded representations share any pattern, we project them using t-SNE\(^8\) (Maaten and Hinton, 2008) for some sentences in all the four languages. From the projection as shown in Figure 6.2, we see that there are well-formed clusters, each representing a sentence in four languages. It means that for a sentence, the shared encoder generates approximately the same hidden contexts for all the four languages.

### 7 Conclusion

In this paper, we propose a multilingual unsupervised NMT framework to jointly train multiple languages using a shared encoder and language-specific decoders. Our approach is based on denoising autoencoding of all languages and back-translating between English and non-English languages. Our approach shows consistent improvement over the baselines in all the translation directions with a maximum improvement of 1.48 BLEU points. We also observe that the network learns to translate between unseen language pairs. This is due to the ability of the shared encoder in our proposed network to generate language-independent representation. In future, we would like to explore other languages with diverse linguistic characteristics.

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A Sample Outputs

We present sample outputs, generated by bilingual and proposed multilingual models, in Table 3. We find that multilingual models are better at lexical selection (see the underlined words in Table 3). Table 4 shows sample outputs on news2013 for unseen language pairs.
Table 3: Sample outputs for bilingual and multilingual models on newstest2013 test set. We observe that the multilingual model is better at lexical selection. Underlined words are some examples of our observation.

| Source | Reference | Bilingual | Multilingual |
|--------|-----------|-----------|--------------|
| La préparation à gérer une classe dans un contexte nord-américain, québécois. Il va y avoir du changement dans la façon dont nous payons ces taxes. | Preparation to manage a class in a North-American and Quebec context. There is going to be a change in how we pay these taxes. | The build-up to manage a class in a Australian, Australian. There will be the change in the course of whom we owe these bills. | The preparation to handle a class in a Latin American context. There will be the change in the way we pay these taxes. |
| Auch diese Frage soll letztlich Aufschluss darüber geben, welche Voraussetzungen es für die Entstehung von Leben gibt. | This question should also provide information regarding the preconditions for the origins of life. | Him will continue to be accused of stealing unlawful information. | This question will ultimately give clues to how there is conditions for the emergence of life. |
| Los estudiantes, por su parte, aseguran que el curso es uno de los más interesantes. | Students, meanwhile, say the course is one of the most interesting around. | No doubt ever answering doubt it would never accept an argument an unknown person. | No doubt in answer that he would never accept a request of a unknown person. |
| Him werde weiterhin vorgeworfen, unerlaubt geheime Informationen weitergegeben zu haben. | He is still accused of passing on secret information without authorisation. | He does not hesitate to reply that he would never accept a request from an unknown person. | No duda en contestar que nunca aceptaría una solicitud de una persona desconocida. |

Table 4: Sample outputs for unseen language pairs on newstest2013 test set.

| Source | Reference | Multilingual |
|--------|-----------|--------------|
| Les dirigeants républicains justifièrent leur politique par la nécessité de lutter contre la fraude électorale. | Los dirigentes republicanos justificaron su política por la necesidad de luchar contra el fraude electoral. | Los dirigentes republicanos <OOV> su política por la necesidad de luchar contra la fraude electoral. |
| Chacun sait que son livre fait partie de cet édifice. | Jeder weiß, dass sein Buch Teil dieses Gebäudes ist. | Jeder weiß, dass sein Buch Teil seines Gebäudes machte. |
| Sus números a nivel de torneos internacionales son impresionantes. | Ces restrictions ne sont pas sans conséquences. | Ces restrictions ne sont pas sans conséquences. |
| Tomemos por caso la elección directa del presidente, que ha sido un logro de la presión pública. | Los inversiones en la materia superan los 1,5 billones de dólares. | Les investissements dans ce domaine dépassent les 1,5 milliards de dollars. |