Language-Independent Representor for Neural Machine Translation

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Abstract

Current Neural Machine Translation (NMT) employs a language-specific encoder to represent the source sentence and adopts a language-specific decoder to generate target translation. This language-dependent design leads to large-scale network parameters and makes the duality of the parallel data underutilized. To address the problem, we propose in this paper a language-independent representor to replace the encoder and decoder by using weight sharing. This shared representor can not only reduce large portion of network parameters, but also facilitate us to fully explore the language duality by jointly training source-to-target, target-to-source, left-to-right and right-to-left translations within a multi-task learning framework. Experiments show that our proposed framework can obtain significant improvements over conventional NMT models on resource-rich and low-resource translation tasks with only a quarter of parameters.

Introduction

End-to-end neural machine translation (NMT) has significantly improved the quality of machine translation in recent several years (Bahdanau, Cho, and Bengio 2015; Gehring et al. 2017; Vaswani et al. 2017). Although NMT has shown superior performance on public benchmarks (Bojar et al. 2017) and rapid adoption in deployments by, e.g., Baidu (Zhou et al. 2016), Google (Wu et al. 2016), and Microsoft (Hassan et al. 2018), it still faces many challenges (Koehn and Knowles 2017).

No matter which basic blocks we use, such as recurrence (Bahdanau, Cho, and Bengio 2015), convolution (Gehring et al. 2017), or self-attention (Vaswani et al. 2017), conventional NMT adopts language-specific encoder to transform the source language and utilizes a language-specific decoder to generate target translation token by token. It is clear that this language-dependent encoder-decoder framework has two problems. First, encoder and decoder have similar structures but contain separate parameters, resulting in the waste of enormous parameters. Second, one NMT model can only perform one unidirectional translation task using parallel corpora, which cannot take full advantage of language duality.

To address the issue of parameters scale, existing studies usually use weight pruning or knowledge distillation (See, Luong, and Manning 2016; Kim and Rush 2016) to compress NMT models. Press and Wolf (2017) conducted the weight tying of input and output embedding in RNN-based NMT. However, their researches are built under the language-dependent encoder-decoder framework which does not consider the language commonality. Being orthogonal to previous work, we are interested in exploiting language-independent model to reduce network parameters.

On the other hand, dual properties and agreement of translation have attracted much attention in NMT (Cheng et al. 2016a; Liu et al. 2016; Tu et al. 2017; Hassan et al. 2018). Cheng et al. (2016a) proposed agreement-based joint training for source-to-target and target-to-source translation directions. Besides, Liu et al. (2016) focused on the agreement between left-to-right and right-to-left on the target side to overcome the unbalanced output problem. Although these approaches have incorporated language duality into NMT, they all use language-specific encoders and decoders for each language and each direction separately. How to integrate multiple translation tasks into one model is still an open question.

In this work, we introduce a simple yet highly effective language-independent NMT framework by using weight sharing and multi-task learning. To reduce model parameters, we first present a language-independent representor by investigating the effectiveness of weight sharing in different hierarchies, including embeddings weight sharing, layer weight sharing and encoder-decoder sharing. With the ability of representing both source and target languages, the shared representor inspires us to make full use of the language duality by jointly training source-to-target, target-to-source, left-to-right, and right-to-left translations within a multi-task learning framework. We verify the effectiveness...
of this framework on resource-rich Chinese↔English and low-resource English↔Japanese translation tasks. Experimental results demonstrate that our model can leverage only a quarter of parameters to achieve substantial improvements over conventional NMT models.

Specifically, we make the following contributions in this paper:

- To the best of our knowledge, this is the first work to introduce a language-independent representor to replace encoder and decoder in conventional NMT by using weight sharing. Specifically, this framework achieves model compression from a very different perspective.
- Our model can perform and combine the advantage of four translation tasks in a representor by utilizing language duality, which contains source-to-target, target-to-source, left-to-right, and right-to-left translations.
- Our proposed framework drastically reduces model parameters and achieves significant improvements especially for low-resource translations, where our framework can be viewed as a data augmentation technique.

**Background**

Both RNN-based NMT (RNMT) (Luong, Pham, and Manning 2015) and Transformer (Vaswani et al. 2017) employ a language-dependent encoder-decoder structure, consisting of stacked encoder and decoder layers. The encoder maps an input sequence of symbol representations \( (x_1, ..., x_m) \) to a sequence of continuous representations \( z = (z_1, ..., z_m) \). Given \( z \), the decoder then generates an output sequence \( (y_1, ..., y_t) \) of symbols one element at a time. At each step the model is auto-regressive, consuming the previously generated symbols as additional input when generating the next.

Here, we mainly introduce the Transformer, as shown in Figure 2. Encoder layers consist of two sublayers: multi-head intra-attention followed by a position-wise feed-forward layer. Decoder layers consist of three sublayers: multi-head intra-attention followed multi-head inter-attention, and then followed by a position-wise feed-forward layer. It uses residual connections around each of the sublayers, followed by layer normalization. The decoder uses masking in its self-attention to preserve the auto-regressive property during training step.

Given a set of training examples \( \{(x^{(n)}, y^{(n)})\}_{n=1}^{N} \), the training algorithm aims to find the model parameters that maximize the likelihood of the training data:

\[
J(\theta) = \sum_{n=1}^{N} \log P(y^{(n)}|x^{(n)}; \theta)
\]

For the sake of brevity, we refer the reader to (Luong, Pham, and Manning 2015) and (Vaswani et al. 2017) for additional details regarding the architecture.

**Our Approach**

We introduce a simple language-independent NMT framework which can not only reduce the model parameters, but also take full advantage of language duality. The central idea is to achieve language-independent representor by weight sharing, and perform multiple translation tasks by multi-task learning, as shown in Figure 3(a).

**Language-Independent Representor**

Transformer and RNMT still employ language-dependent encode-decoder framework which leads to large-scale parameters. In this section, we will introduce a language-independent representor achieved by embedding weight sharing and encoder-decoder sharing, as shown in Figure 2.

**Embedding Weight Sharing (ES):** NMT model uses embeddings to convert input tokens and output tokens to vectors. It also utilizes the linear transformation and softmax function to convert the decoder output to next-token probabilities. Press and Wolf (2017) conducted the weight tying of input and output embedding in RNMT, whose results show that it can reduce the size of NMT models without harming their performance. However, they conducted the experiments on English-German and English-French parallel pairs which are similar languages and have shared source-target vocabulary. What if they are not similar languages, such as Chinese-English or Japanese-English translation?

To address the problem, we design a **frequency-based embedding weight sharing** strategy. The steps are as follows: (1) We first count the frequency of word occurrences in bilingual languages and sort them in descending order. (2) We select a vocabulary according to the predefined vocabulary size. For example, we limit the source and target vo-
Our proposed representor adopts one RNN (LSTM (Hochreiter and Schmidhuber 1997)) or GRU (Cho et al. 2014) to replace encoder and decoder.

Multi-Task Learning for Representor

In the last section, we present a language-independent representor which can reduce large portion of network parameters. With the ability of representing both source and target languages, the shared representor facilitates us to fully explore the language duality consisting of source-to-target, target-to-source, left-to-right and right-to-left translation. In this section, we attempt to conduct multiple translation tasks in the shared representor by leveraging multi-task learning framework.

Source-to-Target and Target-to-Source (S-T&T-S): Conventional NMT directly models the probability of a target-language sentence given a source-language sentence. Some work have noticed the symmetry of translation (Cheng et al. 2016b, He et al. 2016, Tu et al. 2017, Sennrich et al. 2017, Zhang et al. 2018), which bridge source-to-target and target-to-source translation. However, above approaches use two encoder-decoder models or additional reconstructor, in which encoder and decoder have separate parameters. Since the encoder and decoder in our model share a set of parameters where both encoder and decoder are capable of mapping source and target languages, a straightforward idea is to utilize the joint training of source-to-target and target-to-source in the language-independent representor.

Figure 3: Our proposed framework and two decoding methods. Our goal is to perform multiple translation tasks in a language-independent representor by utilizing language duality, as shown in (a) for Chinese-English translation. (b) denotes the mixed decoding which can combine the left-to-right decoding and right-to-left decoding in one beam-search process determined by model. Joint decoding (c) works as a reranking technique to select a better translation from the two k-best candidates generated by the decoder.
We introduce our new training objective as follows:

\[ J(\theta) = \sum_{n=1}^{N} \log P(y^{(n)}|x^{(n)}; \theta) + \sum_{n=1}^{N} \log P(x^{(n)}|y^{(n)}; \theta) \]  

where \( \theta \) is shared model parameters in a single representor. Note that the objective consists of two parts: source-to-target likelihood and target-to-source likelihood. In this way, our representor is able to translate both source-to-target and target-to-source.

**Left-to-Right and Right-to-Left (L-R&R-L):** The decoders of RNN, convolution, or self-attention based usually generate the target words from left to right. Many studies have pointed out the shortcoming of unidirectional decoding, and proposed some approaches to combine the advantage of left-to-right decoding and right-to-left decoding (Liu et al. 2016; Sennrich et al. 2017; Hassan et al. 2018). Our goal in this work is to find a way to combine the left-to-right and right-to-left decoding in one end-to-end model. Formally, the training can be written as the following equation:

\[ J(\theta) = \sum_{n=1}^{N} \log P(y^{(n)}|x^{(n)}; \theta) + \sum_{n=1}^{N} \log P(y^{(n)}|x^{(n)}; \theta) \]  

where \( P(y^{(n)}|x^{(n)}; \theta) \) denotes the sequence generation from left to right, and \( P(y^{(n)}|x^{(n)}; \theta) \) denotes the generation from right to left. All models consisting of an encoder, left-to-right decoder, and right-to-left decoder use a shared representor.

**Combining Four Patterns (CFP):** By integrating the above two train objectives, we present a simple yet highly effective multi-task learning approach that utilizes source-to-target, target-to-source, target left-to-right and target right-to-left translation in one representor to enhance the translation agreement. To this end, the training algorithm aims to maximize the likelihood of the training data:

\[ J(\theta) = \sum_{n=1}^{N} \log P(y^{(n)}|x^{(n)}; \theta) + \sum_{n=1}^{N} \log P(y^{(n)}|x^{(n)}; \theta) \]  

\[ + \sum_{n=1}^{N} \log P(x^{(n)}|y^{(n)}; \theta) + \sum_{n=1}^{N} \log P(x^{(n)}|y^{(n)}; \theta) \]  

where \( \theta \) is shared weight for all translation patterns. Here, our proposed model can conduct four translation tasks for one parallel corpora in a representor, while using half parameters compared to a standard end-to-end model.

**Training and Testing**

In order to train multiple translation tasks in a representor, we design a simple yet smart strategy to indicate the pre-defined translation direction. More specifically, we utilize two special labels \((s2t)\) and \((t2s)\) in the first word of input sentences to guide the translation tasks (source-to-target or target-to-source). Besides, we employ another two special labels \((l2r)\) and \((r2l)\) at the beginning of output sentences to indicate translating from left to right or from right to left. It is easy to use the stochastic gradient descent algorithm to implement duality-based joint learning since the single translation model in four directions uses the same training data and model parameters.

Once a model is trained, we can use a beam search to conduct mixed decoding simply. Alternatively, we introduce a joint decoding method for the proposed framework, as shown in Figure 3(b) and 3(c).

**Mixed Decoding (MD)**: The central idea of mixed decoding is to combine the left-to-right and right-to-left decoding in one beam-search process simultaneously. More specifically, the first input token of decoder is a \( (\text{pad}) \) whose embedding is all zeros for initialization. Instead of adding the label at the beginning of output sentences to guide translating from left to right or from right to left, we predict the first output token \((l2r)\) or \((r2l)\) determined by the model. And we do not need to do anything until the end-of-sentence flag is predicted. That is, our model has the ability to choose left-to-right or right-to-left decoding automatically according to the source representation.

**Joint Decoding (JD)**: Inspired by Liu et al. (2016) and Liu et al. (2017), we adapt a joint decoding method to find a translation that approximately maximizes the likelihood score. For Equation 4, the joint decoding consists of two steps: 1) run beam search for target left-to-right and right-to-left models independently to obtain two k-best lists; 2) rerank the union of two k-best lists using the joint model to get the best candidate.

**Experimental Settings**

**Dataset**

We evaluate our experiments on large-scale NIST Chinese↔English translation tasks, and low-resource KFTT English↔Japanese translation datasets.

For Chinese↔English translation, our training data consists of 2.08M sentence pairs extracted from LDC corpus.

We use NIST 2003 (MT03) dataset as the validation set, NIST 2004 (MT 04), NIST 2005 (MT05), NIST 2006 (MT06) datasets as our test sets. We use BPE (Sennrich, Haddow, and Birch 2016b) to encode Chinese and English respectively, and limit the source and target vocabularies to the most frequent 30K tokens.

For English↔Japanese translation tasks, we use KFTT datasets consisting of 440K sentence pairs, which also is used in (Arthur, Neubig, and Nakamura 2016). Sentences were encoded using BPE, and the vocabulary sizes are 31K and 33K for English and Japanese respectively.

**Training Details**

We use the tensor2tensor library for training and evaluating our Transformer model. Additionally, we utilize the OpenNMT\(^\text{\textcopyright}\) to train and test our RNMT model.

\(^1\)The corpora include LDC2000T50, LDC2002T01, LDC2002E18, LDC2003E07, LDC2003E14, LDC2003T17 and LDC2004T07.

\(^2\)http://isw3.naist.jp/philip-a/emnlp2016/

\(^3\)https://github.com/tensorflow/tensor2tensor

\(^4\)https://github.com/OpenNMT/OpenNMT-py
Table 1: Results of our proposed representor for Chinese-English translation. Although the number of model parameters is drastically reduced, their performance is comparable to baseline. ES and EDS mean embedding weight sharing and encoder-decoder sharing separately. “Transformer + ES + EDS”, namely our proposed representor, will be used in latter experiments. LS denotes layer weight sharing, and the last line shows the results that transformer has two layers encoder and decoder respectively. “‡”: significantly better than baseline (p < 0.05).

For our Transformer model, we employ the Adam optimizer with $\beta_1=0.9$, $\beta_2=0.98$, and $\epsilon=10^{-9}$. We use the same warmup and decay strategy for learning rate as [Vaswani et al. 2017], with 4,000 warmup steps. During training, we employ label smoothing of value $\epsilon_{ls}=0.1$. For evaluation, we use beam search with a beam size of $k=4$ and length penalty $\alpha=0.6$. Additionally, we use 6 encoder and decoder layers, hidden state size $d_e=1024$, 16 attention-heads, and 4096 feed forward inner-layer dimensions.

For RNMT, we use 4 encoder and decoder layers with LSTM. The word embedding dimension and the size of hidden layers are both set to 1,000. we use global attention [Luong, Pham, and Manning 2015] and beam search with beam size $k=12$ in RNMT. Parameter optimization is performed using Adam with the default configuration.

Results and Analysis

Below we discuss the results of our translation experiments about representor and multi-task learning framework, measuring translation quality with case-insensitive BLEU (Papineni et al. 2002).

Language-Independent Representor

We first analyze the effects of representor on both RNMT and Transformer. The results on Chinese-English translation are shown in Table 1. Experimental results demonstrate that our proposed frequency-based embedding weight sharing strategy obtains significant accuracy improvements on RNMT (39.73 vs. 38.92) and Transformer (47.19 vs. 46.74). We find that the weight sharing of encoder and decoder is more effective to Transformer (46.39 vs. 46.74) than RNMT (37.19 vs 38.92), where the number of Transformer parameters is sharply reduced, and their performance is comparable to baseline. Note that even though our proposed model (Transformer + ES + EDS) only uses 39.5% parameters of baseline model, their performance is comparable.

Furthermore, we also compare with the base Transformer model and two layers encoder-decoder Transformer model.

Table 2: Translation performance of Transformer and our proposed representor on English-Japanese. We also provide some experimental results of the first two models on the same data set.

whose results are reported in the last two lines of Table 1. The base Transformer reduces model parameters but decreases dramatically the translation quality. Our proposed weight sharing models outperform the two layer Transformer in terms of BLEU scores and model parameters. Considering the balance between model size and translation performance, we will use this kind of representor without LS (Transformer + ES + EDS) in subsequent experiments.

Table 2 shows the performance of representor on low-resource English-Japanese translation, which demonstrates that even though the weight sharing models contain fewer parameters than the baseline models, it gets an improvement of +1.75 BLEU points. Furthermore, we show that our representor can reduce the size of Transformer models to less than half of their original size while achieving significant improvement for low-resource translation.

Multi-Task Learning for Representor

In this section, we will report and analyze the results of multi-task learning framework, which conducts multiple translation tasks in a language-independent representor.

Results on Chinese↔English Our results of multi-task learning technique on large-scale Chinese↔English translation tasks are presented in Table 3. We find that our CFP model with joint decoding obtains the best results in Ch-En translation, and it outperforms standard Transformer by 1.34 BLEU points. Additionally, L-R&R-L model, getting an improvement of 1.02 BLEU points than Transformer, behaves heads, and 2048 feed forward inner-layer dimensions.

For base model, we use hidden state size $d_e=512$, 8 attention-
better than CFP model on En-Ch translation. Experiments
demonstrate that our single model can conduct source-to-
target and target-to-source translation by using less than a
quarter of parameters, while still achieving better perform-
ance on large-scale datasets.

Results on English$\leftrightarrow$Japanese Three kinds of task-level
weight sharing methods have achieved remarkable improve-
ments in low-resource translation, as demonstrated in Ta-
ble 3. Experiments show that our CFP framework combin-
ing four translation patterns outperforms the Transformer
by $+3.53$ and $+2.89$ BLEU points in bidirectional English-
Japanese translation separately. We think the main reason
is that our proposed framework can be regarded as a data aug-
mentation technique for low-resource translation.

Table 3: Experimental results of multi-task learning framework for four directions on two translation tasks. S-T&T-S and L-
R&R-L extend represnetor by introducing the new training objective Eq.(2) and Eq.(3) respectively. The CFP method means
the multi-task learning technique that utilizes a representer to training four translation directions shown in Eq.(4). The results
marked by † are significantly better than Transformer ($p < 0.01$), and “‡” denotes $p < 0.05$.

Effect of Large Decoding Space (Tu et al. 2017) ob-
erved that general likelihood objective favors short trans-
lations, and can not decode well in a large search space.
We present the effect of CFP model with mixed and joint
decoding on different beam sizes $k$, as shown in Figure 4.
Unlike Transformer, increasing the size of decoding space
leads to improving the BLEU scores for our joint decoding.
Although joint decoding is more complicated than mixed
decoding, it can capture dependency of four translation direc-
tions to select the best candidate.

| System       | Decoding Manner | Chinese$\leftrightarrow$English | English$\leftrightarrow$Japanese |
|--------------|-----------------|---------------------------------|--------------------------------|
|              |                 | Ch$\rightarrow$En | En$\rightarrow$Ch | En$\rightarrow$Ja | Ja$\rightarrow$En |
| Transformer  | Left-to-right   | 46.74 | 22.49 | 29.88 | 23.70 |
| Representer  | Left-to-right   | 46.71 | 21.74 | 31.63 | 25.61 |
| S-T&T-S      | Left-to-right   | 46.72 | 21.12 | 32.81 | 25.88 |
| L-R&R-L      | Mixed Decoding  | 47.41 | 23.51†| 32.84†| 25.55†|
| CFP Method   | Mixed Decoding  | 47.25 | 23.08†| 32.62†| 26.59†|
|              | Joint Decoding  | 48.08†| 23.47†| 33.41†| 26.19†|

Table 4: Translation proportion of L2R and R2L manners on Ch$\leftrightarrow$En and En$\leftrightarrow$Ja translation tasks.

| Direction | Chinese$\leftrightarrow$English | English$\leftrightarrow$Japanese |
|-----------|---------------------------------|--------------------------------|
|           | Ch$\rightarrow$En | En$\rightarrow$Ch | En$\rightarrow$Ja | Ja$\rightarrow$En |
| L2R       | 56.0% | 54.8% | 48.2% | 45.3% |
| R2L       | 44.0% | 45.2% | 51.8% | 54.7% |

Figure 4: Translation qualities (BLEU score) of our joint de-
coding, mixed decoding, and Transformer(L2R) on Chinese-
English translation as beam size become larger.

Figure 5: Length Analysis - performance of translations with
respect to the lengths of the source sentences. Table 5 gives a translation example of
different models. Transformer(L2R) drops out the second
### Related Work

Our work is inspired by three lines of research on improving NMT by:

**Model Compression and Multi-Task Learning** To reduce model parameters, weight pruning and knowledge distillation have been proposed to compress NMT models (See, Luong, and Manning 2016; Kim and Rush 2016). Additionally, a recent line of research has investigated multilingual machine translation by using multi-task learning (Ha, Niehues, and Waibel 2016; Pirat et al. 2016; Johnson et al. 2017). However, we achieve model compression from a very different perspective, even though this is not the main purpose. Besides, our model can also be adapted to these approaches because they are orthogonal to each other.

**Data Augmentation for NMT** For low-resource NMT, most of the existing approaches and models mainly focus on utilizing transfer learning (Zoph et al. 2016; Lakew, Gangi, and Federico 2017) or exploiting large-scale monolingual data (Cheng et al. 2016; Sennrich, Haddow, and Birch 2016a; Zhang and Zong 2016). Fadaee, Bisazza, and Monz (2017) proposed a data augmentation method that generates new sentence pairs by replacing high-frequency words with rare words. In this paper, our proposed framework can be viewed as a novel data augmentation technique that expands training corpora multiple times by data transformation for low-resource translation.

**Translation Duality for NMT** Some work have noticed the symmetry of translation (Cheng et al. 2016; He et al. 2016; Zhang et al. 2018), which attempt to bridge source-to-target translation and target-to-source translation. In the other hand, many studies have pointed out the shortcoming of unidirectional decoding, and proposed some approaches to combine the advantage of left-to-right decoding and right-to-left decoding (Liu et al. 2016; Sennrich et al. 2017; Hassan et al. 2018). However, above methods are designed for alternative translation agreement and use two different encoder-decoder models. We attempt at designing a unified framework to boost the duality of four translation directions by using one representor.

### Conclusions and Future Work

In this work, we propose a novel language-independent NMT framework in which a language-independent representor can perform multiple translation tasks by using weight sharing and multi-task learning. Our proposed framework can drastically reduce model parameters and take full advantage of language duality. Experiments on two resource-rich and low-resource translation tasks show that our framework can use only a quarter of parameters while achieving significant improvements over conventional NMT models. For future work, we plan to design explicit training constraints in the multi-task learning framework to further exploit the language duality. Additionally, it is interesting to extend this approach to monolingual data utilization and unsupervised neural machine translation.

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| Source | Reference | Transformer(L2R) | Transformer(R2L) | Mixed Decoding | Joint Decoding |
|--------|-----------|------------------|------------------|----------------|---------------|
| Source hengfu xiafang shi yi zhang shiduo pingsangmi de wangxuan jufu yixiang, tada zhe yanjing, miannu weixiao, qizhi ruway | Reference below the banner, there was a big picture of wang xuan that was more than ten square meters in size. wang was wearing a pair of glasses, smiling with a scholarly air. | below the scroll is a huge portrait of a 10-square-meter wang xuan. | he had a look on his face, wearing glasses, a smiling face and a refined air. | below the banner is a big portrait of more than 10 square meters, wearing glasses, smiling, and elegant. | below the banner is a huge portrait of wang xuan, which is more than 10 square meters long, he wears glasses, smiles, and is elegant. |

Table 5: Chinese-English translation examples of Transformer decoding in left-to-right and right-to-left ways, our proposed models using mixed decoding (MD) and joint decoding (JD) technique respectively.
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