On the Complementarity between Pre-Training and Back-Translation for Neural Machine Translation

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stract

Pre-training (PT) and back-translation (BT) are two simple and powerful methods to utilize monolingual data for improving the model performance of neural machine translation (NMT). This paper takes the first step to investigate the complementarity between PT and BT. We introduce two probing tasks for PT and BT respectively and find that PT mainly contributes to the encoder module while BT brings more benefits to the decoder. Experimental results show that PT and BT are nicely complementary to each other, establishing state-of-the-art performances on the WMT16 English-Romanian and English-Russian benchmarks. Through extensive analyses on sentence originality and word frequency, we also demonstrate that combining Tagged BT with PT is more helpful to their complementarity, leading to better translation quality. Source code is freely available at https://github.com/SunbowLiu/PTvsBT.

1 Introduction

Neural machine translation (NMT; Bahdanau et al., 2015; Gehring et al., 2017; Vaswani et al., 2017) models are data-hungry and their performances are highly dependent upon the quantity and quality of labeled data, which are expensive and scarce resources (Leong et al., 2021). This motivates the research line of exploiting unlabeled monolingual data for boosting the model performance of NMT. Due to simplicity and effectiveness, pre-training (PT; Devlin et al., 2019; Song et al., 2019) and back-translation (BT; Sennrich et al., 2016b) are two widely-used techniques for NMT, by leveraging a large amount of monolingual data.

While empirically successful, the understandings of PT and BT are still limited at best. Several attempts have been made to better understand them at the data level, e.g. exploring different kinds of noises for the source data (Edunov et al., 2018; Lewis et al., 2020). However, there are few understandings at the model level that how PT and BT affect the internal module (e.g. encoder and decoder) of NMT models. As recent studies start to combine PT and BT for better model performance (Conneau and Lample, 2019; Liu et al., 2020b; Ding et al., 2021c), there is a pressing need to broaden the understandings of them.

To this end, we introduce two probing tasks to investigate the effects of PT and BT on the encoder and decoder modules, respectively. We find that PT mainly contributes to the encoder module while BT brings more benefits to the decoder module. This provides a good explanation for the performance improvement of simply combining PT and BT. Motivated by this finding, we explore a better combination method by leveraging Tagged BT (Caswell et al., 2019). Experiments conducted on the WMT16 English-Romanian and English-Russian benchmarks show that PT can nicely co-work with BT, leading to state-of-the-art model performances. Extensive analyses show that the tagging mechanism is helpful for enhancing the complementarity between PT and BT by improving the translation of source-original sentences and low-frequency words.

Our main contributions are as follows:

• We design two probing tasks to investigate the impact of PT and BT on NMT models.
• We empirically demonstrate the complementarity between PT and BT.
• We show that Tagged BT further improves the complementarity between PT and BT.

2 Preliminaries

2.1 Background

Pre-Training for NMT Self-supervised PT (Devlin et al., 2019; Song et al., 2019), which can ac-
quire knowledge from unlabeled monolingual data, has shown its effectiveness in improving the model performance of NMT, especially for those language pairs with smaller parallel corpora (Conneau and Lample, 2019).

The first research line treats pre-trained models as external knowledge to guidance NMT to learn better representations (Yang et al., 2020a; Zhu et al., 2020) and predictions (Chen et al., 2020). These methods are effective but costly since the NMT architecture needed to be elaborately designed. Another research line is directly taking the weights of pre-trained models to initialize NMT models, which is easy to use and advancing the state-of-the-art (Rothe et al., 2020; Lewis et al., 2020).

In this paper, we treat pre-trained mBART (Liu et al., 2020b) as our testbed for parameter initialization, whose benefits have been sufficiently validated (Tran et al., 2020; Tang et al., 2020; Liu et al., 2021a) by multiple translation directions.

In general, previous studies focus on designing novel architectures (Song et al., 2019) and artificial noises for source sentences (Lin et al., 2020; Yang et al., 2020b) but are still unclear why pre-training can boost the model performance of NMT, which is this paper aims to investigate.

### Back-Translation for NMT
BT is an alternative to leverage monolingual data for NMT (Sennrich et al., 2016b). It first trains a reversed NMT model for translating target-side monolingual data into synthetic parallel data, and then complements them with the original parallel data to train the desired NMT model. To improve BT, previous works put attention to the importance of diversity and complexity in synthetic data, showing that adding symbols (e.g., noises and tags) to the back-translated source can help NMT distinguish the data from various sources and learn better representations (Fadaee and Monz, 2018; Wang et al., 2019; Edunov et al., 2018; Caswell et al., 2019; Marie et al., 2020). The claims and understandings from these works are chiefly at the data-level rather than the model-level.

There also exists some works that combine PT and BT to further boost the model performance (Conneau et al., 2020; Song et al., 2019; Liu et al., 2020b). However, the relation between BT and PT has not been fully studied. In this paper, we take the first step to understand BT and PT at the model-level and improve the complementarity between PT and BT.

### 2.2 Experimental Setup

#### Data
We conducted experiments on the WMT16 English-Romanian (En-Ro) and English-Russia (En-Ru) translation tasks, which are widely-used benchmarks of data augmentation methods for NMT. The training/validation/test sets of the En-Ro include 612K/2K/2K sentence pairs, while those of En-Ru include 2M/3K/3K pairs. Towards better reproducibility, we directly used the BT data provided by Sennrich et al. (2016a)¹, consisting of 2.3M synthetic data for the En-Ro and 2.0M data for the En-Ru. All the data are tokenized and split into sub-words (Sennrich et al., 2016c) by the mBART tokenizer (Liu et al., 2020b).

#### Setting
To make a fair comparison, all the model architectures and parameters are the same as the pre-trained mBART.cc25.² The NMT model augmented with PT directly uses the mBART weights for parameter initialization, while the other models randomly initialize their parameters. The training follows Liu et al. (2020b) except that we tuned the learning rate within [3e-5,1e-3] and the dropout within [0.3,0.5] for the vanilla model and BT models. We used the single model with the best validation perplexity for testing. The length penalty is 1.0 and the beam size is 5. We used sacreBLEU (Post, 2018) to calculate BLEU (Papineni et al., 2002) and TER (Snover et al., 2006) scores with the specific tokenization (Liu et al., 2020b) for Romanian and the default tokenization for Russian.

### 3 Understanding PT and BT

In this section, we aim to better understand the similarities and differences between PT and BT on improving model performance. We design two probing tasks to study the research question: Which module of NMT do PT and BT respectively play a greater role in enhancing translation quality?

#### 3.1 Effects of PT on NMT

Given a pre-trained model, it is common to use its part or all parameters to initialize the downstream tasks. We design four NMT models, which differ from the NMT components (Encoder vs. Decoder) with parameter initialization manners (Random vs. Pre-trained). As shown in Table 1, the variants

¹http://data.statmt.org/rsennrich/wmt16_backtranslations
²https://github.com/pytorch/fairseq/tree/master/examples/mbart
Table 1: The probing tasks of PT and BT. NMT models are trained and evaluated on the WMT16 En-Ro benchmark. “Y” denotes the corresponding parameters are activated when augmented with PT or BT, while “N” denotes the inactive operation. PT and BT respectively contribute more to the NMT encoder and decoder.

| Enc. | Dec. | PT     | BT     |
|------|------|--------|--------|
| N    | N    | 33.7   | 33.7   |
| N    | Y    | 33.5   | 37.8+4.1 |
| Y    | N    | 36.9+3.2 | 35.8+2.1 |
| Y    | Y    | 37.7+4.0 | 38.3+4.6 |

PT Mainly Contributes to Encoder As seen, the YY initialization strategy significantly improves the vanilla NMT model by +4.0 BLEU scores, which reconfirms the effectiveness of PT for translation tasks (Liu et al., 2020b). By comparing NY and YN, we find that the pre-trained encoder can still help the NMT to achieve +3.2 BLEU improvements while the pre-trained decoder can only perform on par with the vanilla model (i.e. -0.2 BLEU). This demonstrates that PT mainly contributes to the encoder part of NMT model, and this claim is consistent with the conclusion with other pre-trained models. For instance, Rothe et al. (2020) show that the NMT encoder initialization is superior to the decoder one when using pre-trained weights of BERT. We hypothesize that the performance boost with PT mainly comes from the better ability of source-side understanding, which is significant to NMT such as on disambiguating word senses (Tang et al., 2019).

3.2 Effects of BT on NMT

A vanilla NMT model is trained on the original bi-text and then fine-tuned on the mixture of the original and synthetic (i.e. back-translated) data. We also design four NMT models, which differ from which parts of parameters are updated at the fine-tuning stage. As shown in Table 1, the variants are: 1) NN is a vanilla NMT model only trained on the original data; 2) NY indicates that parameters of the NMT encoder are fixed while those of decoder are updated during model fine-tuning; 3) YN acts in an opposite way compared with NY; 4) YY means that the whole NMT parameters are updated at the fine-tuning stage.

BT Mainly Contributes to Decoder BT has been sufficiently validated to improve the performance of NMT models (Edunov et al., 2018, 2020). By exploiting additional target sentences, the NMT decoder can be enhanced to generate more fluent sentences in the target language. In contrast, the synthetic source sentences contain noises, which may be less useful for improving the ability of understanding. The results verify our hypothesis: BT mainly improves the decoder module of NMT. As seen, fine-tuning the whole NMT model (i.e. YY) with BT data can gain the best performance (+4.6 BLEU than the vanilla model), which shows the effectiveness of BT method. Surprisingly, only fine-tuning the decoder (i.e. NY) can perform close to YY model (37.8 vs. 38.3 BLEU), which confirms our claims. Compared with NY, the YN model obtains relatively fewer improvements (+4.1 vs. +2.1 BLEU), showing that BT brings more benefits to the decoder than the encoder.

4 Improving PT and BT

The answer of the research question in Section 3 is: PT and BT respectively contribute more to the NMT encoder and decoder, demonstrating that they are orthogonal and complementary to each other. This finding motivates us to better combine these two individual techniques together for further improving NMT models.

4.1 Experiments

As detailed in Section 2.2, we conducted experiments on two commonly-used benchmarks En-Ro and En-Ru. Besides, we train the BT models from scratch instead of fine-tuning in Section 3.2. As YY models (in Table 1) always achieve best performances when augmented PT or BT, we update all parameters of NMT models in next experiments.

The results are shown in Table 2. We use the vanilla model as our baselines, which are trained on original datasets with random initialization. Besides, we report results on existing PT models as our strong baselines, including XLM-R, mRASP,
Table 2: Translation quality on the En-Ro and En-Ru benchmarks. “+” means incorporating PT and (Tagged) BT into NMT models.

As seen, PT can significantly improve the translation quality in all cases compared with vanilla baselines (averagely +2.5 BLEU), which is consistent with (or better than) existing PT models (37.7 vs. 35.6–37.7 BLEU). Furthermore, two BT methods\(^3\) (i.e. BT and Tagged BT) perform closely, which improves the standard NMT models by +3.5/+3.7 BLEU points on average. Simply combining them (+BT+PT) can further boost performances for NMT models across different sizes of datasets, showing the robustness and effectiveness of this approach. Encouragingly, the combination of Tagged BT and PT performs better than the simple one, leading to state-of-the-art performances on the two benchmarks. Similar tendencies are observed in terms of the TER scores. The above results illustrate the better complementarity between PT and Tagged BT on improving translation quality for NMT models.

### 4.2 Analysis

We conducted extensive analyses to better understand the improvement of our approach. All results are reported on the En-Ro benchmark.

**Effects of Sentence Type**  Recent studies have shown that the evaluation of BT is sensitive to the sentences types, thus we report BLEU scores on the subsets of source-original (Src-Ori) and target-original (Tgt-Ori) datasets (Zhang and Toral, 2019; Liu et al., 2021a; Wang et al., 2021).\(^4\) Generally speaking, the translation of Src-Ori is more important than that of Tgt-Ori for practical NMT systems (Graham et al., 2020), thus its performance should be taken seriously. As shown in Table 3, PT performs better on Src-Ori than BT (33.8 vs. 31.9 BLEU) while BT achieves higher scores on Tgt-Ori than PT (45.6 vs. 42.0 BLEU). Besides, simply combining PT and BT improves the model performance, while adding tags to BT data further improves.

Table 3: Translation quality of source-original and target-original sentences on the En-Ro benchmark. “Src” and “Tgt” respectively denote the sub-testsets of source-original and target-original while “All” means the whole testset.

**Effects of Frequency**  We report F-measure of word translation according to frequency on the En-Ro benchmark. “Low” and “High” respectively denote the buckets of low- and high-frequency words while “All” means the whole words in the test set. Simply combining PT and BT improves the model performance, while adding tags to BT data further improves.

Table 4: F-measure of word translation according to frequency on the En-Ro benchmark. “Low” and “High” respectively denote the buckets of low- and high-frequency words while “All” means the whole words in the test set.

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\(^3\)Tagged BT is to add a special token at the beginning of each back-translated source sentence.

\(^4\)Src-Ori denotes the testing data originating in the source language, while Tgt-Ori denotes the data translating from the target language.
Effects of Word Frequency  Data augmentation is an effective way to improve the translation quality of low-frequency words (Sennrich et al., 2016b). Thus, we compare the performance of the models on translating different frequencies of words. Specifically, we employed compare-nt (Neubig et al., 2019) to calculate the f-measure of translating low- and high-frequency words (<50 vs. ≥50).

As shown in Table 4, PT improves more on translating low-frequency words (58.2 vs. 57.5 scores) while BT performs better on high-frequency words (67.3 vs. 66.7 scores). Furthermore, the combination of PT and tagged BT achieves the best performance on both low- and high-frequency words, leading to an overall improvement on the whole words. Similar phenomena can be observed by combining self-training and BT (Ding et al., 2021b).  Takeaway: 1) PT and BT complementary in terms of frequency of words; 2) Tagged BT are more complementary to PT on lexical translation.

5 Conclusion and Future Works

This paper broadens the understandings of pre-training (PT) and back-translation (BT). We propose two probing tasks to investigate the impact of PT and BT on each NMT module and find that PT is more beneficial to the encoder while BT mainly improves the decoder. Experimental results on the WMT16 English-Romanian and English-Russian benchmarks show that PT is nicely complementary to BT. We also demonstrate that Tagged BT (i.e., adding tags to BT data) can further improve the complementarity of translating source-original sentences and low-frequency words.

In the future, we would like to apply curriculum learning (Liu et al., 2020a; Zhan et al., 2021; Ding et al., 2021a) to better organize the learning of PT and BT. It is also worthwhile to explore other kinds of methods utilizing monolingual data (e.g., self-training (Zhang and Zong, 2016; He et al., 2020; Jiao et al., 2021)) and validate the findings on practical NMT systems (Huang et al., 2021) and more generation tasks (Liu et al., 2021b).

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