Revisiting Simple Domain Adaptation Methods in Unsupervised Neural Machine Translation

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Abstract

Domain adaptation has been well-studied in supervised neural machine translation (SNMT). However, it has not been well-studied for unsupervised neural machine translation (UNMT), although UNMT has recently achieved remarkable results in several domain-specific language pairs. Besides the domain inconsistence between parallel training data and test data for SNMT, there sometimes exists domain inconsistence between two monolingual training data for UNMT. In this work, we empirically categorize different domain adaptation scenarios for UNMT. Based on these scenarios, we revisit the effect of the existing representative domain adaptation methods including batch weighting and fine tuning methods in UNMT. Finally, we propose modified methods to improve the performances of domain-specific UNMT systems.

1 Introduction

Neural Machine Translations (NMT) have set several state-of-the-art new benchmarks (Bojar et al., 2018; Barrault et al., 2019). Recently, unsupervised NMT (UNMT) has attracted great interest in the machine translation community (Artetxe et al., 2018; Lample et al., 2018a; Yang et al., 2018; Lample et al., 2018b; Sun et al., 2019). Typically, UNMT relies solely on monolingual corpora in similar domain rather than bilingual parallel data for supervised NMT (SNMT) to model translations between the source language and target language and has achieved remarkable results on several translation tasks (Lample and Conneau, 2019).

The available training data is ever increasing; however, only the related-domain corpora, also called in-domain corpora, are able to improve the NMT performance (Koehn and Knowles, 2017). Additional unrelated corpora, also called out-of-domain corpora, are unable to improve or even harm the NMT performance for some domains such as TED talks and some tasks such as IWSLT (Wang et al., 2017b).

Domain adaptation methods have been well-studied in SNMT (Chu et al., 2017; Chen et al., 2017; Wang et al., 2017a; Wang et al., 2017b; van der Wees et al., 2017; Farajian et al., 2017; Chu and Wang, 2018) while they have not been well-studied in UNMT. For UNMT, in addition to inconsistent domains between training data and test data for SNMT, there also exist other inconsistent domains between monolingual training data in two languages. Actually, it is difficult for some language pairs to obtain enough source and target monolingual corpora from the same domain in the real-world scenario. In this paper, we first define and analyze several scenarios for UNMT with specific domain. On the basis of the characteristics of these scenarios, we revisit the existing domain adaptation methods including batch weighting and fine tuning methods in UNMT. Finally, we proposed modified domain adaptation methods to improve the performance of UNMT in these scenarios.

To the best of our knowledge, this paper is the first work to explore domain adaptation problem in UNMT.

2 UNMT Domain Adaptation Scenarios

In SNMT, all the corpora are parallel and the domains of source and target corpora are the same. Therefore, the domain adaptation technologies focus on the domain shift between the training and test
### Table 1: The statistics of monolingual training corpora for different scenarios.

| Scenarios                          | Abbreviation | $L_1$ in-domain | $L_2$ in-domain | $L_1$ out-of-domain | $L_2$ out-of-domain |
|------------------------------------|--------------|-----------------|-----------------|---------------------|---------------------|
| Monolingual corpora from same domains | II           | ✓               | ✓               | ×                   | ×                   |
|                                    | OO           | ×               | ×               | ✓                   | ✓                   |
|                                    | IIO          | ✓               | ✓               | ✓                   | ✓                   |
| Monolingual corpora from different domains | IOO          | ×               | ✓               | ✓                   | ✓                   |
|                                    | IIO          | ✓               | ✓               | ✓                   | ×                   |
|                                    | IO           | ✓               | ✓               | ×                   | ✓                   |

**Abbreviation**
- ✓: Having this monolingual corpus in one scenario;
- ×: Having no this monolingual corpus in one scenario.

**Monolingual corpora**
- from same domains: $L_1$ and $L_2$ have the same domain.
- from different domains: $L_1$ and $L_2$ have different domains.

In UNMT, there is only monolingual corpora and the domains of source and target corpora are sometimes different. Therefore, there are more scenarios of UNMT domain adaptation. Given two different languages $L_1$ and $L_2$, we define two main scenarios according to the domains of two languages in the training set: monolingual training corpora from the same domain, and monolingual training corpora from different domains, as shown in Table 1.

Take monolingual corpora from different domains as an example, we further divide this scenario into three sub-scenarios: IOO, IIO, and IO, where “I” denotes the in-domain data for one language and “O” denotes the out-of-domain data for one language. Further, IOO denotes there are resource-rich out-of-domain monolingual corpora for both languages and resource-poor in-domain monolingual corpora for language $L_2$. Especially, we regard “$L_2$ in-domain + $L_1$ out-of-domain” as the same scenario IO. Note that scenario II and OO were only as the baselines to evaluate other four scenarios. In this paper, we consider other four scenarios to improve translation performance.

### 3 Domain Adaptation Methods

According to our introduced scenarios, we revisited two simple domain adaptation methods, that is, batch weighting and fine tuning.

#### 3.1 Batch Weighting for UNMT

**Original:** The batch weighting method (Wang et al., 2017b) for SNMT is difficult to be directly transferred to the UNMT training because the training data of the source and target languages are sometimes unbalanced (such as the IO and IIO scenarios). Regardless of training cross-lingual language model or UNMT model, the model causes over-fitting in one language which includes the smaller amount of in-domain monolingual corpus. In other words, the large-scale out-of-domain monolingual corpus for other language is not fully utilized.

**Modified:** To address this issue, we propose a batch weighting method for UNMT domain adaptation to make full use of out-of-domain corpus to build a robust UNMT model when there exists only one large-scale out-of-domain monolingual corpus in one scenario. Specifically, we adjust the weight of out-of-domain sentences to increase the amount of out-of-domain sentences rather than to increase that of in-domain sentences (Wang et al., 2018) in every training batch. In our batch weighting method, the out-of-domain sentence ratio is estimated as

$$R_{out} = \frac{N_{out}}{N_{out} + N_{in}},$$

where $N_{in}$ is the number of mini-batches loaded from in-domain monolingual corpora in intervals of $N_{out}$ mini-batches loaded from out-of-domain monolingual corpora.

For the IO and IIO scenario, we apply the proposed batch weighting method to train cross-lingual language model and UNMT model in turn since the quantity of training data in two languages is quite...
different in the IO and IIO scenario. For IOO and IIOO scenario, there are two large-scale out-of-domain monolingual corpora and their quantity is similar. Therefore, batch weighting method is not so necessary for these scenarios.

3.2 Fine Tuning

**Original:** For the IIOO and IIO scenarios, we first train UNMT model on the corresponding corpora until convergence. Then we further fine tune parameters of the UNMT model on the resource-poor in-domain monolingual corpora for both languages. However, The original fine tuning method is difficult to directly transferred to the UNMT training under the IOO, IO scenarios since there only exist in-domain data for language \( L_2 \) under these scenarios as shown in Table 1.

**Modified:** We propose modified data selection method (Moore and Lewis, 2010; Axelrod et al., 2011) to select pseudo in-domain data from out-of-domain data for another language \( L_1 \). The traditional data selection for SNMT domain adaptation (Wang et al., 2017a; Wang et al., 2018) is not suitable for UNMT because in-domain language model could not be trained where does not exist in-domain corpus for language \( L_1 \).

To address this issue, we back-translate the language \( L_2 \) in-domain data to language \( L_1 \) pseudo in-domain data, using an UNMT baseline system. Then, we use these corpora to train a cross-lingual language model as the in-domain language model. For the IO scenario that just exists out-of-domain corpus for language \( L_1 \) as shown in Table 1, we randomly select language \( L_1 \) out-of-domain corpus that is similar in size to the language \( L_2 \) in-domain corpus and take the same approach to train a cross-lingual language model as the out-of-domain language model. For the IOO scenario that exist out-of-domain corpora for both languages, we randomly select out-of-domain corpora that are similar in size to the language \( L_2 \) in-domain corpus, respectively. Then we train a cross-lingual out-of-domain language model, using these corpora.

In practice, we adopt the data selection method (Moore and Lewis, 2010; Axelrod et al., 2011), and rank an out-of-domain sentence \( s \) using:

\[
CE_I(s) - CE_O(s),
\]

where \( CE_I(s) \) denotes the cross-entropy of the sentence \( s \) computed by the in-domain language model; \( CE_O(s) \) denotes cross-entropy of the sentence \( s \) computed by the out-of-domain language model. This measure biases towards sentences that are both like the in-domain corpus and unlike the out-of-domain corpus. Then we select the lowest-scoring sentences as the pseudo in-domain corpus.

Finally, we further fine tune parameters of the UNMT model on the resource-poor in-domain monolingual corpora for language \( L_2 \) and the pseudo in-domain corpus for language \( L_1 \) after we apply modified data selection method to achieve the pseudo in-domain corpus for language \( L_1 \).

| Scenarios | Batch weighting | Fine tuning |
|-----------|-----------------|-------------|
| IIOO      | -               | ✓           |
| IOO       | ✓               | ✓           |
| IIO       | ✓               | ✓           |
| IO        | ✓               | ✓           |

Table 2: The suitability of the proposed methods for different scenarios. ✓ denotes that the method is used in this scenario; – denotes that the method is not used in this scenario.

Overall, batch weighting method is used in the case that there is no out-of-domain monolingual corpus for one language, including scenario IIO and IO; fine tuning method is suitable to all our considered scenarios, including scenario IIOO, IOO, IIO, and IO, as shown in Table 2.
4 Experiments

4.1 Datasets

We considered two language pairs to do simulated experiments on the French (Fr)↔English (En) and German (De)↔En translation tasks. For out-of-domain corpora, we used 50M sentences from WMT monolingual news crawl datasets for each language. For in-domain corpora, we used 200k sentences from the IWSLT TED-talk based shuffled training corpora for each language. To make our experiments comparable with previous work (Wang et al., 2018), we reported results on IWSLT test2010 and test2011 for Fr↔En and IWSLT test2012 and test2013 for De↔En.

For preprocessing, we followed the same method of Lample et al. (2018b). That is, we used a shared vocabulary for both languages with 60k subword tokens based on BPE (Sennrich et al., 2016b). We used the same vocabulary including in-domain and out-of-domain corpora for different scenarios. If there exists only one in-domain monolingual corpus in one scenario, we chose Fr/De in-domain monolingual corpus; if there exists only one out-of-domain monolingual corpus in one scenario, we chose En out-of-domain monolingual corpus for uniform comparison.

4.2 Language Model and UNMT Settings

We used the XLM UNMT toolkit and followed settings of Lample and Conneau (2019). We first trained cross-lingual language model, and followed settings of Lample and Conneau (2019): 6 layers for the encoder. The dimension of hidden layers was set to 1024. The Adam optimizer (Kingma and Ba, 2015) was used to optimize the model parameters. The initial learning rate was 0.0001, $\beta_1 = 0.9$, and $\beta_2 = 0.98$. We trained a specific cross-lingual language model for each scenario, respectively. The cross-lingual language model was used to initialize the encoder and decoder of the whole UNMT model and select pseudo in-domain monolingual corpus.

The UNMT model included 6 layers for the encoder and the decoder. The other parameters were the same as that of language model. We used the case-sensitive 4-gram BLEU score computed by `multi-bleu.perl` script from Moses (Koehn et al., 2007) to evaluate the test sets. The baselines in different scenarios are the UNMT systems trained on the mixed monolingual corpora including in-domain and out-of-domain data in the corresponding scenarios.

4.3 Main Results

Table 3 shows the detailed BLEU scores of all UNMT systems on the De↔En and Fr↔En test sets. #1 and #2 are the BLEU scores of SNMT and #3-to-#12 are the BLEU scores of UNMT. Our observations are as follows:

1) The BLEU scores of baselines in the IIOO, IOO, IIO, and IO scenario were presented in the #5, #7, #9, and #11, respectively. The BLEU scores of UNMT systems after introducing our proposed methods in these scenarios were reported in the #6, #8, #10, and #12, respectively. Compared with original methods, our modified methods are beneficial for improving the performance of UNMT in the defined four scenarios.

2) In the scenario where monolingual training corpora are from same domains, such as IIOO, fine tuning method could further improve UNMT performance, achieving an average improvement of 4.8 BLEU scores on all test sets.

3) In the scenario where monolingual training corpora are from different domains (unique scenario for UNMT domain adaptation), our modified methods achieved average improvements of 4.4, 11.9, and 6.6 BLEU scores in the scenario IIO, IIO, and IO, respectively.

4) Our modified batch weighting method improved UNMT performance in the case that there is no out-of-domain monolingual corpora for one language such as scenario IIO and IO. Our modified fine tuning method could further improve translation performance in the case that there is no in-domain monolingual corpora for one language such as scenario IIO and IO.
Table 3: The BLEU scores in the different scenarios for En-De and En-Fr language pairs. Base denotes the baseline in the different scenarios; FT denotes fine tuning method; BW denotes batch weighting method. Original denotes the original method for SNMT; modified denotes our modified method for UNMT. #1 and #2 are the results of supervised NMT; others are the results of UNMT. \( N_{\text{in}} = 10 \), \( N_{\text{out}} = 1 \) in original batch weighting method, \( N_{\text{in}} = 1 \), \( N_{\text{out}} = 30 \) in modified batch weighting method, and selected pseudo in-domain corpus size is set to 20K for fine tuning method in scenario IO and IOO. Note that \( L_2 \) in-domain data and all \( L_1 \) out-of-domain data were used in original fine tuning method for scenario IOO.

5 Discussion

We now further analyze batch weighting and fine tuning methods and perform an ablation analysis in the unique scenarios for UNMT domain adaptation.

5.1 Batch Weighting Analysis

In Figure 1, we empirically investigated how the out-of-domain ratio \( R_{\text{out}} \) in Eq. (1) affects the UNMT performance on the En↔De task in the IO scenario. \( N_{\text{in}} \) was set to 1. The selection of \( N_{\text{out}} \) influences the weight of out-of-domain sentences every batch across the entire UNMT training process. Larger values of \( N_{\text{out}} \) enable more out-of-domain sentences utilized in the UNMT training. The smaller the value of \( N_{\text{out}} \) is, the more important are in-domain sentences. As the Figure 1 shows, \( N_{\text{out}} \) ranging from 10 to 100 all enhanced UNMT performance and a balanced \( N_{\text{out}} = 30 \) achieved the best performance.
batch weighting method \cite{Wang2018} used in NMT domain adaptation and our modified batch weighting method focused on UNMT domain adaptation. As shown in Table 4, +BW \cite{Wang2018} ($N_{in} = 10, N_{out} = 1$) achieved worse performance than the baseline. Our modified batch weighting method outperformed the baseline by 4.6~7.2 BLEU scores. This validates that the supervised domain adaptation method proposed by \cite{Wang2018} was not suitable for UNMT. Our modified batch weighting method could build a more robust UNMT model.

| Method    | De-En test2012 | De-En test2013 | En-De test2012 | En-De test2013 |
|-----------|----------------|----------------|----------------|----------------|
| Base      | 10.79          | 10.77          | 11.44          | 11.82          |
| +BW \cite{Wang2018} | 8.15           | 7.05           | 9.28           | 9.70           |
| +BW (our) | 17.78          | 18.00          | 16.01          | 16.60          |

Table 4: The results of two batch weighting methods in IO scenario on En-De language pairs.

In addition, we also investigated the training time cost between our batch weighting method and the baseline in the IO scenario. As shown in Figure 2 both our batch weighting method and the baseline take 30 hours during the whole training process on the IO scenario. The BLEU score of the baseline decreased rapidly after certain epochs due to over-fitting while our proposed batch weight method could continuously improve translation performance during training process. Over the course of training process, our proposed batch weight method performed significantly better than baseline. These demonstrate that our proposed batch weighting method is robust and effective.

![Figure 2: The learning curve between baseline and batch weighting model on the En↔De test2012 in IO scenario.](image)

**5.2 Fine Tuning Analysis**

As shown in Figure 3 we empirically investigated how the selected pseudo in-domain corpus size for fine tuning affects the performance of fine tuning UNMT on the En↔De task in the IO scenario. The larger corpus size brought more pseudo in-domain corpus participate in UNMT further training; the smaller corpus size made pseudo in-domain corpus more precise. Corpus size ranging from 5k to 10M all enhanced UNMT performance and UNMT model achieved the best performance when corpus size was set to 20K as shown in Figure 3. This indicates that our modified fine tuning method is robust and effective.

Moreover, we evaluated the different data selection criteria before fine tuning UNMT system on the En↔De task in IO scenario. CED outperformed CE by approximately 1 BLEU score as shown in Table 5. This demonstrates that pseudo in-domain corpus selected by CED is more precise for improving UNMT performance.

We also investigated the necessity of denoising auto-encoder during fine tuning process in the IIOO scenario on the En-De language pairs. As shown in Table 6 the fine tuning model with denoising
Figure 3: Effect of selected in-domain corpus size for the performance of fine tuning UNMT model on the En-De dataset in the IO scenario. Corpus size “0” indicates the result of the UNMT model only with batch weighting method.

Table 5: Different data selection criteria on the En-De language pairs in IO scenario. CED denotes cross entropy difference criterion $CE_I(s) - CE_O(s)$; CE denotes cross entropy criterion $CE_I(s)$. Pseudo in-domain corpus size is set to 20K.

| Method | De-En test2012 | En-De test2012 | De-En test2013 | En-De test2013 |
|--------|----------------|----------------|----------------|----------------|
| CED    | 19.76          | 18.32          | 20.22          | 18.99          |
| CE     | 18.53          | 17.19          | 18.87          | 17.81          |

Table 6: Denoising analysis on the En-De language pairs in IIOO scenario.

| Method            | De-En test2012 | En-De test2012 | De-En test2013 | En-De test2013 |
|-------------------|----------------|----------------|----------------|----------------|
| w/o denoising     | 29.80          | 26.39          | 30.99          | 27.84          |
| w/ denoising      | 29.82          | 26.48          | 31.57          | 28.18          |

5.3 Ablation Analysis

We performed an ablation analysis to understand the importance of our proposed methods in the IO and IIOO scenarios (unique scenarios for UNMT domain adaptation).

As shown in Table 7, we observed that both of +FT and +BW outperformed the Base in the IO scenario and +BW was more suitable for this scenario, achieving much more improvement in BLEU score. Moreover, +FT+BW can complement each other to further improve UNMT performance, achieving the best performance in the IO scenario.

As shown in Table 8, we observed that both of +FT and +BW outperformed the Base in the IIOO scenario. In particular, the +FT+BW was further better than both +FT and +BW. This means that our modified batch weighting and fine tuning methods can improve the performance of UNMT in this IIOO scenario, especially, both of them can complement each other to further improve translation performance.

6 Related Work

Recently, UNMT [Artetxe et al., 2018; Lample et al., 2018a; Yang et al., 2018], that has been trained via bilingual word embedding initialization, denoising auto-encoder, and back-translation and sharing
Table 7: Ablation analysis on the En↔De dataset in IO scenario. +BW denotes that a UNMT system was trained with batch weighting method; +FT denotes that fine tuning was applied to a UNMT baseline system; +FT+BW denotes that fine tuning was applied to a UNMT system trained with batch weighting.

| Method      | De-En test2012 | De-En test2013 | En-De test2012 | En-De test2013 |
|-------------|----------------|----------------|----------------|----------------|
| Base        | 10.79          | 10.77          | 11.44          | 11.82          |
| +FT         | 12.63          | 12.36          | 12.22          | 13.32          |
| +BW         | 17.78          | 18.00          | 16.01          | 16.60          |
| +FT+BW      | 19.76          | 20.22          | 18.32          | 18.99          |

Table 8: Ablation analysis on the En↔De dataset in IIO scenario.

| Method      | De-En test2012 | De-En test2013 | En-De test2012 | En-De test2013 |
|-------------|----------------|----------------|----------------|----------------|
| Base        | 11.11          | 10.30          | 11.54          | 11.95          |
| +BW         | 18.96          | 18.87          | 20.23          | 20.81          |
| +FT         | 19.78          | 20.70          | 17.24          | 18.02          |
| +FT+BW      | 26.12          | 27.33          | 22.63          | 23.72          |

latent representation mechanisms, has attracted great interest in the machine translation community. Lample et al. (2018b) achieved remarkable results on some similar language pairs by concatenating two bilingual corpora as one monolingual corpus and using monolingual embedding to initialize the embedding layer of UNMT. Wu et al. (2019) proposed an extract-edit approach, to extract and then edit real sentences from the target monolingual corpora instead of back-translation. Sun et al. (2019) proposed bilingual word embedding agreement mechanisms to improve UNMT performance. More recently, Lample and Conneau (2019) achieved state-of-the-art UNMT performance by introducing the pretrained cross-lingual language model. However, previous work only focuses on how to build state-of-the-art UNMT systems on specific domain and ignore the effect of UNMT on different domain. Research on domain adaptation for UNMT has been limited while domain adaptation methods have been well-studied in SNMT.

Chu and Wang (2018) gave a survey of domain adaptation techniques for SNMT. Domain adaptation for SNMT could be categorized into two main categories: data optimization and model optimization. Data optimization methods included synthetic parallel corpora generation using in-domain monolingual corpus (Sennrich et al., 2016a; Hu et al., 2019) and data selection for out-of-domain parallel corpora (Wang et al., 2017a; van der Wees et al., 2017; Zhang et al., 2019). Training objective optimization including instance weighting (Wang et al., 2017b; Chen et al., 2017) and fine tuning (Luong and Manning, 2015; Sennrich et al., 2016a; Freitag and Al-Onaizan, 2016; Servan et al., 2016; Chu et al., 2017), architecture optimization (Kobus et al., 2017; Britz et al., 2017; Gu et al., 2019) and decoding optimization (Freitag and Al-Onaizan, 2016; Khayrallah et al., 2017; Saunders et al., 2019) were common model optimization methods for domain adaptation.

7 Conclusion

In this paper, we mainly raise the issue of UNMT domain adaptation since domain adaptation methods for UNMT have never been proposed. We empirically show different scenarios for domain-specific UNMT. Based on these scenarios, we revisit the effect of the existing domain adaptation methods including batch weighting and fine tuning methods in UNMT. Experimental results show our modified corresponding methods improve the performance of UNMT in these scenarios. In the future, we will try to investigate other unsupervised domain adaptation methods to further improve domain-specific UNMT performance.
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