Zero-shot Domain Adaptation for Neural Machine Translation with Retrieved Phrase-level Prompts

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Abstract

Domain adaptation is an important challenge for neural machine translation. However, the traditional fine-tuning solution requires multiple extra training and yields a high cost. In this paper, we propose a non-tuning paradigm, resolving domain adaptation with a prompt-based method. Specifically, we construct a bilingual phrase-level database and retrieve relevant pairs from it as a prompt for the input sentences. By utilizing Retrieved Phrase-level Prompts (RePP), we effectively boost the translation quality. Experiments show that our method improves domain-specific machine translation for 6.2 BLEU scores and improves translation constraints for 11.5% accuracy without additional training.

1 Introduction

In the past years, neural machine translation (NMT) has shown its great power (Bahdanau et al., 2015; Vaswani et al., 2017). However, domain adaptation is still a challenge for NMT (Koehn and Knowles, 2017). The traditional solution is fine-tuning on domain-specific data. However, this requires multiple extra training. Every time we encounter a new domain, the tuning procedure needs to be conducted again. In this paper, we propose to resolve domain adaptation with a prompt-based method in a zero-shot style.

Prompt-based learning has been an attractive method for adapting pre-trained models to specific tasks in recent years. With handcrafted or automatically created prompts, pre-trained models can achieve good performance in many downstream tasks without fine-tuning (Schick and Schütze, 2020, 2021; Schick et al., 2020).

Among them, machine translation can also be potential (Brown et al., 2020; Garcia and Firat, 2022). With appropriate prompts, we can improve the translation results without traditional tuning in some data-scarce scenes such as domain adaptation. However, the construction of prompts can be difficult. Liu et al. (2021a); Sun et al. (2022) reveal that the performance of downstream tasks relies on the selection of in-context examples heavily. But it is hard to find relevant translation examples since sentences are very sparse.

In this work, we extract phrase-level bilingual prompts to tackle this problem since phrases are much denser than sentences. We build a bilingual phrase-level database which contains phrase pairs and corresponding contextual representation. In the inference stage, we retrieve input-relevant phrases from the database as a prompt. By appending the prompt to the source sentence, we try to improve the translation results.

In the end, we can influence the translation model positively and quickly. On the one hand, relevant prompts can bring in correct translation, especially in unseen domains. On the other hand, the prompt-based methods need no fine-tuning procedure, making the improvements fast and low-cost. Finally, our method can guarantee the data privacy for users since no corpus is exposed to the model except for filtered phrase pairs.

Experimental results show that our method outperforms the baseline for 6.2 BLEU scores on average in domain-specific machine translation and gains 11.5% accuracy boost in lexical constrained machine translation. It is worth noting that these improvements all come without any additional training.

2 Related Work

Prompt-based learning is a new paradigm of adapting pre-trained language models to specific tasks. Different from fine-tuning and feature-based adaptation (Devlin et al., 2019; Peters et al., 2018), prompt-based learning does not need additional training on downstream tasks. It formulates downstream tasks to language model slot filling tasks (Liu et al., 2021b) with prompts. Generally, in prompt-based learning, making predictions on
specific tasks with pre-trained language models contains 3 stages. (i) construct a prompt based on the input, which has some unfilled slots; (ii) fill the unfilled slots with pre-trained models; (iii) derive the final prediction from the filled slots.

The prompt formats depend on the pre-trained models and downstream tasks. There are two main categories of prompts (Liu et al., 2021b): cloze prompts where unfilled slots are pre-defined blanks, and prefix prompts where filling slots is continuing generation with the prefix. Cloze prompts are usually used in natural language understanding tasks (Schick and Schütze, 2020, 2021; Schick et al., 2020; Cui et al., 2021) while prefix prompts are mainly used in natural language generation tasks (Brown et al., 2020).

Our paper is also related to domain adaptation (Chu and Wang, 2018; Hu et al., 2019; Bapna and Firat, 2019), lexical constraint utilization (Dinu et al., 2019; Chen et al., 2021), pre-trained models for NMT (Sun et al., 2021), and memory-based methods (Cao and Xiong, 2018; He et al., 2021; Cai et al., 2021). Differently, we propose to use zero-shot prompt-based methods to tackle domain adaptation for neural machine translation.

3 Methodology

In this section, we first introduce how to construct the bilingual phrase database and how to retrieve the input-relevant prompts. Then we illustrate the prompt-aware co-training which makes the model acquire the ability to translate sentences with or without prompts. The overview of our method is shown in Figure 1.

3.1 Construction and Retrieval of Phrase-level Prompts

Bilingual phrase prompts: A bilingual phrase prompt is concatenated by a few bilingual phrases separated by <r>. Each bilingual phrase pair contains a source language phrase and the corresponding target language phrase translation separated by <q>, such as “based on <q> je nach”.

We hypothesize that input-relevant bilingual phrases provide useful knowledge for machine translation. For an input sentence, we retrieve the input-relevant bilingual phrases from a pre-built phrase database based on representation to construct a prompt.

Offline bilingual phrase database construction: We extract bilingual phrases from parallel translation data and compute the contextualized representations of the source language phrases with multilingual BERT (Devlin et al., 2019). The contextualized representation and the corresponding bilingual phrases constitutes a key-value pair. The phrase database is the dictionary of key-value pairs created from parallel translation data. It is worth noting that there may exist different phrase pairs that share the same source phrase due to the ambiguity (Sun et al., 2020b). They are distinguished by the contextual representation.

We extract bilingual phrases by first extracting word alignments with awesome-align (Dou and Neubig, 2021) and then extracting bilingual phrases from word alignments with the algorithm described in Koehn (2010). The contextualized representation of a phrase is computed by average-pooling on the hidden states of words in the phrase.
Table 1: Test set BLEU scores in domain adaptation for machine translation. Database size represents the number of bilingual phrases in the database. In domain-specific translation, RePP outperforms Vanilla for 6.7 and 5.6 BLEU scores on average in English $\rightarrow$ German and German $\rightarrow$ English directions without additional training.

Online input-relevant prompts retrieval: Figure 1 illustrates the process of constructing a prompt for an input sentence. We extract phrases in the input sentence and compute the contextualized representations of these phrases with multilingual BERT. Using the representation as the searching key, we retrieve the most similar bilingual phrases from the database based on the $L^2$ distance. At last, we concatenate the retrieved bilingual phrases to construct a bilingual phrase prompt.

3.2 Prompt-aware Training and Inference

Mixed training data: To keep the consistency between prompt-aware inference and translation training, it is crucial to involve prompt patterns in the training phase. But we also need to maintain the normal translation ability in the model. Therefore, we mix the original data (general domain) with handcrafted prompt-aware data in the training, as is shown in Figure 2. The idea of constructing prompt-aware data is similar to the inference. We retrieve some phrases in the general domain as a prompt and prepend it to the input sentence to yield a new training instance. It is worth noting that no in-domain data is involved so it is still zero-shot for domains.

Prompt-based prediction After co-training on the mixed data, the model can translate input sentences with or without prompts. Also, the prompts can be created either with automatic input-relevant prompt mining or handcrafting for translation intervention purpose. For example, we can provide bilingual phrases to manually construct a prompt to make a lexical constraint.

4 Experiments

4.1 Experimental Setup

We evaluate the proposed method in English $\rightarrow$ German and German $\rightarrow$ English translation directions. We train the models in general domain translation datasets. Then we evaluate the domain-specific translation performance without additional tuning. For prompt-based translation prediction, we mine input-relevant prompts automatically with in-domain phrase databases.

4.2 Baseline

We compare the proposed RePP with baseline — Vanilla, which is a vanilla Transformer (Vaswani et al., 2017) directly trained on the general domain datasets. The result of fully supervised fine-tuning is also listed for reference only.

4.3 Datasets

We take WMT14 EN-DE dataset as the general domain dataset for baseline and RePP training. We evaluate the domain-specific translation performance on 4 datasets proposed by Koehn and Knowles (2017) and re-splitted by Aharoni and Goldberg (2020). The training data in the specific domains is for prompt mining.

4.4 Implementation Details

We use joint Byte Pair Encoding (Sennrich et al., 2016) with 32k merge operations for subword segmentation. We employ the Transformer Base architecture (Vaswani et al., 2017; Sun et al., 2020a) for RePP and baseline training. We train all the models for ten epochs. The models are implemented based on Fairseq (Ott et al., 2019)\(^2\). For efficient bilingual phrase retrieval, we build an IVFPQ index with FAISS (Johnson et al., 2019)\(^3\).

\(^1\)https://github.com/roeeaharoni/unsupervised-domain-clusters
\(^2\)https://github.com/pytorch/fairseq
\(^3\)https://github.com/facebookresearch/faiss
Table 2: An English→German translation case with different bilingual phrase prompts. Bilingual phrase prompts enforce soft lexical constraints on the translation process.

|                                | Wiktionary | IATE         |
|--------------------------------|------------|--------------|
|                                | BLEU       | Accuracy     |
| Vanilla                        | 30.18      | 82.94        |
| RePP                           | 30.52      | 93.67        |

The results are shown in Table 3. RePP obtains 10.7% and 12.3% absolute lexically constrained translation accuracy improvements over Vanilla in Wiktionary and IATE respectively without additional training. The overall translation performance measured by BLEU scores is improved slightly. These experiments indicate that RePP can incorporate lexical constraint into the translation process effectively. It is also convenient for RePP to incorporate multiple lexical constraints by concatenating multiple bilingual phrases as prompts.

4.5 Results: Significant Improvements

The results of our experiments are shown in Table 1. RePP outperforms Vanilla for 6.7 and 5.6 BLEU scores in English → German and German → English translation without any additional training. The improvements indicate that incorporating in-domain bilingual phrase prompts can significantly help domain-specific machine translation.

Though RePP does not perform as well as fine-tuning, we want to highlight that it needs no extra training, making it a fast and low-cost way to adapt to unseen domains. Besides, RePP only needs one main model while fine-tuning has to maintain n models for n domains.

5 Analysis

5.1 Lexically Constrained Translation

Lexical constraints in machine translation can be naturally represented as bilingual phrase prompts. In other words, a specific phrase x in the input sentence should be translated to a target phrase y in the translation output.

We test the lexically constrained translation ability of Vanilla and RePP in English → German translation. We use the Wiktionary and IATE test sets created by Susanto et al. (2020) for evaluation, which are extracted with Wiktionary and the Interactive Terminology for Europe (IATE) terminology database respectively.

5.2 Case Study

Table 2 shows a case of an English → German translation in the Medical domain. RePP generates different translation outputs with different bilingual phrase prompts. We can explicitly interfere the translation results by revising prompts.

5.3 Bonus: Privacy Protection

RePP has one more benefit. Users do not want to leak their specific parallel data for fine-tuning in many cases. Protecting their privacy while improving the translation quality simultaneously needs elaborate design. Users with RePP only need to provide a self-built phrase prompts database and can keep the model ignorant with the target corpus.

6 Conclusion

In this paper, we propose RePP, a zero-shot method to quickly resolve domain adaptation. By automatically building bilingual phrase-level database and retrieving input-relevant prompts by contextual representation, we successfully improve the translation quality in unseen domains. Considering the cost, speed, and even privacy, RePP is an important alternative for zero-shot domain adaptation in neural machine translation.
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