Enhancing Cross-lingual Prompting with Mask Token Augmentation

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Abstract

Prompting¹ shows promising results in few-shot scenarios. However, its strength for multilingual/cross-lingual problems has not been fully exploited. Zhao and Schütze (2021) made initial explorations in this direction by presenting that cross-lingual prompting outperforms cross-lingual finetuning. In this paper, we conduct empirical analysis on the effect of each component in cross-lingual prompting and derive Universal Prompting across languages, which helps alleviate the discrepancies between source-language training and target-language inference. Based on this, we propose a mask token augmentation framework to further improve the performance of prompt-based cross-lingual transfer. Notably, for XNLI, our method achieves 46.54% with only 16 English training examples per class, significantly better than 34.99% of finetuning.

1 Introduction

Although adapting Pre-trained Language Models (PLMs) (Devlin et al., 2019) to downstream NLP tasks via finetuning is the de facto mainstream paradigm under fully supervised settings (Wang et al., 2018), prompting (Gao et al., 2021; Radford et al., 2019; Brown et al., 2020; Schick and Schütze, 2021a,b) has demonstrated its superiority to finetuning in low-resource scenarios, where the annotated training data is scarce or even not available. Typically, prompting reformulates the classification task as a language modeling problem over manually-designed natural language prompts.

Despite the effectiveness of prompting on English tasks, its potential for cross-lingual and multilingual problems, which assume the availability of the training data in high-resource languages (e.g., English) only, is still under-explored. Zhao and Schütze (2021) is the pioneering work to apply prompting to cross-lingual NLP. However, their major efforts are spent on comparing different training strategies for cross-lingual prompting, and how the key ingredients of prompting, namely prompt-design and inference strategies, affect the cross-lingual transfer is not discussed.

To provide a practical guide for cross-lingual prompting, we first conduct an empirical analysis to explore the effects of each prompting component on the performance of cross-lingual transfer. Surprisingly, in contrast to the complicated designs in Zhao and Schütze (2021), we find that neither template translation nor verbalizer translation for inference is necessary, and the template-free prompting coupled with English-only inference, dubbed as “Universal Prompting” in this paper, generally performs well across different few-shot settings.

In summary, our contributions are as follows:

• We develop a simple yet effective baseline called

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¹This work was done when Meng Zhou was an intern at Alibaba.
²In this work, we generally refer the term “prompting” to prompt-based finetuning, where parameters of PLMs are tuned.
Universal Prompting for cross-lingual prompting.

- Based on Universal Prompting, we further propose a mask token augmentation framework to enhance the performance of prompt-based cross-lingual transfer.

2 Pilot Experiments

In this section, we empirically investigate the significance of the key elements, including template and verbalizer design, in cross-lingual prompting (Zhao and Schütze, 2021). Note that, since soft prompting (SP) and mixed prompting (MP) rely on an external bidirectional LSTM (Hochreiter and Schmidhuber, 1997) to create soft prompts, we mainly investigate discrete prompting (DP) in this work for a clear and fair comparison.

2.1 Universal Prompting across Languages

Zhao and Schütze (2021) achieved prompt-based cross-lingual transfer by directly utilizing the translated prompting words and verbalizers for target-language inference. However, since the translated prompting words are not seen and the translated verbalizers are never modeled by the PLM during training on English, this may result in discrepancies between the source-language training and the target-language inference.

Starting from the above two aspects that result in such source-target discrepancies, we consider 3 possible variants with design choices different from Zhao and Schütze (2021) to alleviate the discrepancies to a certain degree. By combining these variations we end up with a Universal Prompting design, which can treat individual languages in a unified fashion. Table 1 summarizes these different design choices.

Table 1: Prompt templates and verbalizers in English (EN) and Turkish (TR). A and B indicate two sentences of a sentence pair. For XNLI, A is the premise and B is the hypothesis. With the proposed Universal Prompting, we could treat source-language training and target-language inference in a unified fashion.

| Shots | Method | Accuracy |
|-------|--------|----------|
| 16    | Zhao and Schütze (2021) w/o TEMPLATE TRANSLATION | 35.81±0.61 |
|       | Zhao and Schütze (2021) w/o VERBALIZER TRANSLATION | 39.15±0.73 |
|       | Zhao and Schütze (2021) w/o PROMPTING WORDS | 42.32±1.81 |
|       | Universal Prompting | 39.87±0.94 |
| 32    | Zhao and Schütze (2021) w/o TEMPLATE TRANSLATION | 41.42±0.66 |
|       | Zhao and Schütze (2021) w/o VERBALIZER TRANSLATION | 41.72±0.89 |
|       | Zhao and Schütze (2021) w/o PROMPTING WORDS | 46.50±1.54 |
|       | Universal Prompting | 43.66±0.96 |
| 64    | Zhao and Schütze (2021) w/o TEMPLATE TRANSLATION | 46.42±0.65 |
|       | Zhao and Schütze (2021) w/o VERBALIZER TRANSLATION | 46.70±0.91 |
|       | Zhao and Schütze (2021) w/o PROMPTING WORDS | 53.07±1.33 |
|       | Universal Prompting | 54.69±1.69 |

Table 2: The comparison results between Zhao and Schütze (2021) and its variants on XNLI. We calculate the average accuracy over 15 languages. The standard deviation over 5 runs is reported as the subscript.

2.2 Results

Our major experimental setup follows Zhao and Schütze (2021). Please refer to Section 4 for more details. In Table 2, we show that by alleviating discrepancies either in the aspect of verbalizer or template, we could further improve the performance of cross-lingual prompting\(^3\). The derived cross-lingual prompting solution, namely Universal Prompting (UP) across languages, alleviates the discrepancy of prompt templates and verbalizers simultaneously. This yields a much stronger baseline than Zhao and Schütze (2021) in multilingual tasks.

Zhao and Schütze (2021) w/o PROMPTING WORDS is similar to “null prompt” (IV et al., 2021). However, compared with “null prompt”, we mainly aim at alleviating source-target discrepancies in cross-lingual settings, while “null prompt” is proposed to simplify the manual prompt design. We also introduce target-language inference via the En-
English verbalizer, which has even larger impact than simply using a “null prompt” alone as shown in Table 2.

3 Mask Token Augmentation

In prompting methods, the mask token is directly used for inference. In this section, we formalize our augmentation approach for this crucial element of prompting. Our proposed augmentation framework extends the mask token at answer level and representation level simultaneously.

3.1 Answer Augmentation with Multilingual Verbalizers

The derived UP only considers the English verbalizer for source language training, and the translated verbalizers in target languages are not exploited. Intuitively, their rich semantics could serve as high-quality paraphrases (Jiang et al., 2021) of the English verbalizer and provide additional supervision for training multilingual models. Motivated by this, we define a multilingual verbalizer for the English training data, which can be regarded as answer augmentation for mask token. Formally, given the pre-built prompt $x$ filled with input sentences, the training objective is to maximize the likelihood of verbalized label tokens in multiple languages:

$$\arg\max_{\theta} \sum_{x} \frac{1}{|L|} \sum_{\ell \in L} \log P(\langle \text{mask} \rangle = V_\ell(y)|x; \theta)$$

(1)

where $\theta$ denotes parameters of the PLM. $V_\ell$ is the verbalizer in a certain language $\ell \in L$, and it maps from the gold label to a specific word in language $\ell$. In comparison, UP only takes $L = \{\text{EN}\}$, which is a monolingual verbalizer.

3.2 Mask Token Mixup

Previous mixup methods for NLP perform the interpolation at the input embedding level (Zhang and Vaidya, 2021), hidden representation level (Jindal et al., 2020; Chen et al., 2020) or the [CLS] token (Zhang and Vaidya, 2021). However, none of them is directly applicable under the prompting paradigm. A direct application has been shown to even lead to a significant performance drop in Zhou et al. (2021). In prompting-based methods, the most important hidden space representation for classification is encoded at the position of mask tokens. Different training data may have different sequence lengths and their mask tokens may be put at different positions. Previous practices of mixup will result in the interpolation between the representation of a mask token and a normal token, which is pointless in prompting methods. Therefore, we find that the most intuitive way is to apply the interpolation in the last transformer layer’s representations of mask tokens. Then the interpolated representation is fed into the masked language modeling head.

Formally, let $m_i = h(x_i)$ and $m_j = h(x_j)$ be the last transformer layer’s encoding of the mask tokens of two prompts $x_i$ and $x_j$, respectively. Then we perform linear interpolation to produce a virtual representation:

$$\hat{m}_{ij} = \lambda h(x_i) + (1 - \lambda)h(x_j)$$

(2)

where $\lambda \sim \beta(\alpha, \alpha)$. The corresponding answer labels are linearly interpolated correspondingly:

$$\hat{y}_{ij} = \lambda y_i + (1 - \lambda)y_j$$

(3)

Considering an augmented multilingual verbalizer as in Section 3.1, the training objective of this particular virtual example would be:

$$\arg\max_{\theta} \frac{1}{|L|} \sum_{\ell \in L} \left\{ \lambda \log P(\langle \text{mask} \rangle = V_\ell(y_i)|\hat{m}_{ij}; \theta) + (1 - \lambda) \log P(\langle \text{mask} \rangle = V_\ell(y_j)|\hat{m}_{ij}; \theta) \right\}$$

(4)

The interpolation is performed in a dynamic in-batch fashion. For a batch drawn from the training set, we use every two adjacent examples to generate a virtual mask token representation.

4 Experiments

In this section, we evaluate two multilingual tasks to demonstrate the effectiveness of our mask token augmentation approach.

4.1 Setup

Datasets We conduct experiments on two sentence-pair classification tasks: XNLI (Conneau et al., 2018; Williams et al., 2018) for cross-lingual natural language inference and PAWS-X (Yang et al., 2019) for multilingual paraphrase identification. For these two datasets, while the evaluation data is human-translated, the golden training data is only available in English.

Evaluation Following Zhao and Schütze (2021), we conduct our experiments by training the XLM-R base model (Conneau et al., 2020) on English. Then the model will be directly applied to other languages.
target languages, without using any training examples of the target language. To make a reasonable comparison between finetuning and prompting, we ensure finetuning to be better than a random guess on each language. Therefore, we randomly sample without replacement $K \in \{16, 32, 64, 128, 256\}$ per class for XNLI and $K \in \{250, 512\}$ per class for PAWS-X to construct the train set. Then we use the same number of shots from the development split to perform model selection to simulate a realistic few-shot setting (Perez et al., 2021).

The evaluation of few-shot cross-lingual transfer could be with large variance and depend on the selection of few shots (Zhang et al., 2021; Zhao et al., 2021; Keung et al., 2020). In our work, to faithfully reflect the performance of few-shot learning, we do not follow Zhao and Schütze (2021) to fix the training/data development but randomly sample separate training development sets for different runs.

### 4.2 Implementation Details

#### Implementation Package

Our implementation is based on PyTorch (Paszke et al., 2019) and Huggingface Transformer (Wolf et al., 2019) framework.

#### Model Details

XLM-R base model, containing 270M parameters, is pretrained on 2.5TB of filtered CommonCrawl on 100 languages. It contains 12 Transformer layers with hidden space dimensions of 768 and 12 attention heads in each layer.

#### Computing Infrastructure

All of our experiments are conducted on a single Tesla V100-SXM2 32G. Gradient accumulation steps of 4 is used for prompting to overcome resource limitations.

#### Hyperparameter Settings

Our major hyperparameter settings follow Zhao and Schütze (2021). A fixed learning rate $1e$-5 is used for all of our experiments without any learning rate schedule to compare finetuning with prompting (Le Scao and Rush, 2021). We use a smaller batch size of 8 for finetuning and prompting because it achieves slightly better performance. We use the max sequence length of 256. The model is trained for 50 epochs and we select the checkpoint by development.
Table 5: The multilingual verbalizer for PAWS-X.

| Language | Verbalizer |
|----------|------------|
| EN       | Paraphrase → yes  
|          | Non-paraphrase → no |
| DE       | Paraphrase → Ja  
|          | Non-paraphrase → Nein |
| ES       | Paraphrase → sí  
|          | Non-paraphrase → no |
| FR       | Paraphrase → Oui  
|          | Non-paraphrase → non |
| JA       | Paraphrase → はい  
|          | Non-paraphrase → ない |
| ZH       | Paraphrase → 是  
|          | Non-paraphrase → 否 |
| KO       | Paraphrase → ∥  
|          | Non-paraphrase → ᅡm ᅵ |

Table 6: Test accuracy by using different inference strategies. The accuracy is averaged by 15 testing languages of XNLI of 5 random seeds.

| Strategy Num | Accuracy |
|--------------|----------|
| 1            | 56.42_{1.37} |
| 2            | 56.31_{1.15} |
| 3            | 56.25_{1.09} |
| 4            | 56.35_{1.11} |
| 5            | 56.39_{1.21} |

Mask Token Augmentation With the proposed mask token augmentation framework, our prompting method achieves consistent improvement over UP, indicating that multilingual verbalizers as answer augmentation and mask token mixup as representation augmentation are two meaningful ways to enhance cross-lingual prompting. The comparison results in Table 3 and Table 4 also exhibit consistent superiority of our method over cross-lingual finetuning. Even in the most resource-rich settings, compared to FT, our method still obtains 7.1% (256 shots) and 4.9% (512 shots) absolute gains on XNLI and PAWS-X.

Ablation Study The performance of our prompting method will become worse when we remove mask token mixup or multilingual verbalizer, showing that both augmentation strategies contribute positively to the improvement. We also notice that the negative effects brought by OURS W/O MV are generally larger, showing that the guidance from multiple target languages is more helpful for cross-lingual prompting.

4.4 Inference Strategy
A natural extension for our method is to leverage the multilingual verbalizer in some way for target-language inference as well. For comparisons, we heuristically devise the following inference strategies:

(1) English Verbalizer The English verbalizer is still used when transferring to target languages. This strategy is used to produce results in Table 3 and 4. To formalize:

\[ \hat{y} = \arg \max_y P(\langle \text{mask} \rangle = V_{EN}(y) \mid x; \theta) \quad (5) \]

(2) Target Language Verbalizer The verbalizer in the corresponding target language is used, which is the practice of Zhao and Schütze (2021). To

scenarios and our UP can serve as a strong baseline of cross-lingual prompting.
formalize:

\[ \hat{y} = \arg \max_y P(\langle \text{mask} \rangle = V_{\text{target}}(y) | x; \theta) \] (6)

(3) Taking Maximum over the Multilingual Verbalizer In this strategy, we will take the maximum probability over the whole multilingual verbalizer. To formalize:

\[ \hat{y} = \arg \max_y \sum_{\ell \in \mathcal{L}} P(\langle \text{mask} \rangle = V_{\ell}(y) | x; \theta) \] (7)

(4) Taking Sum over the Multilingual Verbalizer In this strategy, we will take the sum of probability over the whole multilingual verbalizer. To formalize:

\[ \hat{y} = \arg \max_y \sum_{\ell \in \mathcal{L}} P(\langle \text{mask} \rangle = V_{\ell}(y) | x; \theta) \] (8)

(5) Bilingual Verbalizer In this strategy, we will take the sum of probability over the target language verbalizer and the English verbalizer. To formalize, the predicted label \( \hat{y} \) is given by:

\[ \hat{y} = \arg \max_y \{ P(\langle \text{mask} \rangle = V_{\text{EN}}(y) | x; \theta) \]

\[ + P(\langle \text{mask} \rangle = V_{\text{target}}(y) | x; \theta) \} \] (9)

We use the checkpoint of XLM-R trained by 128 shots on the XNLI dataset and make inference with different strategies. Table 6 shows the accuracy by employing different inference strategies. We show that with our mask token augmentation framework, the inference is quite robust to the utilization of the verbalizer. This can probably be attributed to answer augmentation via multilingual verbalizers, which help to model label tokens in multiple languages. We choose to simply employ English-only inference due to its simplicity and slightly better performance to produce results in Tables 3 and 4.

5 Conclusion

In this paper, we first derive Universal Prompting, a simple but effective baseline for cross-lingual prompting. The proposed mask token augmentation framework can further enhance cross-lingual prompting as shown on two sentence-pair classification tasks. In the future, we will consider verifying the effectiveness of prompting and the proposed augmentation framework in cross-lingual sequence tagging or text generation tasks.

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