Eliciting Knowledge from Pretrained Language Models for Prototypical Prompt Verbalizer

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Abstract
Recent advances on prompt-tuning cast few-shot classification tasks as a masked language modeling problem. By wrapping input into a template and using a verbalizer which constructs a mapping between label space and label word space, prompt-tuning can achieve excellent results in zero-shot and few-shot scenarios. However, typical prompt-tuning needs a manually designed verbalizer which requires domain expertise and human efforts. And the insufficient label space may introduce considerable bias into the results. In this paper, we focus on eliciting knowledge from pretrained language models and propose a prototypical prompt verbalizer for prompt-tuning. Labels are represented by prototypical embeddings in the feature space rather than by discrete words. The distances between the embedding at the masked position of input and prototypical embeddings are used as classification criterion. For zero-shot settings, knowledge is elicited from pretrained language models by a manually designed template to form initial prototypical embeddings. For few-shot settings, models are tuned to learn meaningful and interpretable prototypical embeddings. Our method optimizes models by contrastive learning. Extensive experimental results on several many-class text classification datasets with low-resource settings demonstrate the effectiveness of our approach compared with other verbalizer construction methods. Our implementation is available at https://github.com/Ydongd/prototypical-prompt-verbalizer.

1 Introduction
In recent years, pretrained language models (PLMs) have shown excellent performance for language understanding and language generation in NLP tasks. By pretraining on large-scale corpora, models with rich semantics and knowledge can significantly benefit downstream tasks [Roberts et al., 2020]. Due to the magnitude and potential of PLMs, it has become a topical issue how to motivate PLMs and appropriately elicit knowledge from them for downstream tasks.

The most widely used method for downstream tasks is fine-tuning [Devlin et al., 2018]. By adding a classifier on the top of PLMs, fine-tuning has achieved remarkable results on supervised tasks compared with traditional methods. For an example, in the task of text classification, after taking the embedding of [CLS] token and applying a classifier upon it, fine-tuning can easily obtain corresponding label for an input [Howard and Ruder, 2018]. However, since the parameters of the classifier in fine-tuning are randomly initialized, it needs sufficient labeled data for training, thus fine-tuning is hard to obtain satisfactory results in scenarios with little labeled data and will hinder the transfer of knowledge in PLMs to downstream tasks.

To alleviate this issue, prompt-tuning, a new paradigm for using PLMs, has been proposed for low-resource works to narrow the gap between pretraining tasks and downstream tasks [Schick and Schütze, 2020]. The main idea of prompt-tuning is to transform a downstream task into a cloze question, which is consistent with the pretraining process of PLMs. Take text classification for an example, the input sentence is wrapped into a task-specific template, e.g.,“[Category: [MASK]] [SENTENCE]”, where

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Figure 1: Prototypical embeddings and [MASK] embeddings on DBPedia processed by prototypical prompt verbalizer and visualized after dimension reduction by t-SNE.
is filled with the input sentence and [MASK] is served as the set of predicted words. After constructing a verbalizer, a mapping between label space and label word space, the predicted words from [MASK] can be easily transformed into corresponding labels. Since the verbalizer directly determines the effectiveness of classification, how to construct a verbalizer becomes a very important issue in prompt-tuning.

The traditional verbalizer construction method uses a word corresponding to a label to construct an one-to-one mapping [Schick and Schütze, 2020], which requires domain expertise and human efforts to determine which word to choose to represent a label because incorrect mapping may lead to extremely significant bias. To mitigate the drawbacks of manually designed verbalizer, some works propose to search for the best label word for a label by gradient descent [Schick et al., 2020]. But these approaches still construct an one-to-one mapping verbalizer, which can’t summarize the semantics of a label well and makes the coverage of a label vulnerable. To expand the coverage of label words for a specific label, one-to-many mapping verbalizers which select related words from multiple large knowledge bases have been proposed [Hu et al., 2021]. Such an approach can greatly enhance the semantics of labels, but due to the excessive number of related words obtained from knowledge bases, related words of different labels may overlap, and deciding which related words are suitable for a certain task also requires domain expertise and human efforts.

To eliminate the impact of discrete words, soft verbalizers have been proposed [Hambardzumyan et al., 2021; Zhang et al., 2021]. Soft verbalizers treat labels as trainable tokens and the optimization objective is set to a cross entropy loss between output of masked language model and the label tokens. Label tokens can be considered as label embeddings to some extent. Such methods are difficult to form highly representational and meaningful label embeddings, and are also hard to apply in zero-shot and few-shot scenarios because both label embeddings and classifiers are randomly initialized, which is also known as a Cold Start problem.

In this paper, we propose prototypical prompt verbalizer to address the above issues. By using prototypical networks, we generate prototypical embeddings for different labels in the feature space to summarize the semantic information of labels. With respect to the classification criterion, we compute distances between the embedding of the input’s [MASK] token and prototypical embeddings in the feature space, then select the label corresponding to embedding with the highest similarity as the label of input. To overcome the difficulties of application in scenarios with few labeled training samples when training from scratch, we use the word corresponding to each label in the instruction document and a small number of sentences containing this word in the unlabeled corpus to form initial prototypical embeddings by a manual template. Note that although we also use some of the label words here, we do not need to do operations such as filtering and expansion, we only use the label words to tackle the Cold Start problem, not to select the final label. Even though there is a lot of noise in the selected sentences containing specific words, the semantics of labels can still be extracted to some extent. Based on contrastive learning, we devise three different objective functions to optimize the models. Results on DBPedia after dimension reduction are shown in Figure 1. In summary, the main contributions of our work are:

- We design a method which can generate prototypical embeddings for labels as semantic representations in the feature space and use contrastive learning at instance-instance and instance-label level to learn meaningful and interpretable prototypical embeddings.
- For zero-shot scenario, to tackle Cold Start problem, we use some unlabeled sentences containing specific words to generate initial prototypical embeddings.
- The results of extensive experiments on three many-class text classification datasets with low-resource settings demonstrate the effectiveness of our approach.

2 Related Work

2.1 Prompt-tuning

Since there exists a huge gap between pretraining tasks and downstream tasks, some works introduce a new method named prompt-tuning to overcome it. GPT-3 [Brown et al., 2020] shows that large-scale language models with prompt-tuning can achieve excellent performance in low-data environments. The work [Schick and Schütze, 2020] shows that prompt-tuning can also perform superiorly in small-scale language models [Devlin et al., 2018; Liu et al., 2019]. While most of current works about prompt-tuning is in text classification tasks, some works have applied it to information extraction tasks [Cui et al., 2021; Han et al., 2021; Si et al., 2021] and text generation tasks [Li and Liang, 2021].

2.2 Verbalizer Construction

In prompt-tuning, there are two key factors: template and verbalizer. When in low-resource settings, how to construct a good verbalizer becomes an essential factor in improving the efficiency of prompt-tuning. Current verbalizers are divided into two main categories: word-based verbalizers [Schick and Schütze, 2020; Schick et al., 2020; Hu et al., 2021] and embedding-based verbalizers [Hambardzumyan et al., 2021; Zhang et al., 2021]. The former may lead to weak label coverage and insufficient semantics for labels. And the construction of such verbalizers may require domain expertise and human efforts. While the latter have a Cold Start problem and it is a challenging issue to form meaningful and interpretable label embeddings with current methods.

2.3 Contrastive Learning

Contrastive learning [Hadsell et al., 2006] aims to learn similar representations for positive instances and different representations for negative instances, and is widely used for self-supervised representation learning mainly in domain of computer vision [Wu et al., 2018]. As for natural language processing, some well-known works also apply the idea of contrastive learning, such as Word2Vec [Mikolov et al., 2013] and BERT [Devlin et al., 2018]. In NLP tasks, contrastive learning is usually used for generating high-quality text representations based on the construction of positive and negative samples [Gao et al., 2021].
Figure 2: Overview of our method. The right side shows the pretraining process, where the model knowledge is elicited through a manual template combined with a specific word. The left side is the training process. Both pretraining and training process are trained with contrastive objective function.

2.4 Prototypical Networks

In few-shot classification tasks, a classifier often needs to generate label representations with insufficient instances. To address this issue, some works [Snell et al., 2017; Ji et al., 2020] have proposed to use prototypical networks to learn representations for labels in the feature space. In contrast to traditional approaches, prototypical networks can learn a metric space where classification can be performed by computing distances from the input representation to prototypical representations of labels. The approach introduces a semantic generalization of labels, which can achieve excellent results with limited data. Some works have applied prototypical networks to other domains, such as information extraction [Ding et al., 2021b].

3 Method

In this section, we present our method to construct prototypical prompt verbalizer. A key motivation behind this is that, eliciting knowledge from pretrained language models and using it to generate prototypical embeddings for labels. Firstly, we describe general paradigm of prompt tuning. Secondly, we elaborate our prototypical prompt verbalizer in detail. Finally, we introduce the different settings in zero-shot and few-shot scenarios.

3.1 Overview

General Prompt-tuning

Formally, denote $\mathcal{M}$, $\mathcal{T}$ and $\mathcal{V}$ as pretrained language model, template function and verbalizer function, respectively. Given an input $x$, template function $\mathcal{T}$ inserts pieces of texts into $x$ to convert it into the corresponding input of $\mathcal{M}$ which has a [MASK] token in it, i.e., $x_{\text{prompt}} = \mathcal{T}(x)$. Let $V$ be the label words set, $Y$ be the label set. $\mathcal{V}: Y \rightarrow V$ is a mapping from label space to label word space, $\mathcal{V}(y)$ represents label words corresponding to label $y$. Then for input $x$, the probability of label $y$ is

$$P(y|x) = \sigma(P_{\mathcal{M}}([\text{MASK}] = v|v \in \mathcal{V}(y)))$$  \hspace{1cm} (1)

where $\sigma(\cdot)$ determines which aggregation function to be used for labels with several different label words, such as max or average.

With prompt-tuning, a classification problem can be transferred into a masked language modeling problem by filling the [MASK] token in the input.

In order to include more semantic information for different labels, we propose prototypical prompt verbalizer based on contrastive learning to extend the scope of prompt-tuning.

Prototypical Prompt Verbalizer

In prototypical prompt verbalizer, instead of directly predicting the corresponding label words from [MASK] token, we first generate prototypical embeddings which capture the main semantic information of labels, then for each input, we compute similarity between the embedding of [MASK] token and prototypical embeddings and finally select the label corresponding to the most similar prototypical embedding as the classification result.

Given an input $x$, we first convert it into a template-based input with a [MASK] token: $x_{\text{prompt}} = \mathcal{T}(x)$, then we feed $x_{\text{prompt}}$ into pretrained language model $\mathcal{M}$ and obtain the last layer’s hidden state of output $h = \mathcal{M}(x_{\text{prompt}})$. We take the embedding of the [MASK] token $h_{[\text{MASK}]} \in \mathbb{R}^M$ as the initial embedding for this input.

For each initial embedding, in order to give it a more compact semantic representation, we use a transforming function $f: \mathbb{R}^M \rightarrow \mathbb{R}^D$ to map it to a new feature space:

$$f(h_{[\text{MASK}]}) = u$$  \hspace{1cm} (2)

For each label $y \in Y$, we generate a prototypical embedding $p \in \mathbb{R}^D$ in the feature space to abstract the essential semantics of $y$. Transforming function and prototypical embeddings are trained from scratch.
We use cosine similarity \( d : \mathbb{R}^D \times \mathbb{R}^D \rightarrow [-1, 1] \) to measure the similarity between transformed embeddings as \( s(u_i, u_j) \) and between a transformed embedding and a prototypical embedding as \( s(p, u) \):

\[
s(u_i, u_j) = \frac{u_i \cdot u_j}{\|u_i\| \|u_j\|}, \quad s(p, u) = \frac{p \cdot u}{\|p\| \|u\|}
\]

(3)

A batch is defined as \( \mathcal{B} = \{u_0, u_1, \ldots, u_n\} \), \( u_i \) is the transformed embedding of the \( i \)-th input \( x_i \). |\( \mathcal{B} | = N \). In each batch, our intuition is to make individual embeddings and prototypical embeddings have meaningful and interpretable representations in the feature space. For this purpose, we define three contrastive objective functions.

The first objective function aims to keep embeddings of the same kind close to each other and embeddings of different kinds away from each other. Inspired by [Soares et al., 2019] and [Ding et al., 2021b], we define it as:

\[
L_s = -\frac{1}{N^2} \sum_{i,j} \log \frac{\Theta(i, j)}{\sum_{j'} \pi(j') \exp(s(u_i, u_j'))} + \log \exp(s(u_i, u_j))
\]

(4)

where \( \Theta(i, j) = \exp(\varphi(i, j) s(u_i, u_j)), \varphi(i, j) \) is an indicator function to indicate whether \( u_i \) and \( u_j \) having the same label, i.e., given two embeddings \( u_i \) and \( u_j \), if these two embeddings have the same label, then \( \varphi(i, j) = 1 \), otherwise 0. \( \pi(i) \) denotes the label of \( u_i \).

The second and third objective functions are used for learning prototypical embeddings of the labels. The second objective function makes an embedding close to the prototypical embedding to which it belongs and away from other prototypical embeddings. While the third objective function keeps a prototypical embedding in \( \mathcal{B} \) away from other embeddings which have different labels from it.

\[
L_{p_1} = -\frac{1}{N} \sum_i \log \frac{\exp(p_{\pi(i)}, u_i)}{\sum_k \exp(u_i, p_k)}
\]

(5)

\[
L_{p_2} = -\frac{1}{N} \sum_i \log \frac{\exp(p_{\pi(i)}, u_i)}{\sum_{j \neq \pi(i)} \exp(p_{\pi(i)}, u_j)}
\]

(6)

Finally, combining the above three objective functions with hyperparameters \( \lambda_1, \lambda_2, \lambda_3 \), the full objective function is computed as:

\[
L = \lambda_1 L_s + \lambda_2 L_{p_1} + \lambda_3 L_{p_2}
\]

(7)

Given an input \( x \), \( u \) is the corresponding embedding for \( x \), then the probability for label \( y \) is:

\[
p(y|x) = \frac{\exp(s(u, p_y))}{\sum_k \exp(s(u, p_k))}
\]

(8)

Our method is shown in Figure 2, we will detail the use of our method in zero-shot and few-shot scenarios with pretraining and training process in following sections.

### 3.2 zero-shot settings

In zero-shot learning settings, it is challenging to initialize prototypical embeddings for labels. Since pretrained language model \( \mathcal{M} \) is trained on large-scale corpora and contains a lot of rich semantic information, we use a manually designed template to elicit knowledge from \( \mathcal{M} \) to form initial prototypical embeddings for labels.

For a specific label \( y \), we use its corresponding literal word \( v \) in the instruction document and sample a small amount of unlabeled sentences \( \mathcal{Q} = \{q_1, q_2, \ldots, q_Q\} \) containing the word \( v \) from the training set with labels removed. Given a specific word \( v \) and a sentence \( q_i \), we wrap them into a template \( \mathcal{T}_v:”[\text{SENTENCE}]” \). In this sentence, \([\text{WORD}]\) means [\text{MASK}]. where \( q_i \) is for [\text{SENTENCE}] blank and \( v \) is for [\text{WORD}] blank.

Then we take the embedding of [\text{MASK}] token in the last layer’s hidden state of \( \mathcal{M}(\mathcal{T}_v(q_i)) \) acting as initial prototypical embedding for \( y \) to perform the optimizing process described in the previous section. In this way, the initial prototypical embeddings can be obtained and we name this process pretraining in our method. Randomly sampled sentences may be very noisy due to different meanings of a specific word, however, the probability of a specific word with different meanings appearing in one sampling process is relatively small, and to the purpose of simplicity, we do not prune them.

### 3.3 few-shot settings

In few-shot learning settings, \( \mathcal{T}_D \) is the set of templates for dataset \( D \). For \( \mathcal{T}_i \in \mathcal{T}_D \), we simply wrap input into \( \mathcal{T}_i \) and take the embedding of [\text{MASK}] token in the last layer of \( \mathcal{M} \)’s output to form prototypical embeddings as mentioned above. We name this process training in our method.

### 4 Experiments

In this section, we conduct experiments on three many-class text classification datasets to empirically demonstrate the effectiveness of our prototypical prompt verbalizer.

#### 4.1 datasets

We evaluate our proposed method on three widely-used topic classification datasets: AG’s News, Yahoo Answers [Zhang et al., 2015] and DBPedia [Lehmann et al., 2015]. Statistics of these datasets are shown in Table 1.

| Dataset       | # Class | Test Size |
|---------------|---------|-----------|
| AG’s News     | 4       | 7600      |
| Yahoo Answers | 10      | 60000     |
| DBPedia       | 14      | 70000     |

Table 1: Statistics for AG’s News, Yahoo Answers and DBPedia

Due to the rich semantics and the high adaptability to different datasets, manual templates have an advantage over automatically generated templates in zero-shot and few-shot scenarios. To alleviate the bias in the results caused by different templates, we use four manual templates for each datasets as in [Schick and Schütze, 2020] and [Hu et al., 2021].

#### 4.2 Baselines

In this subsection, we introduce the baselines we use to demonstrate the effectiveness of our approach, including fine-tuning, general prompt-tuning and soft prompt verbalizer. We compare the baselines with our prototypical prompt verbalizer in both pretraining and without pretraining cases.
4.3 Implementation Details

In zero-shot scenario, models evaluate on the entire test set without training on the labeled training data and we cut sentences from unlabeled corpus by nlkt [Bird et al., 2009]. While in few-shot scenario, we carry out 1, 5, 10 and 20-shot experiments. For a k-shot experiment, We randomly select instances of each class from the training set as the new training set and test the model on the entire test set.

When pretraining prototypical prompt verbalizer, we sample 60 sentences for AG’s News, 40 sentences for Yahoo Answers, 30 sentences for DBPedia.

For all experiments, we use RoBERTa large [Liu et al., 2019] as pretrained language model and use Micro-F1 as test metrics. For fine-tuning, prompt-tuning and prototypical prompt verbalizer, we use our own framework. For soft prompt verbalizer, we use OpenPrompt framework [Ding et al., 2021a]. We select AdamW with the learning rate of 3e−5 for optimization. The size of transformed embedding is set to 256 and the max sequence length is set to 512. We train the model for 10 epochs with the batchsize setting to 8 in each experiment.

4.4 Results and analysis

Experimental results

In this subsection, We detail the results of our method and perform an insightful analysis. Experimental results are shown in Table 2.

In zero-shot scenario, since the randomly sampled sentences used for pretraining are noisy, which leads to unex-

| k | Method | AG’s News | Yahoo Answers | DBPedia |
|---|---|---|---|---|
| 0 | FT | 71.84 ± 5.82 (80.36) | 50.68 ± 10.43 (59.90) | 65.10 ± 4.43 (71.10) |
| 0 | PPV w/ p (avg) | 67.12 ± 9.07 (77.00) | 51.84 ± 11.41 (59.93) | 78.86 ± 3.41 (83.14) |
| 0 | PPV w/ p (max) | 72.14 ± 6.61 (77.00) | 53.85 ± 7.91 (59.93) | 80.65 ± 2.05 (83.14) |
| 1 | FT | 38.38 ± 5.79 (45.23) | 16.50 ± 3.09 (20.80) | 30.67 ± 2.38 (33.56) |
| 1 | PT | 77.69 ± 8.16 (85.72) | 57.77 ± 3.39 (62.19) | 93.97 ± 1.18 (95.96) |
| 5 | SPV | 35.82 ± 6.82 (47.00) | 20.83 ± 3.43 (25.68) | 64.77 ± 11.17 (76.67) |
| 5 | PPV w/ p | 74.29 ± 5.52 (80.27) | 57.79 ± 1.54 (60.16) | 94.21 ± 0.50 (94.96) |
| 5 | PPV w/o p | 57.10 ± 6.34 (70.85) | 24.21 ± 3.23 (28.84) | 61.06 ± 4.47 (70.99) |
| 10 | FT | 62.56 ± 16.02 (75.03) | 56.09 ± 0.41 (56.65) | 94.48 ± 0.87 (95.68) |
| 10 | PT | 83.76 ± 2.08 (86.88) | 61.61 ± 1.94 (65.70) | 95.90 ± 0.77 (96.85) |
| 20 | SPV | 75.81 ± 7.51 (68.96) | 46.67 ± 8.37 (57.61) | 84.74 ± 2.04 (97.49) |
| 20 | PPV w/ p | 81.49 ± 1.59 (83.52) | 63.06 ± 1.55 (65.28) | 96.54 ± 0.41 (97.22) |
| 20 | PPV w/o p | 79.00 ± 5.13 (84.03) | 56.95 ± 5.48 (63.77) | 95.46 ± 1.00 (96.95) |

Table 2: Micro-F1 and standard deviation on AG’s News, Yahoo Answers and DBPedia in zero and few-shot scenarios. The best Micro-F1 scores are shown in the brackets. The best results among all methods for the same k-shot experiment are marked in bold. FT represents fine-tuning. PT represents prompt-tuning. PPV represents soft prompt verbalizer. PPV w/ p and w/o p are whether to apply pretraining process for prototypical prompt verbalizer respectively. We conduct experiments on three different random seeds for four different templates. In zero-shot scenario, the average results of all random seeds and the best results of one random seed are shown as avg and max respectively.
obtains fine results. However, due to the numerous parameters will make it hard to train. Soft prompt verbalizer, trained model and the feature space, where limited trainable parameters will make it hard to train. After pretraining, prototypical prompt verbalizer basically forms prototypical embeddings and the mapping, so it obtains fine results. However, due to the numerous parameters of mask language head, prompt-tuning will achieve better results when the size of training set increases.

Effect of objective function
To illustrate the effectiveness of our objective function, we conduct experiments with different combination of losses. As shown in Table 4, $\mathcal{L}_{p_1}$ and $\mathcal{L}_{p_2}$ are used to form prototypical embeddings while $\mathcal{L}_s$ allows embeddings with identical labels to be aggregated and embeddings with different labels to be dispersed in the feature space.

Pretraining on other data sources
To explore whether the pretraining process works on other data sources as well, we conduct experiments with unlabeled training set and a small part of Wikidata as shown in Table 5, and it is notable that DBPedia is also derived from Wikidata. The results illustrate that pretraining is also valid on other data sources. And no matter what data source is used, fluctuations can be significant due to the large noise in the pretraining process.

4.5 Conclusion
In this paper, we propose prototypical prompt verbalizer to enhance the semantic scope of labels by forming prototypical embeddings and construct a mapping from output of pretrained language models to the feature space. To obtain meaningful and interpretable embeddings, we optimize models with contrastive objective functions. In order to solve the problem of poor results caused by parameter initialization in zero-shot and some few-shot scenarios, we propose to conduct pretraining on a small amount of unlabeled training set. The experiments show the effectiveness and potential of our method. However, the existence of large noise in randomly sampled sentences may seriously affect the pretraining results, and we will mitigate this issue in the future with denoising or self-supervision measures.
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