Prompt-Learning for Fine-Grained Entity Typing

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Abstract

As an effective approach to adapting pre-trained language models (PLMs) for specific tasks, prompt-learning has recently attracted much attention from researchers. By using *cloze*-style language prompts to stimulate the versatile knowledge of PLMs, prompt-learning can achieve promising results on a series of NLP tasks, such as natural language inference, sentiment classification, and knowledge probing. In this work, we investigate the application of prompt-learning on fine-grained entity typing in fully supervised, few-shot and zero-shot scenarios. We first develop a simple and effective prompt-learning pipeline by constructing entity-oriented verbalizers and templates and conducting masked language modeling. Further, to tackle the zero-shot regime, we propose a self-supervised strategy that carries out distribution-level optimization in prompt-learning to automatically summarize the information of entity types. Extensive experiments on four fine-grained entity typing benchmarks under fully supervised, few-shot, and zero-shot settings show the effectiveness of the prompt-learning paradigm and further make a powerful alternative to vanilla fine-tuning.

1 Introduction

In recent years, pre-trained language models (PLMs) have been widely explored and become a key instrument for natural language understanding (Devlin et al., 2019a; Liu et al., 2019) and generation (Radford et al., 2018; Raffel et al., 2020). By applying self-supervised learning on large-scale unlabeled corpora, PLMs can capture rich lexical (Jawahar et al., 2019), syntactic (Hewitt and Manning, 2019; Wang et al., 2021a), and factual knowledge (Petroni et al., 2019) that well benefits downstream NLP tasks. Considering the versatile knowledge contained in PLMs, many efforts of researchers have been devoted to stimulating task-specific knowledge in PLMs and adapting such knowledge to downstream NLP tasks. And fine-tuning with extra classifiers has been one typical solution for adapting PLMs to specific tasks in NLP tasks (Qiu et al., 2020; Han et al., 2021a).

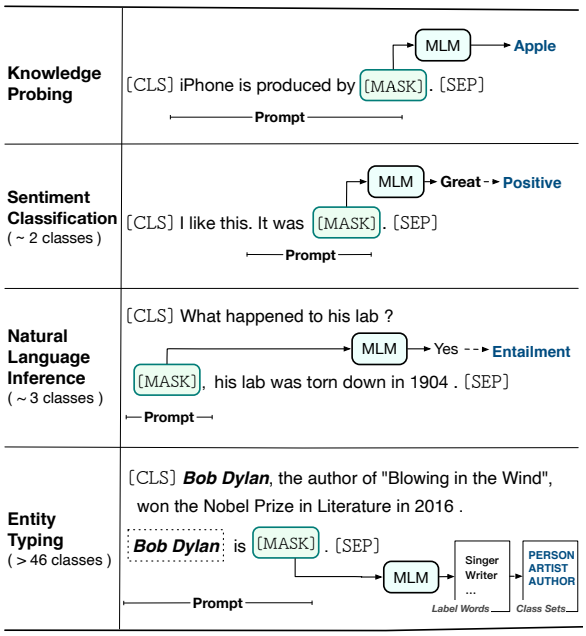

Figure 1: Examples of prompt-learning to stimulate the knowledge of PLMs by formalizing specific tasks as equivalent *cloze*-style tasks.

Some recent efforts on probing knowledge of PLMs show that, by writing some natural language prompts, we can induce PLMs to complete factual knowledge (Petroni et al., 2019). GPT-3 further utilizes the information provided by prompts to conduct few-shot learning and achieves awesome results (Brown et al., 2020). Inspired by this, prompt-learning has been introduced. As shown in Figure 1, in prompt-learning, downstream tasks are formalized as equivalent *cloze*-style tasks, and PLMs are asked to handle these tasks instead of original downstream tasks. Compared with vanilla fine-

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tuning methods, prompt-learning does not require extra neural layers and intuitively bridges the objective form gap between pre-training and fine-tuning. Sufficient empirical analysis shows that, either for manually picking hand-crafted prompts (Liu et al., 2021; Han et al., 2021b) or automatically building auto-generated prompts (Gao et al., 2020; Lester et al., 2021), taking prompts for tuning models is surprisingly effective for the knowledge stimulation and model adaptation of PLMs.

Intuitively, prompt-learning is applicable to fine-grained entity typing, which aims at classifying marked entities from input sequences into specific types in a pre-defined label set. We discuss this topic with a motivating example, "*He is from New York*". By adding a prompt with a masking token [MASK], the sentence becomes "*He is from New York. In this sentence, New York is* [MASK]". Due to the wealth of knowledge acquired during pre-training, PLMs can compute a probability distribution over the vocabulary at the masked position, and a relatively higher probability with the word "city" than the word "person". In other words, with simple prompts, the abstract entity attributes contained in PLMs can be efficiently exploited, which is meaningful for downstream entity-related tasks.

We comprehensively explore the application of prompt-learning to fine-grained entity typing in fully supervised, few-shot and zero-shot settings. Particularly, we first introduce a naive pipeline, where we construct entity-oriented prompts and formalize fine-grained entity typing as a *cloze*-style task. This simple pipeline yields promising results in our experiments, especially when supervision is insufficient. It is worth noting that few-shot and zero-shot fine-grained entity typing is Then, to tackle the zero-shot scenario where no explicit supervision exists in training, we develop a self-supervised strategy under our prompt-learning pipeline. Our self-supervised strategy attempts to automatically summarize entity types by optimizing the similarity of the predicted probability distributions of paired examples in prompt-learning.

Four popular benchmarks are used for our experiments, including FEW-NERD (Ding et al., 2021c), OntoNotes (Weischedel et al., 2013), BBN (Weischedel and Brunstein, 2005), and Open Entity (Choi et al., 2018a). All these datasets have a complex type hierarchy consisting of rich entity types, requiring models to have good capabilities of entity attribute detection. Empirically, our method yields significant improvements on these benchmark datasets, especially under the zero-shot and few-shot settings. We also make an analysis and point out both the superiority and bottleneck of prompt-learning in fine-grained entity typing, which may advance further efforts to extract entity attributes using PLMs[1].

2 Related Work

After a series of effective PLMs like GPT (Radford et al., 2018) and BERT (Devlin et al., 2019a), fine-tuned PLMs have demonstrated their effectiveness on various important NLP tasks (Baldini Soares et al., 2019; Peng et al., 2020; Ding et al., 2021b).

Despite the success of fine-tuning PLMs, the huge objective form gap between pre-training and fine-tuning still hinders the full use of per-trained knowledge for downstream tasks (Liu et al., 2021; Han et al., 2021b; Hu et al., 2021). To this end, prompt-learning has been proposed. The seminal work that stimulates the development of prompt-learning is the birth of GPT-3 (Brown et al., 2020), which uses hand-crafted prompts for tuning and achieves impressive performance on various tasks. A series of hand-crafted prompts have been widely explored in knowledge probing (Petroni et al., 2019; Davison et al., 2019), relation classification (Han et al., 2021b), sentiment classification and natural language inference (Schick and Schütze, 2021; Liu et al., 2021). To avoid labor-intensive prompt design, automatic prompt search has also been extensively explored Schick et al. (2020); Schick and Schütze (2021); Shin et al. (2020); Gao et al. (2020) to generate language phrases for prompts. Recently, some continuous prompts have also been proposed (Li and Liang, 2021; Lester et al., 2021), which directly use a series of learnable continuous embeddings as prompts rather than discrete language phrases.

This paper aims to stimulate PLMs with prompt-learning to capture the attribute information of entities. We take fine-grained entity typing, a crucial task in knowledge extraction to assign entity types to entity mentions (Lin et al., 2012), as the foothold to develop prompt-learning strategies. In fact, Dai et al. (2021) use hypernym extraction patterns to enhance the context and apply masked language modeling to tackle the ultra-fine entity typing problem (Choi et al., 2018b) with free-form

[1]Our source code is released at https://github.com/thunlp/PromptTyping, it is also integrated to the OpenPrompt repository.

labels, which shares a similar intuition with prompt-learning. In our work, we mainly emphasize using prompt-learning to extract entity types that have been pre-defined in low-data scenarios.

3 Background

In this section, we first give a problem definition of the entity typing task (§ 3.1), followed by an introduction of conventional vanilla fine-tuning and prompt-based tuning (§ 3.2) with PLMs.

3.1 Problem Definition

The input of entity typing is a dataset $\mathcal{D} = \{x_1, ..., x_n\}$ with n sentences, and each sentence x contains a marked entity mention m. For each input sentence x, entity typing aims at predicting the entity type $y \in \mathcal{Y}$ of its marked mention m, where $\mathcal{Y}$ is a pre-defined set of entity types. Entity typing is typically regarded as a context-aware classification task.

In the vanilla fine-tuning paradigm of entity typing, the input is structured as a concatenation of original sequence and the entity mention $\{x, m, \texttt{[SEP]}\}$, where $x = \{\texttt{[CLS]}, t_1, \ldots, m, \ldots, t_T, \texttt{[SEP]}\}$ is the original sequence and $m = \{t_i, \ldots, t_j\}$ is the marked entity mention. Empirically, the embedding of the `[CLS]` token produced by PLM, $\mathbf{h}_{\texttt{[CLS]}}$, is fed into an output layer to predict the probability distribution over the label space

$$P(y \in \mathcal{Y}|s) = \texttt{softmax}(\mathbf{W}\mathbf{h}_{\texttt{[CLS]}} + \mathbf{b}), \quad (1)$$

where $\mathbf{W}$ and $\mathbf{b}$ are learnable parameters. $\mathbf{W}$, $\mathbf{b}$ and all parameters of PLMs are tuned by maximizing the objective function $\frac{1}{n}\sum_{i=1}^{n}\log(P(y_i|s_i))$, where y_i is the golden type label of s_i.

3.2 Prompt-based Tuning

Verbalizer and template lie at the heart of prompt-based tuning. A verbalizer maps each label $y \in \mathcal{Y}$ to a subset $\mathcal{V}_y = \{w_1, \ldots, w_m\}$ of the vocabulary $\mathcal{V}$ of the PLM $\mathcal{M}$, i.e., $\mathcal{V}_y \subseteq \mathcal{V}$. By taking the union of the dictionary corresponding to each label, we get an overall dictionary $\mathcal{V}^*$. For example, in sentiment classification, we could map the label y = POSITIVE into a set $\mathcal{V}_y$ = {*great, good, wonderful...*}. A template $T(\cdot)$ modifies the original input x into a prompt input $T(x)$ by adding a set of additional tokens. Conventionally, a [MASK] token is added for PLMs to predict the missing label word $w \in \mathcal{V}^*$. Thus, in prompt-learning, a classification problem is transferred into a masked language modeling problem,

$$p(y \in \mathcal{Y}|s) = p([\texttt{MASK}] = w \in \mathcal{V}_y|T(s)). \quad (2)$$

4 Prompt-learning for Entity Typing

After transferred into masked language modeling, the prompt-learning method is applicable to learning and aggregating type information of entities. In this section, we first introduce a simple yet effective prompt-learning method for entity typing. Then we propose a self-supervised prompt-learning method that automatically learns type information from unlabeled data (§ 5).

4.1 A Naive Prompt-based Pipeline

Verbalizers. For fine-grained entity typing, datasets usually use hierarchical label space such as PERSON/ARTIST (FEW-NERD) and ORGANIZATION/PARTY (OntoNotes). In this case, we use all the words as the label words set $\mathcal{V}^*$ for this entity type. For example, y = LOCATION/CITY $\rightarrow$ $v = \{$*location, city*$\}$. In MLM, we use confidence scores of all the words in $\mathcal{V}_y$ to construct the final score of the particular type y. That is, for an input x (which is mapped to $T(x)$) and its entity type y (which is mapped to $\mathcal{V}_y = \{w_1, ..., w_m\}$), the conditional probability becomes

$$P(y|x) = \frac{1}{m}\sum_{j}^{m} P([\texttt{MASK}] = w_j|T(x)), \quad (3)$$

Templates. We choose hard-encoding templates with natural language and soft-encoding templates with additional special tokens in our work. In the template of hard encoding setting, we first copy the marked entity mention in x, then we add a few linking verbs and articles followed by the [MASK] token. The complete experimented templates are presented in A.2. The main experimental results are obtained with the following template

$$\mathrm{T}_3(x) = x.\ \texttt{In this sentence, [Ent] is a [MASK],}$$

For the soft-encoding strategy, some additional special tokens $[\texttt{P}_1], ..., [\texttt{P}_l]$ are introduced as the template, where l is a pre-defined hyper-parameter. The template begins with a delimiter [P] and a copy of the entity mention [M]:

$$\mathrm{T}_4(x) = x\ \texttt{[P] [Ent] [P}_1\texttt{],..., [P}_l\texttt{] [MASK],}$$

Figure 2: The illustration of prompt-learning for fine-grained entity typing with supervision. We take hard-encoding prompt strategy as an example in this figure.

where each embedding of prompts is randomly initialized and optimized during training. Intuitively, these special tokens can represent a cluster of words with similar semantics in the vocabulary.

4.2 Training and Inference

The strategies of hard or soft encoding provide different initialization of templates, and they both can be parameterized by ϕ and optimized along with $\mathcal{M}$ during training. We train the pre-trained model $\mathcal{M}$ (parameterized by θ) along with the additional prompt embeddings by the cross-entropy loss:

$$\mathcal{L} = -\sum \log P(y|x;\theta,\phi). \quad (4)$$

For inference, we can directly use Eq. 3 to predict the label of the current input instance based on the predicted words of the `[MASK]` position.

This pipeline could be applied to entity typing with explicit supervision, and it is more effective when the training data are insufficient, i.e., the few-shot scenario (§ 6.4). Naturally, we take further step and consider a more extreme situation, that is, a scenario without any training data (zero-shot scenario). In this setting, if we directly use an additional classifier to predict the label, the result is equivalent to random guessing since the parameters of the classifier are randomly initialized. If we use prompts to infer the label based on the predicted words, although its performance is significantly better than guessing, there will also be a catastrophic decline (§ 6.5). To this end, a question emerges: *"Is it possible for PLMs to predict entity types without any explicit supervision? "*

5 Self-supervised Prompt-learning

With prompt-learning, the answer is yes, because in the pre-training stage, the contexts of entities have already implied the corresponding type information, which provides an advantageous initialization point for the prompt-learning paradigm. For example, in the input sentence with the $T_3(\cdot)$ template: "Steve Jobs found Apple. In this sentence, Steve Jobs is a `[MASK]`". In our observations, the probability of PLMs predicting *person* at the masked position will be significantly higher than the probability of *location*. And if we make reasonable use of this superior initialization point, it is possible for PLMs to automatically summarize the type information, and finally extract the correct entity type.

5.1 Overview

In order to create conditions for PLMs to summarize entity types, we consider a self-supervised paradigm that optimizes the similarity of the probability distribution predicted by similar examples over a projected vocabulary $\mathcal{V}^*$. To achieve that in prompt-learning, we need to (1) impose a limit on the prediction range of the model, so that only those words that we need, that is, words that express entity types, participate in the optimization of the gradient; (2) provide an unlabeled dataset, where entity mentions are marked without any types to allow the model to learn the process of inducing type information in a self-supervised manner. The inputs contain a pre-trained model $\mathcal{M}$, a pre-defined label schema $\mathcal{Y}$, and a dataset without labels $\mathcal{D} = \{x_1, ..., x_n\}$ (entity mentions are marked without any types). our goal is to make $\mathcal{M}$ capable to automatically carry out zero-shot entity typing after trained on $\mathcal{D}$ and $\mathcal{Y}$. Using prompt-learning as the training strategy, we first construct a label words set $\mathcal{V}^*$ from $\mathcal{Y}$, and for each sentence x in $\mathcal{D}$, we wrap it with hard-encoding template with a `[MASK]` symbol. The key idea is to make the prediction distributions of the same type of entities on $\mathcal{V}^*$ as similar as possible. In this way, we can

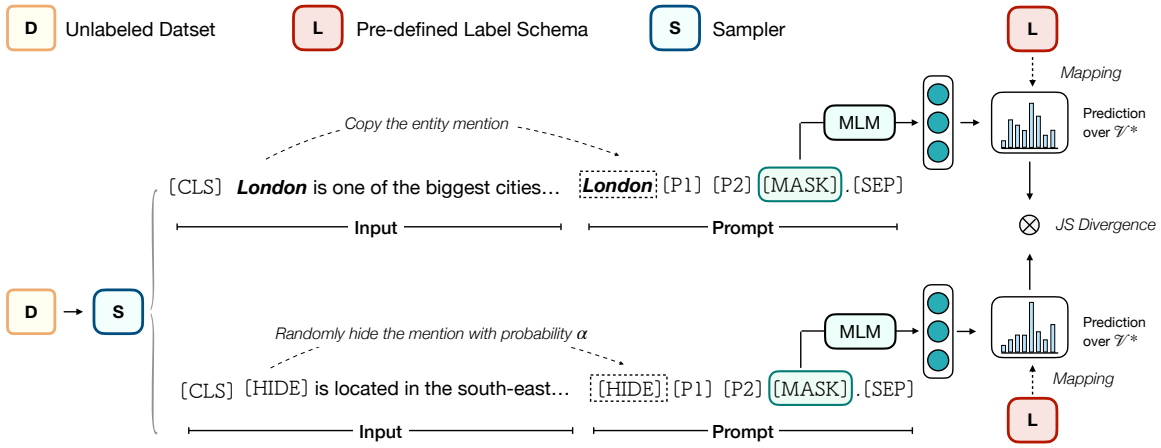

Figure 3: The illustration of self-supervised prompt-learning for fine-grained entity typing with unlabeled data and a pre-defined label set. $\mathcal{V}^*$ denotes the label words projected from the input label set.

perform contrastive learning by sampling positive and negative examples, while ignoring the impact of other words that are not in $\mathcal{V}^*$ on optimization during the MLM process.

5.2 Self-supervised Learning

Although there are no labels in $\mathcal{D}$, we can still develop a sampling strategy based on a simple hypothesis, that is, *same entities in different sentences have similar types*. For instance, we will sample two sentences contain "Steve Jobs" as a positive pair. Moreover, considering entity typing is context-aware, "Steve Jobs" could be *entrepreneur*, *designer*, *philanthropist* in different contexts, we choose to optimize the similarity between distributions of the words over $\mathcal{V}^*$. This strategy not only softens the supervision, but also eliminates the impact of other words in self-supervised learning.

Particularly, we randomly sample c positive pairs, i.e., sentence pairs that share one same entity mention, denoted as $\hat{\mathcal{D}}_{\text{pos}}$, and c negative pairs, i.e., two sentences with different entity mentions marked, denoted as $\hat{\mathcal{D}}_{\text{neg}}$ from a large-scale entity-linked corpus $\mathcal{D}$. To avoid generating false negative samples, the negative samples are further restricted by a large dictionary that contains common entities and their type information. Only sentence pairs with entities of different types in the dictionary are selected as negative samples. Then we wrap them with hard-encoding $\mathrm{T}_3(\cdot)$. To avoid overfitting of the entity names, we randomly hide the entity mention (in the original input and the template) with a special symbol [Hide] with a probability of α. Empirically, α is set to 0.4.

Since the impact of a pair of examples on training should be measured at the distribution level, we choose Jensen-Shannon divergence as a metric to assess the similarity of two distributions. Thus, in a sentence pair (x, x'), the similarity score of two representations of the the predictions $\mathbf{h}$ and $\mathbf{h}'$ of the [MASK] position is computed by:

$$s(\mathbf{h}, \mathbf{h}') = \mathtt{JS}(P_{\mathcal{V}^*}(w|x), P_{\mathcal{V}^*}(w|x')), \quad (5)$$

where JS is Jensen-Shannon divergence, $P_{\mathcal{V}^*}(w|x)$ and $P_{\mathcal{V}^*}(w|x')$ are probability distributions of the predicting token w over $\mathcal{V}^*$ obtained by $\mathbf{h}$ and $\mathbf{h}'$.

As we attempt to make the predictions of the positive pairs similar, the objective is computed by:

$$\begin{aligned}\mathcal{L} = &-\frac{1}{|\hat{\mathcal{D}}_{\text{pos}}|^2}\sum_{x\in\hat{\mathcal{D}}_{\text{pos}}}\sum_{x'\in\hat{\mathcal{D}}_{\text{pos}}}\log(1-s(\mathbf{h},\mathbf{h}')) \\ &-\frac{1}{|\hat{\mathcal{D}}_{\text{neg}}|^2}\sum_{x\in\hat{\mathcal{D}}_{\text{neg}}}\sum_{x'\in\hat{\mathcal{D}}_{\text{neg}}}\log(s(\mathbf{h},\mathbf{h}')),\end{aligned} \quad (6)$$

We use entity-linked Wikipedia corpus as the raw data and generate about 1 million pairs of data each as $\hat{\mathcal{D}}_{\text{pos}}$ and $\hat{\mathcal{D}}_{\text{neg}}$.

6 Experiments

We comprehensively assess the effectiveness of our methods, we use FT and PLET to denote the standard fine-tuning method and method in § 4 and use PLET (S) to denote the self-supervised method in § 5. PLET(T.) denotes the prompt-based method with corresponding template.

We evaluate our methods on four widely used entity typing datasets, including Few-NERD (Ding et al., 2021c), OntoNotes (Weischedel et al., 2013), BBN (Weischedel and Brunstein, 2005), and OpenEntity (Choi et al., 2018a). Our experimental set-

tings contain fully supervised, few-shot, and zero-shot scenarios. The backbone PLMs used in our experiments include BERT (Devlin et al., 2019b), T5 (Raffel et al., 2020) and GPT-2 (Radford et al.).

6.1 Datasets

We use the following four fine-grained entity typing datasets in our experiments.

FEW-NERD We use FEW-NERD (Ding et al., 2021c) as the main dataset, which has the following advantages: (1) FEW-NERD is large-scale and fine-grained, which contains 8 coarse-grained and 66 fine-grained entity types. (2) FEW-NERD is manually annotated, thereby we can precisely assess the capability of entity typing models. We use the supervised setting of the dataset, FEW-NERD (SUP), and the official split in our experiments.

OntoNotes We also use the OntoNotes 5.0 dataset (Weischedel et al., 2013). Following previous works for fine-grained entity typing, we adopt 86-classes version of OntoNotes, while each class has at most 3 levels of the type hierarchy. And the data split is identical to (Shimaoka et al., 2017).

BBN BBN dataset is selected from Penn Treebank corpus of Wall Street Journal texts and labeled by (Weischedel and Brunstein, 2005). We follow the version processed by (Ren et al., 2016a), and the data split by (Ren et al., 2016b). The dataset contains 46 types and each type has a maximum type hierarchy level of 2.

OpenEntity OpenEntity (Choi et al., 2018b) is a multi-label ultra-fine-grained dataset with 10331 entity types, including 9 general types. We only use the crowd-sourced part of the released data.

6.2 Experimental Settings

The experiments are performed under three different settings to evaluate the effect of the prompt-learning method and semi-supervised training. In table 1, we show the statistics of all the settings on the four datasets.

Supervised Setting. In a fully supervised setting, all training data are used in the training phase. FT and PLET are used to train the model. We run the experiments on all four datasets with BERT-base-cased backbone. Both hard and soft encodings are used for PLET.

Few-shot Setting. In a few-shot setting, we randomly sample 1, 2, 4, 8, 16 instances for each entity type for training. We apply both FT and PLET methods with hard encoding on all four datasets.

Zero-shot Setting. In zero-shot setting, no training data with labels are available. The model is required to infer the entity type without any supervised training. Since fine-tuning is not applicable in this setting, we only conduct experiments on PLET and PLET (S).

Metrics. In terms of evaluation metrics, we follow the widely used setting of Ling and Weld (2012), which includes strict accuracy (Acc), loose macro F1-score (MaF), and loose micro F1-score (MiF) to evaluate the performances of models. The loose F1-score calculation concerns type labels by different granularities.

6.3 Fully Supervised Entity Typing

Overall Results. The results on all four datasets across different models are reported in Table 2. Overall, the prompt-based methods have shown certain improvements compared to directly fine-tuned models. It shows that the prompt-based method does help with capturing entity-type information from a given context. It is also observed that the magnitude of the improvement and the preference of prompt encoding strategy may vary with different datasets. The prompt-based method seems less effective on FEW-NERD dataset than the others. It could be attributed to the fact that FEW-NERD is manually annotated and less noisy, leveraging the performance of the standard FT method. Moreover, the effect of soft and hard templates show dataset-related dynamics. For the OntoNotes and OpenEntity datasets, soft encoding outperforms hard encoding, while for the other two datasets the effect seems reversed. Evidence indicates that the effect of the prompt-based method partially depends on the characteristics of the dataset and that different prompt designs may suit different data.

Effectiveness on Ultra-fine Entities. It is worth noting that for OpenEntity, a dataset with over 10000 fine-grained types, the improvement of prompt-learning over FT is striking. This points to the advantage of the prompt-based method in ultra-fine-grained entity typing. Meanwhile, OpenEntity has a typing schema in the form of freely defined text instead of strict hierarchical semantics, and some of the types in the test set do not appear in the training set. This poses a fatal challenge to the FT method and could be a contributing factor to the overwhelming performance of prompt-learning, as such type expressions may be more similar to the common corpora that pre-trained lan-

Dataset	#Type	Supervised			Few-shot			Zero-shot		
		$\lvert\mathcal{D}_{\text{train}}\rvert$	$\lvert\mathcal{D}_{\text{dev}}\rvert$	$\lvert\mathcal{D}_{\text{test}}\rvert$	$\lvert\mathcal{D}_{\text{train}}\rvert$	$\lvert\mathcal{D}_{\text{dev}}\rvert$	$\lvert\mathcal{D}_{\text{test}}\rvert$	$\lvert\mathcal{D}_{\text{train}}\rvert$	$\lvert\mathcal{D}_{\text{dev}}\rvert$	$\lvert\mathcal{D}_{\text{test}}\rvert$
Few-NERD	66	340,382	48,758	96,901	66~1,056	$= \lvert\mathcal{D}_{\text{train}}\rvert$	96,901	0	0	96,901
OntoNotes	86	253,239	2,200	8,962	86~1,376	$= \lvert\mathcal{D}_{\text{train}}\rvert$	8,962	0	0	8,962
BBN	46	86,077	12,824	12,824	46~736	$= \lvert\mathcal{D}_{\text{train}}\rvert$	12,824	0	0	12,824
OpenEntity	10,331	1,998	1,998	1,998	-	-	-	0	0	1,998

Table 1: Statistics of FEW-NERD, OntoNotes, BBN and OpenEntity from three experimental settings. For all three settings, the test sets are identical. For the training set of the few-shot setting, we report the summation from 1-shot to 16-shot.

Dataset	Metric	Method		
		FT	PLET(T_3)	PLET(T_4)
Few-NERD	Acc	79.75	**79.90**	79.86
	MiF	85.74	**85.84**	85.76
	MaF	85.74	**85.84**	85.76
OntoNotes	Acc	59.71	60.37	**65.68**
	MiF	70.47	70.78	**74.53**
	MaF	76.57	76.42	**79.77**
BBN	Acc	62.39	**65.92**	63.11
	MiF	68.88	**71.55**	68.68
	MaF	67.37	**70.82**	67.81
OpenEntity	MiF	27.14	42.39	**43.15**
	MaF	31.06	45.22	**46.11**

Table 2: Fully supervised entity typing results. FT denotes the vanilla fine-tuning method, T. denotes the template used. Note that the result is reported on all 10331 ultra-fine labels for OpenEntity, instead of only 9 general types as most previous works do (Zhang et al., 2019; Wang et al., 2021b). The accuracy metric is generally not reported for OpenEntity.

guage models are pre-trained with. It further illuminates the ability of pre-trained language models to extract information from weakly structured data. We also compare our methods to previous baselines in appendix B, results demonstrate that our method could largely outperform baselines with only 1,998 training examples in the training set.

6.4 Results of Few-shot Entity Typing

Table 3 shows the results on few-shot entity typing. Since OpenEntity has scarce training data compared with its enormous entity type numbers, which makes it a "few-shot" dataset already, we exclude it here. It is shown that the prompt-based model outperforms fine-tuning by a large margin under the few-shot setting, especially when only $1 \sim 2$ training instances per type are available. It should be noted that for OntoNotes and BBN datasets, sampling 16 instances for each entity type already amounts to over 0.5% of the total training data. Meanwhile, some of the data in BBN are distantly supervised and potentially erroneous. It brings more randomness to few-shot training. The results support the idea that a well-designed prompt has much potential in mining the learned knowledge in pre-trained models and thus yields better performance in few-shot settings.

6.5 Results of Zero-shot Entity Typing

Table 4 shows the results on zero-shot entity typing task on FEW-NERD dataset. We did not report the performance of the vanilla fine-tuning approach because it cannot produce reasonable results with a randomly initialized classifier. And it also should be noted that the prompt method without fine-tuning already outperforms random guessing. It indicates that adding a prompt is informative for a model pre-trained on masked-language-model task (e.g. BERT) and can induce reasonable predictions in entity typing tasks. Second, the performance of the model improves by a large margin if trained on unlabeled data. It shows the effectiveness of the proposed self-supervised training approach and points to the potential of a pre-trained prompt-based model under the zero-shot setting when no labeled data are available. To explore the more subtle changes in performance, we carry out case study for the zero-shot entity typing, please refer to Appendix C for details.

6.6 Analysis

Effect of Templates. As stated in previous studies (Zhao et al., 2021), the choice of templates has considerable impact on the performance in prompt-learning, We carry out experiments under the 8-shot setting on FEW-NERD dataset to investigate such influence. We use 3 different hard templates and 4 soft templates (by changing the number of prompt tokens l). Table 5 shows that the choice of templates exerts a considerable influence on the performance of prompt-based few-shot learning. For

Shot	Metric	Few-NERD		OntoNotes		BBN	
		FT	PLET(T_3)	FT	PLET(T_3)	FT	PLET(T_3)
1	Acc	8.94	43.87 (+34.93)	3.70	38.97 (+35.27)	0.80	40.70 (+39.90)
	MiF	19.85	60.60 (+45.75)	18.98	59.91 (+40.93)	5.79	49.25 (+43.46)
	MaF	19.85	60.60 (+40.75)	19.43	61.42 (+41.99)	4.42	48.48 (+43.06)
2	Acc	20.83	47.78 (+26.95)	7.27	39.19 (+31.92)	6.68	41.33 (+34.65)
	MiF	32.67	62.09 (+29.42)	24.89	61.09 (+36.20)	13.70	54.00 (+40.30)
	MaF	32.67	62.09 (+29.42)	25.64	62.68 (+37.04)	13.23	51.97 (+38.74)
4	Acc	33.09	57.00 (+23.91)	11.15	38.39 (+27.24)	19.34	52.21 (+32.87)
	MiF	44.14	68.61 (+24.47)	27.69	59.81 (+32.12)	27.03	61.13 (+34.10)
	MaF	44.14	68.61 (+24.47)	28.26	60.89 (+32.63)	24.69	58.91 (+34.22)
8	Acc	46.44	55.75 (+9.31)	18.37	39.37 (+21.00)	27.01	44.30 (+17.29)
	MiF	57.76	68.74 (+10.98)	38.16	57.97 (+19.81)	40.19	56.21 (+16.02)
	MaF	57.76	68.74 (+10.98)	37.77	58.32 (+20.55)	39.50	55.15 (+15.65)
16	Acc	60.98	61.58 (+0.60)	32.26	42.29 (+10.03)	39.67	55.00 (+15.33)
	MiF	71.59	72.39 (+0.80)	51.40	60.79 (+9.39)	49.01	62.84 (+13.83)
	MaF	71.59	72.39 (+0.80)	51.45	61.80 (+10.35)	47.09	62.38 (+15.29)

Table 3: Results of few-shot entity typing on FEW-NERD, OntoNotes and BBN, all the methods use $\text{BERT}_{\text{base}}$ with same initialization weights as the backbone encoder. The training set and dev set have the same size.

Dataset	Metric	Method	
		PLET	PLET (S)
Few-NERD	Acc	17.55	23.99 (+6.44)
	MiF	28.39	47.98 (+19.59)
	MaF	28.39	47.98 (+19.59)
OntoNotes‡	Acc	25.10	28.27 (+3.17)
	MiF	33.61	49.79 (+16.18)
	MaF	37.91	49.95 (+12.04)
BBN	Acc	55.82	57.79 (+1.97)
	MiF	60.64	63.24 (+2.60)
	MaF	59.99	64.00 (+4.01)
OpenEntity	Acc	11.37	18.78(+7.41)

Table 4: Results of zero-shot entity typing on FEW-NERD, OntoNotes, and BBN. ‡ means that we remove the "`Other`" class during testing.

Type	Template	Acc	MiF	MaF
Hard	$T_1(x)$	54.45	67.34	67.34
	$T_2(x)$	53.93	66.44	66.44
	$T_3(x)$	**55.75**	**68.74**	**68.74**
Soft	l = 2	**59.25**	**69.58**	**69.58**
	l = 3	53.66	66.06	66.06
	l = 4	52.96	66.01	66.01
	l = 5	55.44	68.39	68.39

Table 5: Effect of templates. The results are produced under 8-shot setting on FEW-NERD dataset by PLET. l is the number of soft tokens.

the hard templates, the phrase that describes the location "in this sentence" contributes a remarkable improvement in performance. For the soft templates, surprisingly, the prompt-learning model yields the best result with the fewest special tokens.

Behavior of Different PLMs. We also investigate the behavior of different PLMs. Specifically, we experiment with masked language model (BERT-base), sequence-to-sequence (T5-base), and autoregressive (GPT-2) model. The results on zero-shot and fully supervised settings are shown in Table 6. Overall, GPT-2 achieves best result in zero-shot setting and T5 performs the worst. However, with enough training, the gap disappears. This finding indicates that entity typing task in the form of prompt-learning more closely resembles autoregressive generation task, and the least similar to sequence-to-sequence task, which fits our intuition. While the results after supervised training also show that given appropriate training method, the inherent ability of language models may not differ as much as we suppose.

Random Verbalizer To explore the effect of verbalizer, we experiment with a random verbalizer that casts random projection from entity label to overall label words set $\mathcal{V}^*$. We conduct experiments on 1∼128 shots setting with template T_3. As shown in Figure 4, it could be observed that when

Dataset	Metric	PLET(T_3) ZeroShot			PLET(T_3) Supervised		
		BERT-BASE	T5-BASE	GPT-2	BERT-BASE	T5-BASE	GPT-2
Few-NERD	Acc	17.55	8.98	**26.91**	**79.90**	79.13	77.71
	MiF	28.39	14.30	**41.83**	**85.84**	85.30	84.02
	MaF	28.39	14.30	**41.83**	**85.84**	85.30	84.02
OntoNotes‡	Acc	25.10	**26.52**	23.80	**60.37**	57.09	53.65
	MiF	33.61	**37.58**	34.84	70.78	**72.24**	69.31
	MaF	37.91	**41.65**	39.85	**76.42**	73.40	70.69
BBN	Acc	**55.82**	14.69	55.34	**65.92**	64.90	63.35
	MiF	60.64	16.63	**62.66**	**71.55**	70.76	69.60
	MaF	59.99	15.87	**61.35**	**70.82**	69.87	68.44

Table 6: Results of zero-shot and fully supervised entity typing on FEW-NERD, OntoNotes, and BBN with different PLMs. ‡ means that we remove the "`Other`" class during testing.

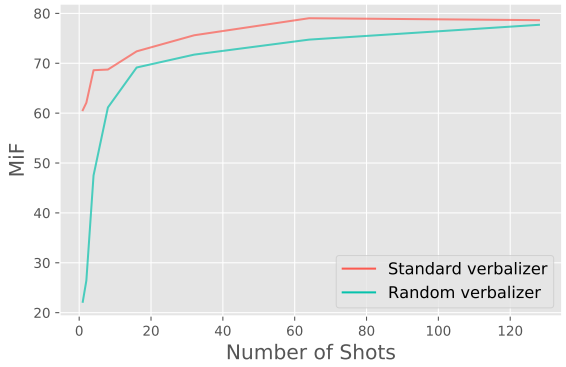

Figure 4: Effects of random verbalizer compared with standard verbalizer on FEW-NERD.

training samples are very scarce, the random verbalizer performs significantly worse than the standard one, indicating the importance of a reasonable label word selection and the power of PLM to learn contextual information with prompts. However, as training samples increase, the gap between the verbalizers become smaller and almost vanishes when the number of shots reaches 128, meaning the PLLM can be adapted to an arbitrary label word setting given adequate training samples. This further sheds light on the comparative easiness and high cost-effectiveness of the down-stream model adaptation to pre-training stage.

7 Conclusion

This work investigates the application of prompt-learning on fine-grained entity typing in in fully supervised, few-shot and zero-shot scenarios. We first investigate a simple and effective prompt-learning pipeline that could be used to extract entity types with both sufficient and insufficient supervision. Furthermore, to handle the zero-shot setting, we propose a self-supervised prompt-learning approach that automatically learns and summarizes entity types based on unlabeled corpora and a pre-defined label schema, which utilizes prompts to take advantage of prior knowledge distributed in PLMs, and could learn pre-defined type information without overfitting by performing distribution-level optimization. The experimental results verify that prompt-learning is a strong alternative to fine-tuning for fine-grained entity typing, we comprehensively explore and analyze various attributes under this scenario.

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Ning Ding and Yulin Chen conduct experiments and draft the paper. Xu Han, Guangwei Xu, and Pengjun Xie participate in the discussion and modify the paper. Hai-Tao Zheng, Zhiyuan Liu, Juanzi Li, and Hong-Gee Kim advise the project and proofread the paper.

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A Experimental Settings and Details

A.1 Experimental Details

We use BERT-base (Devlin et al., 2019a) as the backbone structures of our model and initialized with the corresponding pre-trained cased weights[2]. The hidden sizes are 768, and the number of layers is 12. Our experiments are developed by OpenPrompt (Ding et al., 2021a) and models are implemented by Pytorch framework[3] (Paszke et al., 2019) and Huggingface transformers[4] (Wolf et al., 2020). BERT models are optimized by AdamW (Loshchilov and Hutter, 2019) with the learning rate of 5e-5. The training batch size used is 16 for all models. In the supervised setting, each model is trained for 10 epochs and evaluated on the dev set every 2000 steps. In the few-shot setting, each model is trained for 30 epochs and evaluated every 10∼50 steps, each time the evaluation is run for 200 steps. For the methods with hard-encoding, we report the experimental results of $T_3(\cdot)$. For the soft-encoding method, we report the results of $m = 2$. Experiments are conducted with CUDA on NVIDIA Tesla V100 GPUs.

A.2 Templates

For hard template, with the marked entity mention [Ent], we use the following templates:

$\mathrm{T}_1(x) = x.$ [Ent] is [MASK],

$\mathrm{T}_2(x) = x.$ [Ent] is a [MASK],

$\mathrm{T}_3(x) = x.$ In this sentence, [Ent] is a [MASK],

where [Ent] is the entity mention in x. In § 6, we report the the results of $\mathrm{T}_3(\cdot)$.

B Comparisons with Previous Methods

In this section, we make comparisons with other baselines under the ultra-fine setting of the OpenEntity (Choi et al., 2018a) dataset. We compare our methods to the following approaches:

- UFET (Choi et al., 2018a) is the baseline approach proposed in the original paper of OpenEntity, including a bi-LSTM and a character-level CNN encoder.

[2] https://github.com/google-research/bert

[3] https://pytorch.org

[4] https://github.com/huggingface/transformers

Method	OpenEntity		
	Precision	Recall	MaF
UFET	47.1	24.2	32.0
LabelGCN	50.3	29.2	36.9
LDET+ElMo	50.7	33.1	40.1
LDET+BERT	51.6	32.8	40.1
Box Embedding	52.8	**38.8**	44.8
PLET(T_3)	59.2	36.6	45.2
PLET(T_4)	**61.4**	36.9	**46.1**

Table 7: Fully supervised entity typing results of the coarse-grained entity types on Open Entity. The data splits and settings follow.

- LabelGCN (Xiong et al., 2019) is a graph-based approach for ultra-fine grained entity typing. A GCN layer is used to encode the global label co-occurrence and statistics and word-level similarities.

- LDET (Onoe and Durrett, 2019) is a denoising approach that firstly uses the filtering function to denoise the weakly supervised data, and then a relabeling function is applied to repair the retained examples.

- Box Embedding (Onoe et al., 2021) use box embeddings to represent the type information of named entities and capture the latent type hierarchies. The backbone encoder is BERT-base.

Note that the test data and the evaluation is identical to our method, but some methods use the weakly supervised data provided by OpenEntity and ours does not use any other data rather than the 1,998 examples in the training set. The results are shown in Table 7, from which we can observe that our PLET consistently outperforms the previous baselines with only the limited examples in the training set. Notably, the improvements are mainly contributed by precision.

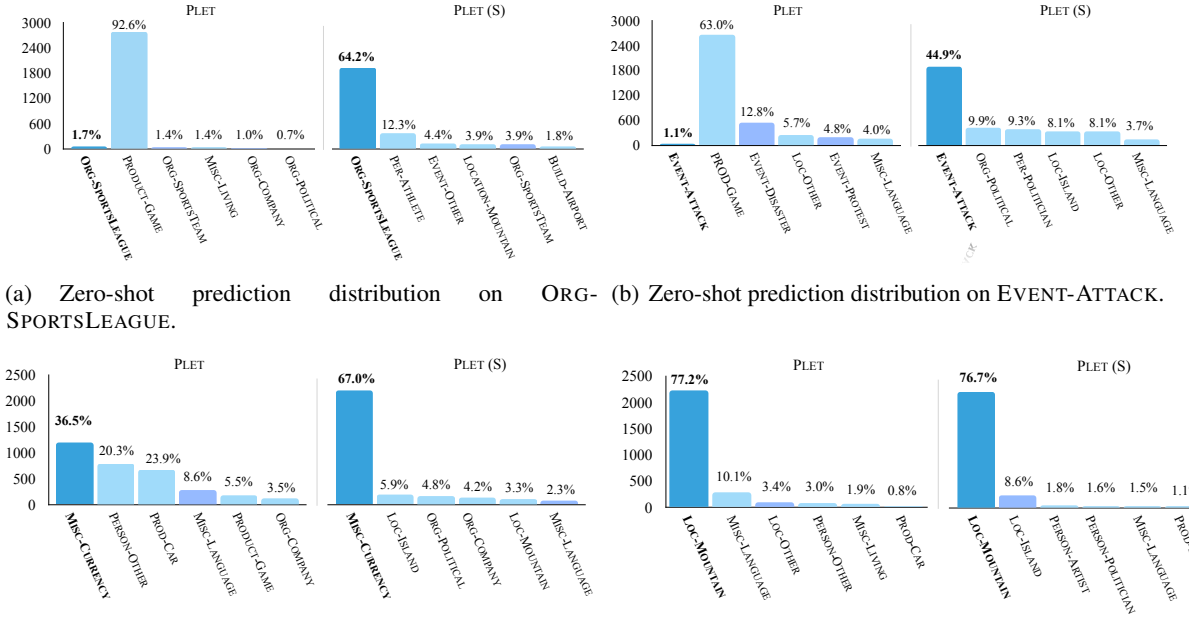
C Case Study under the Zero-shot Setting

In Figure 5, we illustrate the zero-shot prediction distribution (the correct prediction and other top-5 predictions) for four entity types in FEW-NERD. We could observe that with self-supervised prompt-learning, PLET (S) could summarize entity type information and infer the related words to a certain extent. In Figure 5 (a) and Figure 5 (b), the PLET model suffers from a severe bias and almost predict

no correct labels in the zero-shot setting since such words are low-frequency. And although there is no explicit supervision in the pre-training stage of UNPLET, the model could still find the corresponding words that express the ORG-SPORTSLEAGUE and the EVENT-ATTACK types. In Figure 5 (c), self-supervised learning increases the performance of the original encoder. Further, in Figure 5 (d), PLET has been able to make satisfying predictions for this type LOC-MOUNTAIN. In this case, the use of self-supervised learning has hardly weakened the performance, which means that the process of automatically summarizing type information has a little negative impact on high-confidence entity types.

D Discussion

We comprehensively explore the practical application of prompt-learning for fine-trained entity typing. From the bright sight, the prompt-based paradigm could be significantly effective across different numbers of types, and the self-supervised method could produce non-trivial results without seeing any of the training data. However, the prompt-based entity typing has limitations. Although very effective under the few-shot setting, its gap with fine-tuning decreases as the amount of data increases, and it does not significantly exceed the upper bound of the model itself when supervision is sufficient. Another limitation is that although PLET (S) could significantly outperform the baselines under the zero-shot setting (fine-tuning cannot work), the results is still a long way from being able to be used fully automatically to predict entity types in real-world. The misuse of the proposed methods may produce false information and has potential risks.



(a) Zero-shot prediction distribution on ORG-SPORTSLEAGUE.

(b) Zero-shot prediction distribution on EVENT-ATTACK.

(c) Zero-shot prediction distribution on MISC-CURRENCY.

(d) Zero-shot prediction distribution on LOC-MOUNTAIN.

Figure 5: Zero-shot prediction distribution on 4 types in FEW-NERD. In each subgraph, the left part illustrates the results of PLET and the right part are PLET (S). ■ denotes the correct predictions, ■ denotes the wrong predictions with correct coarse-grained types, and ■ denotes the wrong predictions with wrong coarse-grained types.