LightNER: A Lightweight Generative Framework with Prompt-guided Attention for Low-resource NER

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Abstract

Most existing NER methods rely on extensive labeled data for model training, which struggles in the low-resource scenarios with limited training data. Recently, prompt-tuning methods for pre-trained language models have achieved remarkable performance in few-shot learning by exploiting prompts as task guidance to reduce the gap between training progress and downstream tuning. Inspired by prompt learning, we propose a novel lightweight generative framework with promptguided attention for low-resource NER (LightNER). Specifically, we construct the semantic-aware answer space of entity categories for prompt learning to generate the entity span sequence and entity categories without any label-specific classifiers. We further propose prompt-guided attention by incorporating continuous prompts into the self-attention layer to re-modulate the attention and adapt pre-trained weights. Note that we only tune those continuous prompts with the whole parameter of the pre-trained language model fixed, thus, making our approach lightweight and flexible for low-resource scenarios and can better transfer knowledge across domains. Experimental results show that LightNER can obtain comparable performance in the standard supervised setting and outperform strong baselines in low-resource settings by tuning only a small part of the parameters.

1 Introduction

Pre-trained language models (PLMs) (Devlin et al. 2019) have shown amazing improvement in NER. The current dominant studies with PLMs mainly formulate NER as a sequence labeling problem, and employ adding label-specific classifiers (LC) (Strubell et al. 2017; Cui and Zhang 2019) or CRF (Ma and Hovy 2016; Luo, Xiao, and Zhao 2020) output layers on top of representations. However, these methods usually lack generalizability to unseen entity classes, partially because the output layers require maintaining a consistent label set between training and testing. Note that these models have to re-train the whole model to adapt to a target domain with new entity classes, thus, achieving unsatisfactory performance when the target labeled data is limited.

		Complexity	Complexity Zero-Sh				
	Mode	Prompt	\triangle	\Rightarrow			
LC	classification	_	$O(n^2d)$	×			
Prototype	metrics	_	$O(n^2d)$	×			
Template	generative	manual/single layer	$O(nm\hat{n}\cdot n^2d)$	√			
Ours	generative	learnable/multi layer	$O(n^2d)$	√			

Figure 1: We show the formulations of different NER models and illustrate their corresponding strengths, where d donates the dimension of the LMs; \mathbf{n} , \mathbf{m} , $\hat{\mathbf{n}}$ imply the length of input, number of entity classes and n-grams; zero-shot refers to zero-shot learning ability; LC is short for label-specific classifier (vanilla sequence labeling).

Unfortunately, this problem is very common in real-world application scenarios, where labeled data may be rich for specific domains such as news but very limited for other specific domains. This draws attention to a challenging but practical research problem: low-resource NER. To address this issue, previous approaches (Wiseman and Stratos 2019a; Zhang et al. 2020b; Fritzler, Logacheva, and Kretov 2019; Wiseman and Stratos 2019b; Yang and Katiyar 2020; Ziyadi et al. 2020) utilize prototype-based metrics and essentially reduce the domain adaptation cost compared with sequence classification methods. However, those approaches mainly focus on finding the best hyper-parameter settings to utilize similar patterns between the source domain and the target domain rather than updating the network parameters of the NER model; though being less costly, they fail to improve the representation for cross-domain instances.

Recently, prompt-tuning (Brown et al. 2020; Schick, Schmid, and Schütze 2020; Schick and Schütze 2020; Gao, Fisch, and Chen 2021; Liu et al. 2021d) has emerged to bridge the gap of objective forms in pre-training and finetuning. Previous studies (Li and Liang 2021) demonstrate that taking prompts for tuning models is surprisingly effective for the model adaptation of PLMs, especially in the low-resource setting. Intuitively, prompt-learning is applicable to low-resource NER. Cui et al. (2021) take the first step to propose template-based BART (abbreviated as *Tem*-

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plate) for few-shot NER, which enumerates all $\hat{\mathbf{n}}$ -gram possible spans in the sentence and fills them in the pre-defined templates, classifying each candidate span based on the corresponding template scores. Yet it dominantly remains the following limitations: (1) **labor-intensive manual prompt engineering.** It manually utilizes discrete templates for labeled entities, which is labor-intensive and template sensitive (Liu et al. 2021d). (2) **sizeable computational complexity.** Template-based BART assigns $\hat{\mathbf{n}}$ -grams to numerate all possible spans and synchronously constructs templates of \mathbf{m} (nums of entity classes) corresponding to entity types, which complexity is $\mathbf{m} \times \mathbf{n} \times \hat{\mathbf{n}}$ times that of other methods as shown in the Figure 1.

To this end, we propose a lightweight generative framework for low-resource NER with prompt-guided attention (LightNER). Specifically, instead of tackling the sequence labeling through the training label-specific output layer, we reformulate the NER task as a generation problem and construct a semantic-aware answer space for prompt learning. Therefore, our approach can directly leverage any new or complicated entity types without modifying network structure and is generalizable to low-resource domains. Moreover, we propose prompt-guided attention by incorporating continuous prompts into the self-attention layer in the generation framework to guide the focus of attention, indicating no labor-intensive prompt engineering. We only tune the prompt's parameters with the whole PLM's parameter fixed, making our model flexible, parameter-efficient, and better transferring knowledge from the source domain to the target domain. In a nutshell, we conclude our contributions as follows:

- We convert sequence labeling to the generative framework and construct semantic-aware answer space for prompt learning without label-specific layers.
- We take the first step to introduce a prompt-guided attention layer that explicitly conditions the LM on the prompts, which is flexible and pluggable to PLMs.
- We conduct experiments on four NER datasets, and by tuning only little parameters, LightNER can achieve comparable results in standard supervised settings and yield promising performance in low-resource settings.

2 Related Work

2.1 NER

PLMs recently have significant impact on NER (Zhang et al. 2021), where Transformer-based models (Peters et al. 2018; Devlin et al. 2019; Zheng et al. 2021; Nan et al. 2021) are utilized as backbone network for acquiring plentiful representations. The current dominant methods (Chiu and Nichols 2016; Ma and Hovy 2016; Liu et al. 2019; Strubell et al. 2017; Zhang et al. 2020a; Liu et al. 2021a,b) treat NER as a sequence tagging problem with label-specific classifiers or CRF. Another line of work utilize a seq2seq framework (Yan et al. 2021) to solve NER tasks. Specifically, Yan et al. (2021) propose unified-NER, which formulates the NER subtasks as an entity span generation task. Unified-NER leverages hand-crafted one-one mapping from the to-

ken in the vocabulary to the entity type; thus, it fails to generate complicated entity types with multiple tokens, such as $return_date.month_name$ in ATIS (Hakkani-Tur et al. 2016) and $restaurant_name$ in MIT Restaurant (Liu et al. 2013).

For low-resource NER, one line of research is prototypebased methods, which involve meta-learning and have recently become popular few-shot learning approaches in the NER area. Most of the approaches (Fritzler, Logacheva, and Kretov 2019; Wiseman and Stratos 2019b; Yang and Katiyar 2020; Ziyadi et al. 2020; Henderson and Vulić 2020; Hou et al. 2020; Lin et al. 2019; Xu, Jiang, and Watcharawittayakul 2017; Ding et al. 2021b) utilize the nearest-neighbor criterion to assign the entity type, which depends on similar patterns of entity between the source domain and the target domain without updating the NER task's network parameters, making them unable to improve the neural representation for cross-domain instances. Another line of research leverages transfer learning methods (Bao et al. 2019; Huang, Ji, and May 2019; Bari, Joty, and Jwalapuram 2020; Rahimi, Li, and Cohn 2019; Rijhwani et al. 2020; Zhou et al. 2019; Wang et al. 2021) to conduct cross-lingual or cross-domain knowledge transfer for enhancing the performance in lowresource scenarios.

Recently, Cui et al. (2021) propose template-based BART for few-shot NER, which enumerates all $\hat{\mathbf{n}}$ -gram possible spans in the sentence and fills them in the hand-crafted templates, classifying each candidate span based on the corresponding template scores. Unlike their approach, we do not need template engineering since we construct semanticaware answer space for generative NER, leveraging implicit semantic knowledge in entity categories. Moreover, we propose prompt-guided attention with learnable embeddings to better stimulate knowledge in PLMs. Finally, the most important difference is that our model only tunes little parameters, which is lightweight, thus applicable to large-scale pretrained language models.

2.2 Prompt-tuning

Since the emergence of GPT-3 (Brown et al. 2020), prompttuning has received considerable attention. A series of research work (Schick and Schütze 2020; Schick, Schmid, and Schütze 2020; Shin et al. 2020) have emerged, which implies that prompt-tuning can effectively stimulate knowledge from PLMs compared with standard fine-tuning, thus, inducing better performances on few-shot and zero-shot tasks. While most of the researches (Gao, Fisch, and Chen 2021; Lester, Al-Rfou, and Constant 2021; Min et al. 2021) concentrate on text classification, some works extend the impact of prompt-tuning into other tasks, e.g., text generation (Li and Liang 2021), relation extraction (Han et al. 2021; Chen et al. 2021), entity typing (Ding et al. 2021a), NER (Cui et al. 2021) and visual-language understanding (Zhou et al. 2021). Unlike the approaches that place a template in the raw input sequence, we incorporate continuous prompts into the selfattention layer and leverage prompts to guide the distribution of attention, which is sufficiently flexible and lightweight to increase training efficiency and enable rapid adaptation with minimal overhead.

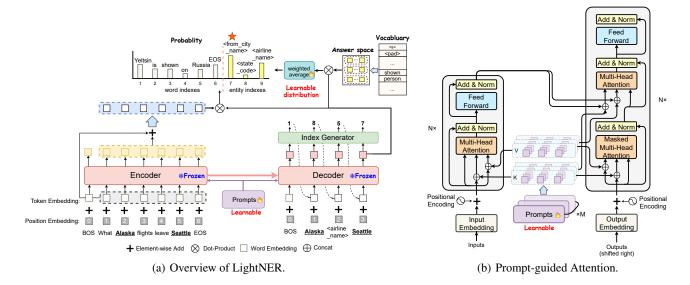


Figure 2: Overview of our LightNER framework. The PLM is frozen and the prompts are the only learnable parameters.

3 Preliminaries

3.1 Low-resource NER

Given a rich-resource NER dataset $\mathbb{H}=\{(\mathbf{X}_1^H,\mathbf{Y}_1^H),...,(\mathbf{X}_R^H,\mathbf{Y}_R^H)\}$, where the input is a text sequence of length $n,\ \mathbf{X}^H=\{x_1^H,\dots,x_n^H\}$, we use $\mathbf{Y}^H=\{y_1^H,\dots,y_n^H\}$ to denote corresponding labeling sequence of length n, and adopt \mathcal{C}^H to represent the label set of the rich-resource dataset $(\forall y_i^H,y_j^H\in\mathcal{C}^H)$. Traditional NER methods are trained in the standard supervised learning settings, which usually require many pairwise examples, *i.e.*, R is large. However, only a few labeled examples are available for each entity category in real-world applications due to the intensive annotation cost. This issue yields a challenging task of low-resource NER, in which given a low-resource NER dataset, $\mathbb{L}=\{(\mathbf{X}_1^L,\mathbf{Y}_1^L),...,(\mathbf{X}_r^L,\mathbf{Y}_r^L)\}$, the number of labeled data in low-resource NER dataset is quite limited (i.e., $r\ll R$) compared with the rich-resource NER dataset. Regarding the issues of low resource and cross domain, the target entity categories \mathcal{C}^L $(\forall l_L^I, l_J^I) \in \mathcal{C}^L$) may be different from \mathcal{C}^H , which is challenging for model optimization.

3.2 Label-specific Classifier for NER

Traditional sequence labeling methods usually assign a label-specific classifier over the input sequence, which identifies named entities using BIO tags. A label-specific classifier with parameter $\theta = \{\mathbf{W}_{\mathcal{C}}, \mathbf{b}_{\mathcal{C}}\}$ followed by a softmax layer is used to project the representation \mathbf{h} into the label space. Formally, given $x_{1:n}$, the label-specific classifier method calculates:

$$\mathbf{h}_{1:n} = \text{ENCODER}(x_{1:n}),$$

$$q(\mathbf{y}|\mathbf{x}) = \text{SOFTMAX}(\mathbf{h}_i \mathbf{W}_{\mathcal{C}} + \mathbf{b}_{\mathcal{C}}) \ (i \in [1, ..., n]),$$
(1)

where $\mathbf{W}_{\mathcal{C}} \in \mathbb{R}^{d \times m}$, $\mathbf{b}_{\mathcal{C}} \in \mathbb{R}^{m}$ are trainable parameters and m is the numbers of entity categories. We adapt BERT (Devlin et al. 2019) and BART (Lewis et al. 2020) as our EN-

CODER to encoder the representation of text sequence, together with label-specific classifier layer. These methods are our baselines recorded as **LC-BERT** and **LC-BART** respectively. Since the label sets may be different between source and target domain, and consequently parameters of the label-specific classifier layer $\theta_{\mathcal{S}}$ and $\theta_{\mathcal{T}}$ are different across domains.

4 Methodology

4.1 Task Formulation

Low-resource NER usually involves the class transfer, where new entity categories exist in target domains; however, the traditional sequence labeling method needs a label-specific output layer based on PLMs, hurting its generalization. Therefore, we reformulate the NER as a generative framework to maintain the consistency of architecture and enable the model to handle different entity types. For a given sentence X, we tokenize it into a sequence of tokens X = $\{x_1, x_2, ...x_n\}$. The NER task aims to provide the start and end index of an entity span, along with the entity type, represented by e, t in our framework, respectively. e is the index of tokens and $t \in \{\text{"person"}, \text{"organization"}, ..., \}$ is the set of entity types. Superscript start and end denote the start and end index of the corresponding entity token in the sequence. For our generative framework, the target sequence Y consists of multiple base prediction $p_i = \{e_i^{start}, e_i^{end}, t_i\}$ and $Y = \{p_1, p_2, ..., p_n\}$. We take a sequence of tokens X as input and hope to generate the target sequence Y as defined above. The input and output sequence starts and ends with special tokens "<s>" and "</s>". They should also be generated in Y, but we ignore them in equations for simplicity. Given a sequence of tokens X, the conditional probability is calculated as:

$$P(Y|X) = \prod_{t=1}^{n} p(y_t|X, y_0, y_1, ..., y_{t-1}).$$
 (2)

4.2 Generative Framework

To model the conditional probability P(Y|X), we adopt the seq2seq architecture with the pointer network to generate the index of entity span in the input and entity type labels. Therefore, our generative module consists of two components:

Encoder The encoder is to encode X into the hidden representation space as a vector H_{en} .

$$H_{en} = \operatorname{Encoder}(X)$$
 (3)

where $H_{en} \in \mathbb{R}^{n \times d}$ and d is the hidden state dimension.

Decoder The decoder part takes the encoder outputs H_{en} and previous decoder outputs $y_1, y_2, ..., y_{t-1}$ as inputs and decode y_t . $y_{i=1}^{t-1}$ indicates the token indexes; an index-to-token converter is applied for the conversion.

$$\tilde{y}_i = \begin{cases} X_{y_i}, & \text{if } y_i \text{ is a pointer index} \\ C_{y_i-n}, & \text{if } y_i \text{ is a class index} \end{cases}$$
 (4)

where $C = [c_1, c_2,c_l]$ is the set of entity categories (such as "Person", "Organization", etc.), which are answer words corresponding to the entity category for prompt-tuning¹. After this, we then decoder the hidden state for y_t .

$$h_t = \operatorname{Decoder}(H_{en}; \tilde{y_i}_{i=1}^{t-1}) \tag{5}$$

where $h_t \in \mathcal{R}^d$; moreover, the probability distribution p_t of token y_t can be computed as follows:

$$\begin{split} E_{seq} &= \text{WordEmbed}(X), \\ \tilde{H}_{en} &= \alpha \cdot H_{en} + (1 - \alpha) \cdot E_{seq}, \\ p_{seq} &= \tilde{H}_{en} \otimes h_t, \\ p_t &= \text{Softmax}([p_{seq}; p_{tag}]), \end{split} \tag{6}$$

where E_{seq} , $\tilde{H}_{en} \in \mathcal{R}^{n \times d}$; p_{seq} and p_{tag} refer to the predicted logits on index of entity span and entity categories respectively; $p_t \in \mathcal{R}^{(n+m)}$ is the predicted probability distribution of y_t on all candidate indexes; $[\cdot;\cdot]$ donates concatenation in the first dimension. In particular, the details of p_{tag} are in the following subsection.

4.3 Construction of Semantic-aware Answer Space for Prompt-tuning

Existing studies (Liu et al. 2021c; Le Scao and Rush 2021) have shown that answer engineering has a strong influence on the performance of prompt-tuning. As for the prediction of entity categories in NER, adding extra label-specific parameters representing different entity types will hinder the applicability of prompt learning and hurt knowledge transfer between classes in low-resource NER. Meanwhile, it is challenging to manually find appropriate tokens in the vocabulary to distinguish different entity types. Besides, some entity type may be very long or complicated in the specific target domain, such as $return_date.month_name$ in ATIS

(Hakkani-Tur et al. 2016) and $restaurant_name$ in MIT Restaurant (Liu et al. 2013).

To address the above issues, we construct **semanticaware answer space** containing multiple label words related to each entity class and leverage the **weighted average** approach for the utilization of the answer space \mathcal{V} . Concretely, we define a mapping \mathcal{M} from the label space of entity categories \mathcal{C} to the semantic-aware answer space \mathcal{V} , i.e., $\mathcal{M}:\mathcal{C}\mapsto\mathcal{V}$. We utilize \mathcal{V}_c to represent the subset of \mathcal{V} that is mapped by a specific entity type $c, \cup_{c\in\mathcal{C}}\mathcal{V}_c=\mathcal{V}$. Take the above $c_1=$ "return_date.month_name" as example, we define $\mathcal{V}_{c_1}=$ {"return", "date", "month", "name"} according to decomposition of c_1 . Since the direct average function may be biased, we adopt learnable weights α to average the logits of label words in answer space as the prediction logit:

$$E_{tag} = \text{WordEmbed}(\mathcal{M}(\mathcal{C}))$$
 (7)

$$p_{tag} = Concat \left[\sum_{v \in \mathcal{V}_c} \alpha_v^c * E_{tag}^c \otimes h_t \right]$$
 (8)

where α_v^c donates the weight of entity type c; $\sum_{v \in \mathcal{V}_c} \alpha_v^c = 1$; $p_{tag} \in \mathcal{R}^m$. Through the construction of semantic-aware answer space, LightNER can perceive semantic knowledge in entity categories without modifying the PLM.

4.4 Prompt-guided Attention

Parameterized Setting Specifically, LightNER adds two sets of trainable embedding matrices $\{\phi^1,\phi^2,..,\phi^N\}$ for the encoder and decoder, respectively, and sets the number of transformer layers as N, where $\phi_\theta \in \mathbb{R}^{2\times |P|\times d}$ (parameterized by θ), |P| is the length of the prompt, d represents the $dim(h_t)$, and 2 indicates that ϕ is designed for the key and value. In our method, the LM parameters are fixed, and the prompt parameters θ and the learnable distribution of α are the only trainable parameters.

Prompt-guided Attention Layer LightNER inherits the architecture of the transformer (Vaswani et al. 2017), which is a stack of identical building blocks wrapped up with a feedforward network, residual connection, and layer normalization. As a specific component, we introduce the prompt-guided attention layer over the original query/key/value layer to achieve flexible and effective prompt-tuning.

Given an input token sequence $X = \{x_1, x_2, ..., x_n\}$, following the above formulation, we can incorporate the representation of the prompt into x with the calculation of self-attention. In each layer l, the input sequence representation $X^l \in \mathbb{R}^d$ is first projected into the query/key/value vector:

$$\boldsymbol{Q}^{l} = \boldsymbol{X}^{l} \boldsymbol{W}^{Q}, \boldsymbol{K}^{l} = \boldsymbol{X}^{l} \boldsymbol{W}^{K}, \boldsymbol{V}^{l} = \boldsymbol{X}^{l} \boldsymbol{W}^{V}, \quad (9)$$

where $m{W}_l^Q, m{W}_l^K, m{W}_l^V \in \mathbb{R}^{d \times d}.$ Then, we can redefine the attention operation as:

$$Attention^{l} = softmax(\frac{\mathbf{Q}^{l}[\mathbf{K}^{l}; \boldsymbol{\phi}_{k}^{l}]^{T}}{\sqrt{d}})[\mathbf{V}; \boldsymbol{\phi}_{v}^{l}]. \quad (10)$$

Based on these representations of inputs and prompts, we aggregate them and compute the attention scores to guide the

 $^{^{1}}$ The index of entity categories always starts after the pointer indexes of the given sequence, at n+1.

final self-attention flow. The proposed prompt-guided attention can re-modulate the distribution of attention according to the prompt words. Consequently, the model benefits from the guidance of prompts.

4.5 Computational Complexity

For a given sequence, the computational complexity of our LightNER is $O\left(n^2d\right)$, where n and d imply the length of the input and the dimension hidden layers in PLMs, respectively. Note that our approach does not need to enumerate all possible spans and construct templates, which is efficient than (Cui et al. 2021). Moreover, we only tune 2.2% parameters of the whole model (the tuned params divided by params of the LM), making it memory efficient during training.

5 Experiments

We conduct extensive experiments in standard and low-resource settings. We use CoNLL-2003 (Tjong Kim Sang and De Meulder 2003) as the rich-resource domain. Following the settings in Ziyadi et al. (2020) and Huang et al. (2020), we use the Massachusetts Institute of Technology (MIT) Restaurant Review (Liu et al. 2013), MIT Movie Review (Liu et al. 2013), and Airline Travel Information Systems (ATIS) (Hakkani-Tur et al. 2016) datasets as the crossdomain low-resource datasets². Our experiments are evaluated in an exact match scenario and implementation details are presented in the appendix.

5.1 Standard Supervised NER Setting

We adopt the CoNLL-2003 dataset to conduct experiments in the standard supervised settings. A comparison of the results of LightNER and the SOTA methods are listed in Table 1. Mainly, LC-BERT and LC-BART provide a strong baseline. We identify that even though LightNER is designed for the low-resource NER, it is highly competitive with the best-reported score in the rich-resource setting as well. Note that, although both LC-BART and our method LightNER utilize BART as the backbone, our method outperforms LC-BART by 2.33% on the F1-score, indicating the effectiveness of our decoding strategy and promptguided attention. It is also worth noting that LightNER tune only small part parameters of PLM. Overall, LightNER is a practical and parameter-efficient method for steering the BART to generate the entity pointer index sequence and entity categories accurately.

5.2 In-Domain Few-Shot NER Setting

Following (Cui et al. 2021), we construct few-shot learning scenarios on CoNLL-2003 by downsampling, which limits the number of training instances for certain specific categories. Particularly, we choose "LOC" and "MISC" as the low-resource entities and "PER" and "ORG" as the rich-resource entities. The rich and low-resource entity categories

Traditional Models	P	R	F
Yang, Liang, and Zhang (2018)	-	-	90.77
Ma and Hovy (2016)	-	-	91.21
Yamada et al. (2020)	-	-	92.40
Gui et al. (2020)	-	-	92.02
Li et al. (2020) †	92.47	93.27	92.87
Yu, Bohnet, and Poesio (2020) ‡	92.85	92.15	92.50
LC-BERT	91.93	91.54	91.73
LC-BART	89.60	91.63	90.60
Few-shot Friendly Models	P	R	F
Wiseman and Stratos (2019b)	-	-	89.94
Template (Cui et al. 2021)	90.51	93.34	91.90
LightNER	92.39	93.48	92.93

Table 1: Model performance on the CoNLL-2003 dataset . "†" indicates that we reran their code with BERT-LARGE (Devlin et al. 2019). "‡" indicates our reproduction with only the sentence-level context.

Models	PER	ORG	LOC*	MISC*	Overall
LC-BERT	76.25	75.32	61.55	59.35	68.12
LC-BART	75.70	73.59	58.70	57.30	66.82
Template	84.49	72.61	71.98	73.37	75.59
LightNER	90.96	76.88	81.57	52.08	78.97

Table 2: In-domain few-shot performance on the CoNLL-2003 dataset. * indicates the few-shot entity type.

have the same textual domain. Specifically, we downsample the CoNLL-2003 training set and generate 4,001 training instances, including 2,496 "PER," 3,763 "ORG," 100 "MISC," and 100 "LOC" entities. As shown in Table 2, our method outperforms other methods for both rich- and low-resource entity types. This proves that our proposed method has a more substantial performance for in-domain few-shot NER and demonstrates that it can effectively handle the class transfer, which is a challenging aspect in few-shot NER tasks.

5.3 Cross-Domain Few-Shot NER Setting

In this section, we evaluate the model performance in the scenarios in which the target entity categories and textual style are specifically different from the source domain, and only limited labeled data are available for training. Specifically, we randomly sample a specific number of instances per entity category³ from the training set as the training data in the target domain to simulate the cross-domain low-resource data scenarios. Table 3 lists the results of training models on the CoNLL-2003 dataset as a generic domain and its evaluations on other target domains. The results of Light-NER are based on running the experiments five times on random samples and calculating the average of their F1 scores.

Competitive Baselines We consider six competitive approaches in our experiments, divided into three types: *prototype-based*, *label-specific classifier*, and *prompt-based*

²We do not conduct experiemnts on Few-NERD (Ding et al. 2021b) since our setting follows (Ziyadi et al. 2020) which is different from the N-way K-shot settting.

³Note that if an entity has a smaller number of support examples than the fixed number, we use all of them as our support examples.

Source	Methods	ethods MIT Movie				MIT Restaurant				ATIS						
		10	20	50	100	200	500	10	20	50	100	200	500	10	20	50
	LC-BERT	25.2	42.2	49.6	50.7	59.3	74.4	21.8	39.4	52.7	53.5	57.4	61.3	44.1	76.7	90.7
None	LC-BART	10.2	27.5	44.2	47.5	54.2	64.1	6.3	8.5	51.3	52.2	56.3	60.2	42.0	72.7	87.5
None	Template	37.3	48.5	52.2	56.3	62.0	74.9	46.0	57.1	58.7	60.1	62.8	65.0	71.7	79.4	92.6
	LightNER	41.7	57.8	73.1	78.0	80.6	84.8	48.5	58.0	62.0	70.8	75.5	80.2	76.3	85.3	92.8
	Neigh.Tag.	0.9	1.4	1.7	2.4	3.0	4.8	4.1	3.6	4.0	4.6	5.5	8.1	2.4	3.4	5.1
	Example.	29.2	29.6	30.4	30.2	30.0	29.6	25.2	26.1	26.8	26.2	25.7	25.1	22.9	16.5	22.2
	MP-NSP	36.4	36.8	38.0	38.2	35.4	38.3	46.1	48.2	49.6	49.6	50.0	50.1	71.2	74.8	76.0
CoNLL03	LC-BERT	28.3	45.2	50.0	52.4	60.7	76.8	27.2	40.9	56.3	57.4	58.6	75.3	53.9	78.5	92.2
	LC-BART	13.6	30.4	47,8	49.1	55.8	66.9	8.8	11.1	42.7	45.3	47.8	58.2	51.3	74.4	89.9
	Template	42.4	54.2	59.6	65.3	69.6	80.3	53.1	60.3	64.1	67.3	72.2	75.7	77.3	88.9	93.5
	LightNER	62.9	75.6	78.8	82.2	84.5	85.7	58.1	67.4	69.5	73.7	78.4	80.1	86.9	89.4	93.9

Table 3: Model performance in the cross-domain few-shot setting.

methods. The prototype-based methods primarily include the following: (i) Neigh.Tag. (Wiseman and Stratos 2019b) copies token-level labels from weighted nearest neighbors; (ii) Example-based NER (Ziyadi et al. 2020) is the SOTA method related to a training-free NER, which identifies the starting and ending tokens of unseen entity categories; (iii) Multi-prototype + NSP (referred to as MP-NSP) is a SOTA prototype-based method reported in (Huang et al. 2020), utilizing noisy supervised pretraining. (iv) LC-BERT and (v) LC-BART is the adoption of the label-specific classifiers on top of corresponding PLMs, whereas (vi) Template-based BART (Cui et al. 2021) recently propose a template-based method for few-shot NER,

Performance Training from Scratch on Target Domain

We first consider direct training on the target domain from scratch without any available source domain data. However, prototype-based methods cannot be used in this setting. When compared to the LC-BART, LC-BERT, and template-based BART, the results of our approach is consistently more persistent, indicating LightNER can better exploit few-shot data. Particularly, LightNER achieve an F1-score of 67.3% in the 20-shot setting, which is higher than the results of LC-BERT and template-based BART in the 100-shot setting. Notably, LC-BERT, LC-BART, and template-based BART should fine-tune 100% of the parameters in PLMs; however, our method merely updates the parameters of prompt-guided attention. This observation reveals that our approach is not only advantageous in low-data settings but also parameter-efficient.

Performance Transferring Knowledge from a General Domain to Specific Domains We observe that the performance of prototype-based methods remains approximately the same as the number of labeled data increases. This result is attributed to the fact that prototype-based methods do not update the network parameters. When compared to the prototype-based methods, LightNER continues to improve when the number of target-domain labeled data increases. Table 3 shows that on all three target-domain datasets, Light-NER significantly outperforms the other three types of baselines in the case of both 10 and 500 instances per entity type. From the perspective of quantifying the knowledge

transferred, when the number of instances is 10, the performance of our model increased the F1-scores to 21.2, 9.6, and 10.6 on the MIT movie, MIT restaurant, and ATIS datasets, respectively, which is significantly greater than the results of *LC-BERT*. This demonstrates that our model is more successful in transferring the knowledge learned from the source domain. However, as the number of training instances increased, the knowledge transferred by our method decreased. One possible explanation is that our model can fully exploit the limited data in the target domain and mine the knowledge in the data and PLMs, where the knowledge learned in the source domain exerts only a minor influence.

6 Analysis

6.1 Ablation and Comparison

As shown in the above experiments that our LightNER possess the outstanding ability of knowledge transfer in the cross-domain few-shot setting, we think that the promptguided attention contributes to the cross-domain improvement. To this end, we ablate the prompt-guided attention and semantic answer space to validate the effectiveness. prompt-guided attention refers the model without prompts, indicating full parameter (100%) tuning. - semantic answer space donates our model only assigns one token in the vocabulary to represent the entity type. From Table 4, we notice that only - prompt-guided attention in the vanilla fewshot setting performs a little better than LightNER, but decreases significantly in the cross-domain few-shot setting. However, - semantic answer space drop both in the two settings. It further demonstrates that the design of promptguided attention is parameter-efficient and beneficial for knowledge transfer, while semantic answer space involves the ability to solve class transfer issues, which is also essential for low-resource NER. We further compare Light-NER with several popular prompt-tuning methods such as P-tuning (Liu et al. 2021d) and prefix-tuning (Li and Liang 2021). We try to apply them with a label-specific classifier on BERT (LC-BERT) to experiment in low-resource scenarios. We set the length of continuous template words to be 10 and 100 respectively for P-tuning and Prefix-tuning. Specifically, the tuned params of Prefix-tuning is only the prefix. We observe that LC-BERT equipped with P-tuning achieves a few improvements both in vanilla few-shot and cross-domain few-shot settings. While lightweight prefixtuning makes performance drop significantly because LC-BERT cannot handle the class transfer, thus the few tuned parameters yield unsatisfactory performance.

Source	Methods	MIT Restaurant				
		10	20	50		
None	Ours [BART] - prompt-guided attention - semantic answer space	48.5 50.3 45.5	58.0 59.4 55.5	62.0 63.5 59.8		
	LC-BERT P-tuning [LC-BERT] Prefix-tuning [LC-BERT]	21.8 24.9 12.8	39.4 41.2 15.5	52.7 53.5 22.4		
CoNLL03	Ours [BART] - prompt-guided attention - semantic answer space	58.1 52.6 48.7	67.4 62.9 58.8	69.5 65.7 62.5		
CONLLUS	LC-BERT P-tuning [LC-BERT] Prefix-tuning [LC-BERT]	27.2 30.3 14.2	40.9 46.8 17.9	56.3 58.2 23.5		

Table 4: Comparison with several prompt-based methods.

6.2 Impact of Length of Prompt

We set the length of the prompt to 10 in the above experiment and further conduct an analysis to verify whether the size of the prompt has a significant impact on the performance. From Figure 3 (left), we notice that a longer prompt implies more trainable parameters but does not guarantee more expressive power. It also reveals that our prompt-guided attention mechanism is stable; as the length changes, the performance fluctuation does not exceed 1%.

6.3 Low-high Layer vs. High-low Layer

In the aforementioned experiments, we assign the promptguided attention method to all layers in PLM. However, it is intuitive to investigate which layer is more sensitive with our approach. Intuitively, basic syntactic information may appear earlier in the PLM, while high-level semantic information emerges in higher-level layers. We conduct experiments by applying our prompt-guided attention from the lowest to the highest layer and from the highest to the lowest layer separately. These two progressive methods are briefly denoted as low-high and high-low, respectively. As Figure 3 (right) shows, the performance on CoNLL-2003 only achieves an F1-score of 40 by adding prompt-guided attention at the lowest layer, whereas an F1-score of 87.5 is performed at the highest layer. Furthermore, by applying prompt-guided attention at the six highest layers, the performance on CoNLL-2003 increases up to an F1-score of 91.2, which is close to the original result (F1-score of 92.9) obtained after adding full-layer prompt-guided attention for tuning. This phenomenon also appears in the cross-domain few-shot setting (A detailed analysis is presented in the appendix.). This proves that prompts applied to higher layers of LMs can better stimulate knowledge from PLMs for downstream tasks more efficiently. WE think this is an interesting discovery for the research on prompt-tuning, which may inspire research direction for further investigation.

Target	arget CoNLL Movie			Restaurant					
Source	M	R	Mix	C	R	Mix	C	M	Mix
LC-BERT	0.2	0.4	0.0	0.5	0.3	0.0	0.3	0.2	0.0
LC-BERT Template LightNER	8.5	0.2 8.8	0.0 15.8	0.3 12.6	0.2 9.0	0.0 18.9	0.1 11.0	0.0 8.5	0.0 18.4

Table 5: Cross-domain zero-shot performance. C, M, and R refer to the dataset of CoNLL03, Movie, and Restaurant, respectively. The Mix column refers to the methods of averaging the parameters from the other two source domains (average the prompt for LightNER).

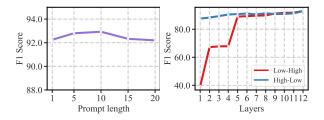


Figure 3: Performances on CoNLL03 as the prompt length varies (left) and prompt layers varies (right).

6.4 Cross-Domain Zero-Shot Analysis with Mixed Prompt

We utilize one dataset as the source domain and evaluate the zero-shot performance on target domains. From Table 5, the value 8.5 implies the cross-domain zero-shot performance from the Movie (source) to CoNLL (target). We observe that our method can achieve F1-scores of approximately 10 in the cross-domain zero-shot setting, significantly higher than other methods, which reveals that a task-specific prompt can instruct the generative framework to generalize to target domains. Considering that the prompt can be flexibly disassembled and integrated, we attempt to investigate the performance of mixing different prompts. Specifically, we directly average the parameters of prompts from two source domains as a mixed prompt for the target domain and insert it into the generative framework to evaluate the target performance. Since LC-BERT and Template methods have labelspecific layers, we adopt the parameters of LM to mix up for them. From Table 5, we notice that mixed prompt achieving promising improvement, which is close to the addition of the results of the original two sources prompt-based model. Looking at the bigger picture, this finding may also inspire future research directions of prompt-tuning.

7 Conclusion and Future Work

In this paper, we propose a novel generative framework with prompt-guided attention (LightNER), which can recognize unseen entities using a few examples. By constructing semantic-aware answer space of entity types for prompt-tuning, LightNER can maintain consistent pre-training and fine-tuning procedures. Meanwhile, the design of prompt-guided attention can better transfer knowledge across domains. Our model is efficient in terms of the parameters by only tuning the prompt parameters. Experimental results

demonstrate that LightNER can obtain competitive results in the rich-resource setting and outperform baseline methods in the low-resource setting. In the future, we plan to explore more sophisticated methods to augment prompts and apply our approach to more tasks in low-resource settings.

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