UNIFIED PROMPT LEARNING MAKES PRE-TRAINED LANGUAGE MODELS BETTER FEW-SHOT LEARNERS

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ABSTRACT

Language prompting induces the model to produce a textual output during the training phase, which achieves remarkable performance in few-shot learning scenarios. However, current prompt-based methods either use the same task-specific prompts for each instance, losing the particularity of instance-dependent information, or generate an instance-dependent prompt for each instance, lacking shared information about the task. In this paper, we propose an efficient few-shot learning method to dynamically decide the degree to which task-specific and instance-dependent information are incorporated according to different task and instance characteristics, enriching the prompt with task-specific and instance-dependent information. Extensive experiments on a wide range of natural language understanding tasks demonstrate that our approach obtains significant improvements compared to prompt-based fine-tuning baselines in a few-shot setting with about 0.1% parameters tuned. Moreover, our approach outperforms existing state-of-the-art efficient few-shot learning methods on several natural language understanding tasks.

Index Terms— Unified prompt learning, parameter-efficient, fine-tuning, prompt tuning

1. INTRODUCTION

Recently, prompt-based methods for few-shot language model tuning achieve remarkable performance by utilizing a task-specific prompt and a few labeled samples [1] or carefully engineering of prompts and verbalizers to convert inputs to cloze-format [2, 3]. For example, a textual entailment task can be designed by converting the input text **x** to a *prompt pattern* "**x** The answer is [MASK]" where the [MASK] token can be replaced by the *verbalizers* (e.g., 'entailment' and 'not entailment'). However, designing the appropriate prompts is labor-intensive and requires relevant domain knowledge, several efforts attempt to search for discrete prompt tokens automatically [4, 5]. Recent studies [6, 7] have demonstrated that discrete prompt tokens can be sub-optimal, which would make model performance vary from random guessing to state-of-the-art. Therefore, a lot of studies begin to focus on continuous prompts, which mainly includes Prefix Tuning [8] and Prompt tuning [9].

Prefix tuning and Prompt tuning prepend task-specific prompt vectors to the input layer and optimize these vectors during the training stage. The learnable task-specific prompts learn the general information of the task and provide the same task-specific information for each instance. However, these approaches do not take into account the particularity of each instance and focus more on task-specific information. Therefore, task-specific prompts may not be the best option for model predictions. More recently, several works propose the instance-dependent prompt tuning approaches [10, 11, 12]. These learnable instance-dependent prompts are generated based on each input sentence, aiming at finding a proper prompt for each instance. However, these approaches go to an extreme, ignoring the importance of task-specific information for model predictions. In light of these limitations, we believe that a good prompt should reflect both task-specific and instance-dependent information.

In this paper, we propose a **U**nified **P**rompt **L**earning method, named UPL, which incorporates different prompt tuning methods as submodules and learns prompts with both task-specific and instance-dependent information. The approach can efficiently tune large-scale PLMs with as few as 16 end-task examples of each class. First, following the route of prefix tuning [8] for task-specific prompts, we retain the general prompt information of each task. Second, we design a lightweight and low-rank bottleneck architecture to generate instance-dependent prompts for each instance. Then the activation of each submodule in UPL is controlled by *gating mechanism*, which dynamically decides the degree to which task-specific and instance-dependent information are incorporated according to different task characteristics.

We conduct extensive experiments on 13 natural language understanding tasks with RoBERTa-large [13]. Experimental results on a wide variety of NLP tasks demonstrate that our approach can obtain better performance with only a few training instances across all the tasks and only 0.1% parameters of PLMs tuned.

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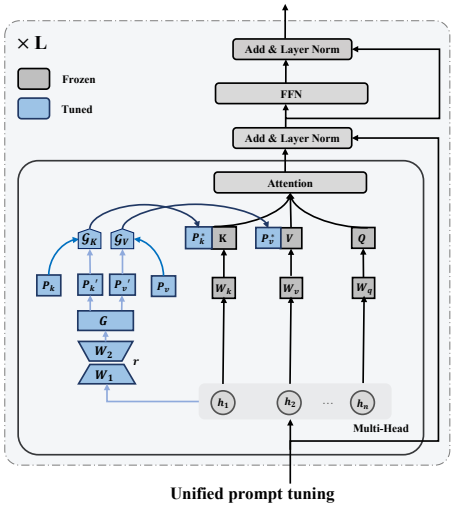


Fig. 1: Illustration of our method. The blue blocks refer to the trainable module, while the gray blocks refer to the frozen module.

2. BACKGROUND

2.1. Task-specific Prompt Tuning

Prefix tuning [8] and P-tuning v2 [14] prepend learnable task-specific vectors $\boldsymbol{P_k}, \boldsymbol{P_v}$ to Key($\boldsymbol{K}$) and Value($\boldsymbol{V}$) of the multi-head attention at each layer of the Transformer:

$$\text{Attn}(\boldsymbol{Q}, concat(\boldsymbol{P_k}, \boldsymbol{K}), concat(\boldsymbol{P_v}, \boldsymbol{V})) \tag{1}$$

Prompt tuning [9] and P-tuning [15] insert learnable task-specific vectors into the input sequence at the embedding layer, which can be formulated as follows:

$$\boldsymbol{E_{in}} = concat(\boldsymbol{W_p}, \boldsymbol{E}(\text{ [SEP] } X \text{ [EOS] })) \tag{2}$$

where $\boldsymbol{E_{in}}$ is the input embeddings, $\boldsymbol{W_p}$ is the embeddings of the inserted prompts, X is the input sentence, and $\boldsymbol{E}$ is the embedding table of the input sentence.

2.2. Instance-dependent Prompt Tuning

Different from the task-specific prompt tuning approaches, the instance-dependent prompt tuning methods aim to generate an instance-dependent prompt for each input sequence [10, 11, 12]. Specifically, given $D_{train} = \{(x_i, y_i)\}_{i=1}^{K}$ of the task T, they suppose that the generation of prompt should correspond to the input sequence x_i. Let $\mathcal{M}$ be the masked language model, and the instance-dependent prompt can be generated as follows:

$$\boldsymbol{W_p}(x_i, T) = \boldsymbol{G}(\mathcal{M}(x_i), T) \tag{3}$$

where $\boldsymbol{G}$ is a generator with a lightweight bottleneck architecture, $\mathcal{M}(x_i)$ is the representation of the input sequence, and the $\boldsymbol{W_p}(x_i, T)$ is the instance-dependent prompt based on each instance of the task T.

3. OUR APPROACH

We propose UPL, a unified and efficient prompt learning method that enriches the prompt with instance-dependent and task-specific information. As shown in Figure 1, the success of UPL consists of three main components: a) the prompts with task-specific information tell the model about the given task; b) a low-rank generator helps the model obtain instance-dependent information; c) a dynamical gating mechanism that can incorporate the task-specific and instance-dependent information according to different task characteristics. We detail the components of our UPL model below.

Let $x_{in} = \{x_1, x_2, \cdots, x_n\}$ be the input sentence of the model $\mathcal{M}$, and let $\boldsymbol{h} = \{\boldsymbol{h_1}, \boldsymbol{h_2}, \cdots, \boldsymbol{h_n}\} \in \mathbb{R}^{n \times d}$ be the hidden states in each layer of the model $\mathcal{M}$, where n is the length of input $\boldsymbol{h}$ and d is the the dimension of the hidden states. We suppose that a good prompt should reflect both task-specific and instance-dependent information. Following the previous works [8, 14], we firstly define two task-specific prompt vectors at each layer of the Transformer: $\boldsymbol{P_k} = \{\boldsymbol{p_{k1}}, \boldsymbol{p_{k2}}, \cdots, \boldsymbol{p_{kt}}\} \in \mathbb{R}^{t \times d}$ and $\boldsymbol{P_v} = \{\boldsymbol{p_{v1}}, \boldsymbol{p_{v2}}, \cdots, \boldsymbol{p_{vt}}\} \in \mathbb{R}^{t \times d}$, where t is the number of tokens in prompt representation and d is the hidden dimension. Different from the previous methods, to reduce the number of trainable parameters, we do not use a reparameterization encoder such as an MLP to generate learnable prompt vectors $\boldsymbol{P}$.

Secondly, we take inspiration from the recent works [19, 20, 18], which show that the learned large-scale models reside on a low intrinsic dimension. Therefore, we design a lightweight and low-rank generator to generate instance-dependent prompt vectors for each input sequence. Specifically, as illustrated in Figure 1, we first project the original d-dimensional sentence representation $\boldsymbol{h}$ into r dimensions through the low-rank matrix $\boldsymbol{W_1}$, then we project the hidden representation back to a d dimensions representation $\hat{\boldsymbol{h}}$ with the low-rank matrix $\boldsymbol{W_2}$, where $\boldsymbol{W_1} \in \mathbb{R}^{d \times r}$, $\boldsymbol{W_2} \in \mathbb{R}^{r \times d}$, and the rank $r \ll d$ (i.e., r in Figure 1 (d) can be two or four).

$$\hat{\boldsymbol{h}} = \boldsymbol{h}\boldsymbol{W_1}\boldsymbol{W_2},\ \hat{\boldsymbol{h}} \in \mathbb{R}^{n \times d} \tag{4}$$

Subsequently, the instance-dependent prompt vectors $\boldsymbol{P'_k} = \{\boldsymbol{p'_{k1}}, \boldsymbol{p'_{k2}}, \cdots, \boldsymbol{p_{kt'}}\} \in \mathbb{R}^{t \times d}$ and $\boldsymbol{P'_v} = \{\boldsymbol{p'_{v1}}, \boldsymbol{p'_{v2}}, \cdots, \boldsymbol{p'_{vt}}\} \in \mathbb{R}^{t \times d}$ can be generated through the linear mapping matrix $\boldsymbol{G} \in \mathbb{R}^{t \times n}$:

$$\begin{aligned} \boldsymbol{P'_k} &= \boldsymbol{G}\hat{\boldsymbol{h}} \\ \boldsymbol{P'_v} &= \boldsymbol{G}\hat{\boldsymbol{h}} \end{aligned} \tag{5}$$

where t is the number of instance-dependent prompt vectors, n is the length of the input, and d is the hidden dimension.

Finally, considering that a good prompt should vary appropriately according to different task characteristics and instance characteristics, we design a dynamical gating mechanism to control the proportion of task-specific and instance-dependent information. As shown in Figure 1, $\boldsymbol{\mathcal{G}_K} \in \mathbb{R}^{t \times t}$ and $\boldsymbol{\mathcal{G}_V} \in \mathbb{R}^{t \times t}$ are two gating matrices that estimate the importance of task-specific and instance-dependent information,

Method	#Params	SST-2 Acc.	SST-5 Acc.	MR Acc.	CR Acc.	MPQA Acc.	Subj Acc.	TREC Acc.	Avg
Single-Sentence									
Prompt-based zero shot [4] †	0%	83.6	35	80.8	79.5	67.6	51.4	32.0	61.4
"GPT-3" in-context learning [4] †	0%	84.8(1.3)	30.6(0.9)	80.5(1.7)	87.4(0.8)	63.8(2.1)	53.6(1.0)	26.2(2.4)	70.0(1.5)
Fine-tuning [13] †	100%	81.4(3.8)	43.9(2.0)	76.9(5.9)	75.8(3.2)	72.0(3.8)	90.8(1.8)	88.8(2.1)	75.7(3.2)
LM-BFF [4] †	100%	92.3(1.0)	49.2(1.6)	85.5(2.8)	89.0(1.4)	**85.8(1.9)**	**91.2(1.1)**	88.2(2.0)	83.0(1.7)
Adapter tuning [16]	3%	92.2(1.8)	50.4(3.2)	87.7(2.6)	90.4(3.9)	73.8(5.8)	90.8(1.6)	88.6(6.4)	82.0(3.6)
Bitfit [17]	0.09%	92.8(1.6)	48.6(3.4)	87.7(3.7)	90.5(1.2)	64.3(9.4)	88.8(3.8)	85.7(10.3)	79.8(4.8)
LoRA [18]	0.1%	**93.0(2.4)**	49.2(2.3)	87.2(2.0)	90.5(2.7)	68.7(7.8)	90.1(2.4)	88.8(5.8)	81.1(3.6)
Prefix tuning [8]	0.2%-1%	91.9(1.5)	49.6(2.0)	87.4(2.3)	90.6(2.2)	74.2(3.1)	88.4(2.3)	88.5(3.7)	81.5(2.4)
IDPT [12]	0.08%	91.5(1.6)	49.0(2.5)	86.4(3.2)	90.9(2.0)	67.3(7.4)	89.7(1.2)	86.4(3.4)	80.2(3.0)
Fixed-UPL	0.1%	92.5(1.2)	**50.8(1.9)**	87.9(2.2)	91.6(1.8)	76.4(4.0)	89.3(1.7)	89.6(3.0)	82.6(2.3)
Dynamic-UPL	0.12%	92.6(1.4)	50.6(1.3)	**88.3(1.6)**	**91.6(1.4)**	78.1(2.3)	90.5(1.4)	**90.4(3.6)**	**83.2(1.9)**

Method	#Params	MNLI Acc.	MNLI-mm Acc.	SNLI Acc.	QNLI Acc.	RTE Acc.	MRPC F1.	QQP F1.	Avg
Sentence-Pair									
Prompt-based zero shot [4] †	0%	50.8	51.7	49.5	50.8	51.3	61.9	49.7	52.2
"GPT-3" in-context learning [4] †	0%	52.0(0.7)	53.4(0.6)	47.1(0.6)	53.8(0.4)	60.4(1.4)	45.7(6.0)	36.1(5.2)	49.8(2.1)
Fine-tuning [13] †	100%	45.8(6.4)	47.8(6.8)	48.4(4.8)	60.2(6.5)	54.4(3.9)	76.6(2.5)	60.7(4.3)	56.3(5.0)
LM-BFF [4] †	100%	68.3(2.5)	**70.1(2.6)**	**77.1(2.1)**	68.3(7.4)	**73.9(2.2)**	76.2(2.3)	67.0(3.0)	71.6(3.2)
Adapter tuning [16]	3%	67.6(4.3)	67.5(4.1)	74.0(4.6)	64.3(4.9)	68.8(7.4)	81.8(2.9)	67.5(4.6)	70.2(4.7)
Bitfit [17]	0.09%	67.2(5.7)	67.6(4.6)	74.4(3.7)	64.7(3.7)	66.6(10.7)	76.6(10.4)	66.8(3.7)	69.1(6.1)
LoRA [18]	0.1%	68.3(4.2)	67.4(2.7)	75.9(2.1)	**68.6(3.9)**	69.6(6.7)	81.0(4.8)	**68.1(2.6)**	71.3(3.3)
Prefix tuning [8]	0.2%-1%	68.1(3.5)	68.3(2.4)	75.4(1.8)	67.5(3.5)	70.2(5.1)	81.4(2.8)	66.8(6.5)	71.1(3.7)
IDPT [12]	0.08%	66.3(3.6)	66.0(2.1)	73.5(2.3)	66.6(3.7)	70.3(4.3)	80.6(3.4)	66.4(4.6)	70.0(3.4)
Fixed-UPL	0.1%	68.9(1.5)	68.7(1.9)	76.2(1.1)	68.2(1.4)	71.2(5.3)	81.8(1.3)	66.1(2.8)	71.6(2.2)
Dynamic-UPL	0.12%	**69.3(2.4)**	68.8(2.2)	75.9(2.1)	68.3(2.4)	72.8(3.9)	**82.1(2.1)**	66.6(3.2)	**72.0(2.6)**

Table 1: Performance of all methods on RoBERTa-large. † indicates the results in [4]. We report average(and standard deviation) performance over 5 different splits. Bold fonts indicate the best results.

where t is the length of prompt vectors. We apply a sigmoid function σ to obtain the contribution scores for task-specific and instance-dependent prompts.

$$\begin{aligned} \boldsymbol{P_k^\star} &= \sigma(\boldsymbol{\mathcal{G}_K P_k}) \cdot \boldsymbol{P_k} + \sigma(\boldsymbol{\mathcal{G}_K P_k'}) \cdot \boldsymbol{P_k'} \\ \boldsymbol{P_v^\star} &= \sigma(\boldsymbol{\mathcal{G}_V P_v}) \cdot \boldsymbol{P_v} + \sigma(\boldsymbol{\mathcal{G}_V P_v'}) \cdot \boldsymbol{P_v'} \end{aligned} \tag{6}$$

We then concatenate the prompt vectors $\boldsymbol{P_k^\star}$ and $\boldsymbol{P_v^\star}$ that contain task-specific and instance-dependent information with the original key $\boldsymbol{K}$ and value $\boldsymbol{V}$:

$$\text{Attn}(\boldsymbol{Q}, concat(\boldsymbol{P_k^\star}, \boldsymbol{K}), concat(\boldsymbol{P_v^\star}, \boldsymbol{V})) \tag{7}$$

4. EXPERIMENTAL RESULTS

4.1. Experimental Settings

We conduct our experiments with the same setting following LM-BFF [4] and DART [21], which measure the average performance of models trained on 5 different randomly sampled D_{train} and D_{dev} splits. We train the model for 100 epochs for each split and take the best checkpoint as measured on D_{dev}. We report the accuracy and F1-score for 13 NLU tasks and use a default setting training for a batch size of 8, a learning rate of 4e-4, and a prompt length of 16. We set the rank r of the low-rank matrix to 4. We train our proposed UPL on one NVIDIA A100 with 80G of memory. We explore two versions of unified prompt learning methods: Fixed-UPL, and Dynamic-UPL. The first version uses a fixed hyperparameter $\alpha = 0.3$ (e.g.,$\alpha \in (0, 1)$) to control the proportion of task-specific and instance-dependent information. The second one uses learnable gating matrices that can incorporate task-specific and instance-dependent information dynamically.

4.2. Main Results

Table 1 shows the results of all methods on RoBERTa-large [13] with 5 different randomly sampled splits (e.g., each split contains 16 examples of each class) across 13 NLU tasks. UPL outperforms all other methods and achieves new state-of-the-art results for few-shot learning on several NLU tasks.

First, our proposed method Dynamic-UPL improves the performance compared to Prefix tuning [8] by 1.7 and 0.9 points for single-sentence and sentence-pair datasets respectively with fewer model parameters tuned. Compared to IDPT [10, 12], Dynamic-UPL improves the performance by 3.0 and 2.0 points for single-sentence and sentence-pair datasets respectively. Dynamic-UPL performs better than Prefix tuning and IDPT across 12 and 13 datasets respectively (e.g., especially on RTE, TREC, and SST-5), demonstrating that incorporating task-specific and instance-dependent prompt tuning methods as submodules is advantageous.

Second, compared with the currently prevailing parameter-efficient tuning methods, Dynamic-UPL obtains state-of-the-art results. Our method Dynamic-UPL performs better than Adapter [16], LoRA [18], and BitFit [17] across 11 tasks, 10 tasks, and 12 tasks respectively. Moreover, we report the percentage of trained parameters for parameter-efficient tuning methods in Table 1. Dynamic-UPL requires fewer parameters and achieves a better performance than Adapter tuning. For LoRA, BitFit, and Dynamic-UPL, only about 0.1% parameters are tuned, while Dynamic-UPL learns the task-specific and instance-dependent information and yields better performance.

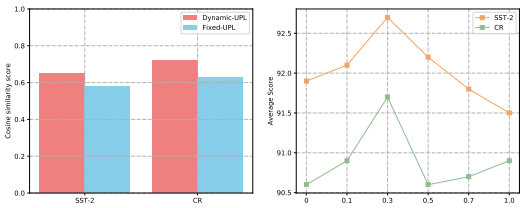
Third, compared with LM-BFF [4], a prompt-based fine-tuning method with all parameters tuned, Dynamic-UPL achieves comparable results with LM-BFF on average and even outperforms LM-BFF across 7 datasets with only about 0.1% parameters tuned.

Finally, these promising results illustrate that Dynamic-UPL has better generalization in few-shot settings and makes the pre-trained language model a better efficient few-shot learner. As an ablation, when learning prompts with a hyperparameter α to control the proportion of task-specific and instance-dependent information in Fixed-UPL, we observe that the performance consistently lags behind the Dynamic-UPL but performs better than other methods (except on LM-BFF), showing that learn prompts with both task-specific and instance-dependent information is a good alternative for few-shot learning.

5. ANALYSIS AND DISCUSSION

5.1. Dynamic-UPL or Fixed-UPL?

As shown in Figure 2(a), we calculate the cosine similarity scores of task-specific prompts and instance-dependent prompts under both Dynamic-UPL and Fixed-UPL. The Dynamic-UPL obtains high scores than Fixed-UPL on both SST-2 and CR, showing that incorporating task-specific and instance-dependent information dynamically can further enhance the degree of information integration and yield better performance. To further analyze how Fixed-UPL influences the fusion of task-specific and instance-dependent information, we control the degree of incorporating task-specific and instance-dependent information through the proportion of hyperparameter α. As shown in Figure 2(b), for the two datasets SST-2 and CR, Fixed-UPL performs better than task-specific prompt tuning and instance-dependent prompt tuning when the hyperparameter α is between 0.1 and 0.4, showing that Fixed-UPL does need both the task-specific and instance-dependent information.



(a) (b)

Fig. 2: (a) The cosine similarity scores of task-specific prompts and instance-dependent prompts under both Dynamic-UPL and Fixed-UPL. (b) We utilize the hyperparameter α to control the degree of incorporating task-specific and instance-dependent information.

Dataset	r=2	r=4	r=8	r=16	r=64
SST-5	49.8	50.3	50.5	49.9	50.0
CR	90.8	91.2	91.4	91.2	91.1

Table 2: Validation accuracy on SST-5 and CR with different rank r. We conduct the experiments with the hyperparameter $\alpha = 0.3$.

5.2. Impact of the Rank r

We utilize a low-rank matrix to generate the instance-dependent prompt vectors. To explore the impact of low rank r on the instance-dependent prompt generation, in Table 2, we show the accuracy of SST-5 and CR with different rank r. Surprisingly, Dynamic-UPL performs competitively with a very small rank r, which suggests that a low-rank generation matrix is sufficient.

6. CONCLUSION AND FUTURE WORK

This paper presents UPL, a simple and efficient method that improves few-shot learning with pre-trained language models. Our approach enriches the prompt with task-specific and instance-dependent information by dynamically controlling the proportion of the two types of prompts. Through extensive experiments over 13 NLP tasks, we demonstrate that UPL generalizes better than the existing state-of-the-art efficient methods in few-shot learning scenarios. Intuitively, the simplicity and effectiveness of UPL proposed in this study makes it a promising method and can stimulate future research directions in the few shot with PLMs.

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