# **Instance-aware Prompt Learning for Language Understanding and Generation**

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### **Abstract**

Recently, prompt learning has become a new paradigm to utilize pre-trained language models (PLMs) and achieves promising results in downstream tasks with a negligible increase of parameters. The current usage of discrete and continuous prompts assumes that the prompt is fixed for a specific task and all samples in the task share the same prompt. However, a task may contain quite diverse samples in which some are easy and others are difficult, and diverse prompts are desirable. In this paper, we propose an instance-aware prompt learning method that learns a different prompt for each instance. Specifically, we suppose that each learnable prompt token has a different contribution to different instances, and we learn the contribution by calculating the relevance score between an instance and each prompt token. The contribution weighted prompt would be instance aware. We apply our method to both unidirectional and bidirectional PLMs on both language understanding and generation tasks. Extensive experiments demonstrate that our method obtains considerable improvements compared to strong baselines. Especially, our method achieves the state-of-the-art on the SuperGLUE few-shot learning benchmark.<sup>1</sup>

## 1 Introduction

Prompt learning aims to design or learn appropriate prompts which can induce the capacity from pre-trained language models (PLMs) to perform specific tasks, and it becomes a new paradigm to use PLMs due to its flexibility and fewer extra parameters. There are typically two kinds of prompts, namely discrete prompt and continuous prompt. Discrete prompt such as GPT-3 [Brown *et al.*, 2020] uses the task instructions and task-related instances as prompt for zero-shot and few-shot learning respectively. PET/iPET [Schick and Schütze, 2021a; Schick and Schütze, 2021b] utilizes the manually-designed prompts to reformulate many tasks as cloze questions (e.g., by appending phrases such as "Similar

Instance 1	"word": "acquisition", "sentence1": "The child's acquisition of language.", "sentence2": "That graphite tennis racquet is quite an acquisition." label: false.
Instance 2	"word": "sense", "sentence1": "Particle detectors sense ionization.", "sentence2": "She immediately sensed her disdain." label: false .
D-# 1	The child's acquisition of language, That graphite tennis racquet is quite an acquisition. Similar sense of "acquisition"? FALSE.
Pattern 1	Particle detectors sense ionization, She immediately sensed her disdain. Similar sense of "sense"? TRUE.
D 2	The child's acquisition of language, That graphite tennis racquet is quite an acquisition.  Does acquisition have the same meaning in both sentences? TRUE.
Pattern 2	Particle detectors sense ionization, She immediately sensed her disdain. Does sense have the same meaning in both sentences? FALSE.

Figure 1: The example is chosen from WiC dataset in SuperGLUE. The color words indicate the manually-designed patterns which are used to formalize the instance into close-style questions.

sense of two sentences?") and performs gradient-based finetuning with smaller PLMs. To simplify PET/iPET, ADAPET [Tam et al., 2021] decouples the losses for the label tokens and a label-conditioned masked language modeling objective over the full original input. Considering that manually designing the discrete prompts is time-consuming and laborintensive, several efforts focus on searching proper discrete prompts automatically [Shin et al., 2020; Gao et al., 2021; Zhong et al., 2021].

Although discrete prompts can reflect rationality from the perspective of humans, it may not be necessarily suitable for PLMs. To tackle this problem, a lot of studies begin to focus on continuous prompts. Continuous prompts can be thought of as special tokens. [Lester et al., 2021] proposes prompt tuning and concatenates the continuous prompts with the embedding layer of PLMs. When using small PLMs, the performance of prompt tuning has a clear gap with fine-tuning. [Li and Liang, 2021] proposes prefix tuning and shows comparable results with fine-tuning on generation tasks. Prefix tuning concatenates continuous prompts with each layer in the decoder and only optimizes 0.1\% of the model parameters. However, the current usage of discrete and continuous prompts assumes that all samples in one task share the same prompt, and does not consider the diversity of the instances in which some are easy and others are difficult. Therefore, it is desirable to learn a special prompt for each instance.

In this paper, we propose an Instance-aware Prompt Learning method (abbreviated as IPL) which learns a unique prompt for each instance. As shown in Figure 1, we use two different manually-designed patterns to formalize the in-

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<sup>&</sup>lt;sup>1</sup>Our code is available in https://github.com/jinfeihu-stan/IPL

stances into cloze-style questions and feed them into the pretrained language model (PLM). As we can see, for each instance, using different prompts can get different answers. Pattern 1 is suitable for instance 1, while pattern 2 fits instance 2, which means that every instance needs a specific prompt for itself. However, it is difficult to dynamically find an appropriately discrete prompt for each instance. Therefore, we consider to utilize a look-up module and obtain a dynamic continuous prompt for each instance. Specifically, we take each learnable prompt token as a query and calculate its contribution to each instance through the look-up module. After doing this, each learnable prompt token has a different contribution to the instance and the contribution weighted continuous prompts are then utilized to guide the PLMs to perform the downstream task more instance-aware.

We evaluate our approach on natural language understanding (NLU) and generation (NLG) tasks. For NLU tasks, we conduct experiments on SuperGLUE [Wang et al., 2019] with both GPT2 [Radford et al., 2019] and RoBERTa [Delobelle et al., 2020]. For NLG tasks, we conduct experiments on table-to-text generation and summarization using GPT2. Experimental results on various tasks demonstrate that our method obtains considerable improvements compared to strong baselines. Especially, our method achieves the new state-of-the-art on the SuperGLUE few-shot learning benchmark. In summary, our key contributions can be listed as follows:

- We propose an instance-aware prompt learning method that can learn a unique prompt for each instance.
- Extensive experiments on both language understanding and generation tasks under both unidirectional and bidirectional PLMs verify the effectiveness of our method.
- Detailed analyses verify that IPL can indeed dynamically learn appropriate continuous prompts for each instance.

## 2 Approach

In this section, we present the details of our model IPL. Previous studies demonstrate that prompt learning is promising for downstream tasks. However, using fixed prompts (e.g., discrete prompts like "convert the table into a sentence" or continuous prompts after optimization) for diverse instances in one task ignores the peculiarity of different instances. To address this problem, our instance-aware prompt learning method IPL can learn a special prompt for each specific instance. Next, we introduce prompt learning first and then present our IPL model.

### 2.1 Prompt Learning

For the standard paradigm of pre-training and fine-tuning, there is a gap (e.g., inconsistent objective function) between the pre-training stage and the fine-tuning stage. Fortunately, prompt learning bridges this gap by formalizing the downstream tasks into the form of a conditional language model or masked language model. Discrete prompt is an important method in prompt learning, for instance, given a masked language model  $\mathcal{M}$ , we first use the prompt to formulate a question and answer instance x (e.g., [passage]. Can you have too

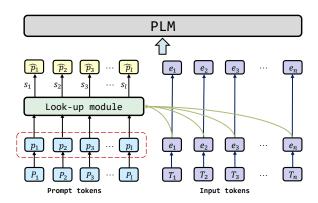


Figure 2: Illustration of our approach.  $[P_1, P_2, P_3, \cdots, P_l]$  represents the prompt tokens.  $[T_1, T_2, T_3, \cdots, T_n]$  represents the input tokens.  $\{e_1, e_2, \cdots, e_n\}$  represents the embeddings of input tokens.  $\{p_1, p_2, \cdots, p_n\}$  is the learnable prompt, and  $[\hat{p_1}, \hat{p_2}, \cdots, \hat{p_l}]$  refers to the weighted representation for the input instance.

much oxygen in your body?) as:

$$\hat{x} = x$$
 the answer is [MASK].

Then  $\hat{x}$  is fed into  $\mathcal{M}$ , and let  $\mathcal{M}$  determine whether "Yes" or "No" is more appropriate to replace [MASK] [Gao *et al.*, 2021].

Continuous prompt is an alternative approach in prompt learning. Suppose we get the embedding sequence  $\{e_1, e_2, \cdots, e_n\}$  of the instance x, and we concatenate the continuous prompt (e.g., as shown in the red dotted box in Figure 2)  $\{p_1, p_2, \cdots, p_l\}$  with the embedding sequence, which can be formalized as follows:

$$\hat{x} = \{p_1, p_2, \cdots, p_l; e_1, e_2, \cdots, e_n\}$$

Then,  $\hat{x}$  is fed into  $\mathcal{M}$  to generate the target labels.

In this paper, we combine the advantages of continuous prompts with discrete prompts and propose an instance-aware prompt learning method which learns a unique prompt for each instance. Next, we detail our proposed IPL mdoel.

## 2.2 Instance-aware Prompt Learning

We denote  $\mathcal{T}$  as an instance in a form of a sequence consisting of n tokens  $\mathcal{T}=\{T_1,T_2,\cdots,T_n\}$ . We follow [Li and Liang, 2021; Lester et al., 2021], and use learnable prompts of special tokens  $\mathcal{P}=\{P_1,P_2,\cdots,P_l\}$  and update the embeddings of these prompt tokens during prompt learning. As shown in Figure 2, we first use the pre-trained language model to obtain the embedding sequence  $\{e_1,e_2,\cdots,e_n\}$  of  $\mathcal{T}$ , and get a matrix  $X\in\mathbb{R}^{n\times d_e}$ , where n is the length of instance  $\mathcal{T}$ ,  $d_e$  is the dimension of the embedding space. Then we create a learnable matrix  $P=\{p_1,p_2,\cdots,p_l\}$  of  $\mathcal{P}$ , where l is the length of the prompt, and  $P\in\mathbb{R}^{l\times d_e}$ . After we get the prompt matrix P and embedding matrix P, we use the projection matrices P0 and P1 and P2 and P3 and P4 and P5 and P6 and P8 and P9 and P9 and P8 into matrix P9 and P9 and P9 and P9 and P9 in the dimension of projection space.

$$M = PW^{M}$$

$$N = XW^{N}$$
(1)

Method	BoolQ Acc.	CB Acc./F1	MultiRC EM/F1a	RTE Acc.	WiC Acc.	COPA Acc.	WSC Acc.	ReCoRD Acc./F1	Avg
GPT-3 <sup>†</sup>	77.5	82.1/57.2	32.5/74.8	72.9	55.3	92.0	75.0	<b>89.0</b> /90.1	73.2
$\operatorname{PET}^\dagger$	79.4	85.1/59.4	37.9/77.3	69.8	52.4	95.0	80.1	86.0/86.5	74.1
${ m iPET}^{\dagger}$	80.6	<b>92.9</b> /92.4	33.0/74.0	74.0	52.2	95.0	80.1	86.0/86.5	76.8
ADAPET <sup>‡</sup>	80.3	89.3/86.8	39.2/80.1	<b>76.5</b>	54.4	89.0	81.7	85.4/92.1	77.3
IPL	79.2	92.9/94.8	38.5/76.8	76.2	64.6	91.0	84.8	83.6/ <b>91.1</b>	79.3

Table 1: Few-shot learning (32 examples) on SuperGLUE validation set with ALBERT-xxlarge-v2. † indicates the results reported in [Schick and Schütze, 2021b], and ‡ indicates the results reported in [Tam et al., 2021].

Method	BoolQ Acc.	CB Acc./F1	MultiRC EM/F1a	RTE Acc.	WiC Acc.	COPA Acc.	WSC Acc.	ReCoRD Acc./F1	Avg
GPT-3 <sup>†</sup>	76.4	75.6/52.0	30.5/75.4	69.0	49.4	92.0	80.1	90.2/90.1	71.8
$\operatorname{PET}^\dagger$	79.1	87.2 / 60.2	36.4 / 76.6	67.2	50.7	90.8	88.4	85.4 / 85.9	74.0
iPET <sup>†</sup>	81.2	88.8/79.9	31.7/74.1	70.8	49.3	90.8	88.4	85.4 / 85.9	75.4
ADAPET <sup>‡</sup>	80.0	<b>92.0</b> /82.3	35.7 / 76.2	<b>75.0</b>	53.5	85.4	85.6	85.5 / 86.1	76.0
IPL	78.4	92.0/85.9	35.1/75.9	74.9	60.9	85.6	84.9	83.5/84.3	76.6

Table 2: Few-shot learning (32 examples) on SuperGLUE test set with ALBERT-xxlarge-v2. † indicates the results reported in [Schick and Schütze, 2021b], and ‡ indicates the results reported in [Tam et al., 2021]

We suppose that each learnable prompt token has a different contribution to different instances and we learn the contribution scores by calculating the relevance score between matrix  $M = \{p'_1, p'_2, \cdots, p'_l\}$  and  $N = \{e'_1, e'_2, \cdots, e'_n\}$ . After we get the relevance score, we pass the score to the look-up module. In the look-up module, we adopt a method of mean operation and apply a sigmoid function  $\sigma$  to obtain how much does each learnable prompt token contributes to the instance  $\mathcal{T}$ . The detailed calculation is as follows:

$$s_{j} = \sigma\left(\frac{1}{n} \sum_{i=1}^{n} \mathbf{p}'_{j} \cdot \mathbf{e}'_{n}^{T}\right) \tag{2}$$

$$\hat{\boldsymbol{p}}_{i} = \boldsymbol{s}_{i} \cdot \boldsymbol{p}_{i} \tag{3}$$

where  $e_n'^T$  is the transpose of  $e_n$ .  $p_j'$  is the contribution of the j-th prompt token to the instance  $\mathcal{T}$ .  $s_j$  is the contribution score of the j-th prompt token after applying a sigmoid funtion  $\sigma$ , and  $\hat{p_j}$  is the j-th weighted representation for the instance. After doing such a calculation for all prompt tokens, we get the weighted prompt as  $\hat{P} = \{\hat{p_1}, \hat{p_2}, \cdots, \hat{p_l}\}$ . Then we concatenate weighted continuous prompt with the embedded instance as a new matrix  $[\hat{P}; X] \in \mathbb{R}^{(l+n) \times d_e}$ , and feed it into the pre-trained language model.

During training, we optimize the parameters of prompt module and PLMs. We do not freeze the model parameters as [Lester *et al.*, 2021] does, because their results demonstrates that the gap between prompt tuning and fine-tuning disappear only when the model size increases to 10 billion parameters.

## 3 Experiments

To evaluate our method IPL, we conduct experiments on both NLU tasks and NLG tasks. For NLU tasks, we evaluate IPL on SuperGLUE<sup>2</sup> [Wang *et al.*, 2019]. And we evaluate IPL for few-shot learning by using 32 labeled examples per task from FewGLUE<sup>3</sup> [Schick and Schütze, 2021b]). For NLG tasks, we select 3 standard table-to-text generation tasks: E2E [Novikova *et al.*, 2017], WebNLG [Gardent *et al.*, 2017], DART [Radev *et al.*, 2021] and a dialogue summarization task: SamSum [Gliwa *et al.*, 2019].

## 3.1 Experiments on NLU Tasks

Our code is implemented based on PET<sup>4</sup> using HuggingFace [Wolf *et al.*, 2020]. The experiment results include the fewshot learning results and fully-supervised learning results.

## **Few-shot Learning Results**

For a fair comparison, we choose ALBERT-xxlarge-v2 [Lan et al., 2020] for experiments and use the same data split as [Schick and Schütze, 2021b], which consists of 32 labeled examples for each task. We use a default setting training for 20 epochs, using a learning rate of 1e-5, a batch size of 8, and a prompt length of 16.

Our main results on the validation and test sets on Super-GLUE are shown in Table 1 and Table 2. We compare against GPT-3, PET/iPET and ADAPET. Initially, ADAPET does not use the unlabeled data and achieves the state-of-the-art on

<sup>&</sup>lt;sup>2</sup>https://supergluebenchmark.com/

<sup>&</sup>lt;sup>3</sup>https://github.com/timoschick/fewglue

<sup>&</sup>lt;sup>4</sup>https://github.com/timoschick/pet

Method	BoolQ Acc.	CB Acc./F1	MultiRC F1a/EM	RTE Acc.	WiC Acc.	BoolQ Acc.	CB Acc./F1	MultiRC F1a/EM	RTE Acc.	WiC Acc.
			GPT2-base					GPT2-large		
PET	74.55	94.05/95.58	70.36/ <b>22.87</b>	67.14	65.67	80.43	92.86/94.75	75.81/32.42	78.70	70.22
PT	74.16	92.86/94.70	69.84/21.16	67.03	64.16	79.66	96.43/97.37	75.81/ <b>34.10</b>	75.45	69.12
IPL	74.89	94.64/96.03	<b>70.54</b> /22.35	69.68	66.72	80.80	98.21/98.67	<b>76.00</b> /33.26	80.14	69.59

Table 3: Fully-supervised learning on SuperGLUE validation set with unidirectional pre-trained language models. PET means PET fine-tuning with a single pattern, and PT refers to prompt-tuning. For a fair comparison, we use the same pattern for all models.

Method	BoolQ	СВ	MultiRC	RTE	WiC	BoolQ	СВ	MultiRC	RTE	WiC
	Acc.	Acc./F1	F1a/EM	Acc.	Acc.	Acc.	Acc./F1	F1a/EM	Acc.	Acc.
			RoBERTa-base					RoBERTa-large		
PET	80.03	96.43/95.56	76.05/ <b>35.12</b>	82.67	69.28	85.47	98.81/99.12	83.36/ <b>51.07</b>	87.12	70.85
PT	80.32	96.43/94.76	76.05/33.44	80.14	68.86	85.44	98.81/99.12	83.23/50.75	87.01	72.14
IPL	80.63	96.43/95.56	<b>76.19</b> /34.59	82.91	70.85	85.66	99.40/99.56	<b>83.40</b> /50.89	87.48	73.51

Table 4: Fully-supervised learning on SuperGLUE validation set with bidirectional pre-trained language models. PET means PET fine-tuning with a single pattern, and PT refers to prompt tuning. For a fair comparison, we use the same pattern for all the models.

SuperGLUE few-shot learning tasks compared to PET/iPET which uses the unlabeled data. And for IPL, we train IPL with a single pattern and do not use the unlabeled data.

As can be seen from Table 1, on average, IPL outperforms GPT-3 by 6 points; outperforms PET's iterative variant, iPET, by 2.5 points, and even outperforms the previous state-of-theart model ADAPET by 2 points on the dev set. Specifically, compared with iPET and GPT-3, IPL achieves improvements on 5 out of the 8 tasks and 6 out of the 8 tasks respectively, demonstrating the effectiveness of our method in few-shot NLU tasks. We will conduct detailed analysis in 4.2.

We also report the test set on SuperGLUE in Table 2, IPL outperforms all other models including ADAPET, which is the previous state-of-the-art model, and obtains the new state-of-the-art for few-shot learning on SuperGLUE.

#### **Fully-supervised Learning Results**

To verify IPL on various PLMs, we perform experiments on 5 out of the 8 tasks of SuperGLUE benchmark including BoolQ, MultiRC, RTE, CB, and WiC, where we choose both unidirectional PLMs GPT-2 and bidirectional PLMs RoBERTa. We report the performance of fine-tuning with PET [Schick and Schütze, 2021a], prompt tuning [Lester *et al.*, 2021], and our method IPL. We use a default setting training for 20 epochs, using a learning rate of 2e-5, a batch size of 32, and a prompt length of 16.

Table 3 and Table 4 show our main results on GPT-2 and RoBERTa. On unidirectional PLMs like GPT2-base and GPT2-large, IPL outperforms PET fine-tuning and prompt tuning on all 5 tasks with GPT2-base and 4 out of 5 tasks on GPT2-large. On bidirectional PLMs like RoBERTa-base and RoBERTa-large, IPL outperforms all other RoBERTa-based models on all 5 tasks. Based on the experiment results, we demonstrate that IPL can achieve great results on both GPT-2 and RoBERTa models.

## 3.2 Experiment on NLG Tasks

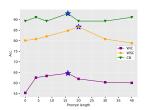
For NLG tasks, we compare IPL on GPT2-base and GPT2large with two baseline methods: the standard fine-tuning, and prompt tuning, where we do not freeze the model parameters as IPL does. The experiment results are illustrated in Table 5 and Table 6. We choose three table-to-text tasks and a summarization task. For table-to-text tasks, on E2E, we use the official evaluation script, which reports BLUE [Papineni et al., 2002], NIST [Belz and Reiter, 2006], ROUGE-L [Lin, 2004], and CIDEr [Vedantam et al., 2015]. On WebNLG, we use the official evaluation script, which reports BLEU, ME-TEOR [Lavie and Agarwal, 2007], and TER [Snover et al., 2006]. On DART, we use the official evaluation script and report BLEU, METEOR, TER, and BERTScore [Zhang et al., 2020]. As for the summarization task: SamSum, we report ROUGE-1, ROUGE-2, and ROUGE-L. The hyperparameters we tune include the number of epochs, batch size, learning rate, and prefix length. For table-to-text tasks, we set batch size as 32, prefix length as 10, the number of epochs as 10 for both GPT2-base and GPT2-large, in addition to the learning rate as 5e-5 for GPT-base, 5e-6 for GPT-large. For the summarization task, we set the prefix length as 100 and other hyperparameters keep consistent with table-to-text tasks.

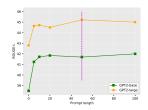
#### **Results on NLG Tasks**

As shown in Table 5, on GPT2-base, IPL performs better than fine-tuning and prompt tuning on E2E and WebNLG, while on DART, which is an open domain table-to-text dataset, IPL slightly underperforms prompt tuning. On GPT2-large, IPL outperforms fine-tuning and can be comparable or better than prompt tuning. Additionally, IPL obtains better performance on WebNLG unseen domains suggesting that IPL can generalize to other domains better. For the summarization task, the results in Table 6 show IPL performs better than fine-tuning and prompt tuning on both GPT2-base and GPT2-large models, suggesting it has the potential to scale to even larger models. Above all, the results demonstrate that IPL can achieve

		E	2E						WebNLG						DA	ART	
	BLUE	NIST	R_L	CIDEr		BLUE			MET			$TER\downarrow$		BLUE	MET	$TER\downarrow$	BERT
					Seen	Unseen	All	Seen	Unseen	All	Seen	Unseen	All				
									GPT2-base								
FT	69.55	8.79	71.52	2.49	56.01	26.46	41.70	39.33	25.04	32.46	46.40	81.80	62.63	42.08	35.17	52.58	94.12
PT	69.78	8.81	71.55	2.49	60.55	28.03	45.51	43.25	28.82	36.30	38.03	74.17	54.60	45.27	37.62	49.83	94.76
IPL	69.82	8.82	71.65	2.49	60.93	29.94	46.46	43.27	29.15	36.50	37.76	72.23	53.56	42.98	35.62	48.50	95.43
									GPT2-large								
FT	68.32	8.76	71.25	2.48	62.11	43.52	53.61	44.56	37.39	41.21	37.06	53.62	44.65	47.16	38.24	47.35	94.43
PT	68.32	8.65	71.04	2.49	64.18	46.04	55.85	45.30	38.62	42.17	34.81	50.92	42.19	48.57	39.04	46.12	94.90
IPL	68.53	8.68	71.2	2.51	64.06	46.12	55.90	45.24	38.64	42.12	35.28	50.55	42.28	48.38	39.15	46.17	95.47

Table 5: The best score is in bold for both GPT2-base and GPT2-large. The FT refers to fine-tuning. PT refers to prompt tuning. For the metrics, the higher the better except for TER.





- (a) Prompt length (Few-shot)
- (b) Prompt length (SamSum)

Figure 3: (a) Performance on validation set in the few-shot of SuperGLUE including WiC, WSC, and CB, while the prompt length varies in {0,4,8,16,20,30,40}. (b) Performance on SamSum while the prompt length varies in {0,5,10,20,50,100}.

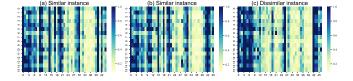


Figure 4: Attention visualization of different instances. (a) and (b) are similar instances, (a) and (c) or (b) and (c) are dissimilar instances. X-axis represents the input sequence without prompt, and Y-axis represents the prompt sequence.

great results on NLG tasks with GPT-2 model.

### 4 Analysis

We conduct detailed analyses on IPL. Section 4.1 studies the effect of the prompt length on the performance of few-shot learning on SuperGLUE. Section 4.2 visualizes the attention matrix of similar instances and dissimilar instances to verify the effectiveness of our approach. Section 4.3 shows the results of different methods on different instances.

## 4.1 Prompt Length

We visualize the relationship between the performance and different prompt lengths (other settings are fixed). For NLU tasks, we conduct experiments on three tasks of SuperGLUE including CB, WSC, WiC using ALBERT-xxlarge-v2. Figure 3(a) shows that performance increases as the prompt length increases up to a threshold (16 for CB and WiC, 20 for WSC), and then the performance slightly drops. Figure 3(b) shows the effect of prompt length on the performance of different model sizes on SamSum. We can see that the performance consistently increases until the prompt length is up to 50. Continuing to increase the prompt length cannot yield significant improvements.

## 4.2 Visualization of Instance-aware Prompt

We choose similar instances and dissimilar instances from WSC [Levesque *et al.*, 2012] for analysis. Figure 4 shows the analysis results for IPL on similar instances and dissimilar instances. We visualize the attention matrix of the instance and prompt. As shown in 4(a) and 4(b), the attention matrices between 4(a) and 4(b) are similar, which means IPL can produce similar prompts for similar instances. Comparing 4(a) and 4(c) or 4(b) and 4(c), we find that the attention matrices are not similar, suggesting that IPL can produce different prompts for dissimilar instances. Consequently, our approach learns a special prompt for each instance and can be aware of the important information of the instance.

## 4.3 Case study

As shown in Figure 5, for indistinguishable instances, PET utilizes a fixed discrete prompt and makes a wrong judgment on the meaning of the word 'put' and 'department'. Prompt tuning prepends the fixed continuous prompt with the two instances based on the pattern of PET and also gives wrong answers. In contrast, our method IPL learns a unique prompt for each instance and contains much information of the instance yielding the correct answer.

### 5 Related Work

GPT-3 [Brown *et al.*, 2020], which uses the task description and several typical examples as prompt to guide the generation, indicates the language models are few-shot learners and leads to the waves of prompt learning. Recently,

Method	R-1	R-2	R-L	R-1	R-2	R-L
	GP	T2-ba	.se	GPT	2-lar	ge
FT PT	42.6 46.5	18.9	38.5 41.8	47.2	22.2	42.8
IPL			42.0			

Table 6: Results for summarization on SamSum using GPT2 models. The FT refers to fine-tuning. PT refers to prompt tuning, and the best score is in bold.

Instance 1	"word": "put", "sentence1": "He put all his efforts into this job.", "sentence2": "The teacher put an interesting twist to the interpretation of the story." label: true .
Instance 2	"word": "department", "sentence1": "His work established a new department of literature.", "sentence2": "Baking is not my department." label: true.
PET	He put all his efforts into this job, The teacher put an interesting twist to the interpretation of the story. Similar sense of "put" ? FALSE.
	His work established a new department of literature, Baking is not my department. Similar sense of "department"? FALSE.
DT	$[P_1 P_2 \cdots P_l]$ He put all his efforts into this job, The teacher put an interesting twist to the interpretation of the story. Similar sense of "put" ? FALSE.
PT	$[P_1\ P_2\ \cdots\ P_l]$ His work established a new department of literature, Baking is not my department. Similar sense of "department"? FALSE,
IPL	$[P_1' P_2' \cdots P_l']$ He put all his efforts into this job, The teacher put an interesting twist to the interpretation of the story. Similar sense of "put", ? TRUE.
	$[P_1' P_2' \cdots P_l']$ His work established a new department of literature, Baking is not my department. Similar sense of "department"? TRUE.

Figure 5: The instances are chosen from WiC dataset in Super-GLUE, which is shown on the top. We use the manually-designed pattern from PET. PT refers to prompt tuning. Our method is shown on the bottom, and the color words mean our approach can be aware of the important words in the instance.

PET/iPET [Schick and Schütze, 2021b] utilizes the manually-designed prompts to reformulate natural language understanding tasks as cloze-style questions with gradient-based fine-tuning. There are also a lot of studies that utilize the manually-designed prompt to mine the knowledge from the PLMs [Jiang et al., 2020; Trinh and Le, 2018]. Since manual-designed prompt is time-consuming and the search space is huge, researches focus on automatic prompt search [Gao et al., 2021; Shin et al., 2020; Zhong et al., 2021].

However, the handcrafted prompt can only reflect rationality from the perspective of humans, which midwifery the exploration in continuous prompts. [Li and Liang, 2021] proposes prefix tuning and concatenates learnable prompt at each layer of transformer while only optimizing the prefix parameters. In contrast, prompt tuning [Lester *et al.*, 2021] concatenates learnable prompt only in the embedding layer and only optimizes the prompt parameters in the embedding layer. Although [Lester *et al.*, 2021] demonstrates the effectiveness of light-weight prompt-tuning, the gap with full parameter finetuning still exists especially when the PLM is small.

There are also a lot of works that interleave the prompt throughout the input layer. [Hambardzumyan *et al.*, 2021] proposes WARP, initializing the prompt parameters either with word embeddings of [MASK] or similar to the vectors from the word embedding layer. Their work is based on a series of masked language models [Delobelle *et al.*, 2020; Lan *et al.*, 2020] and uses a learnable output layer to project the mask to class logits, which restricts the model and only

produces a single output. [Liu *et al.*, 2021] proposes P-tuning, using the patterns based on human design and putting the continuous prompts interleave throughout the embedded input. When optimizing the model, P-tuning jointly updates both the prompt and model parameters to perform on SuperGLUE. Similarly, we borrow the idea of human designed patterns to convert different tasks into the form of conditional language model or masked language model, and also apply our method on GPT-2 and RoBERTa.

However, the above usage of the discrete and continuous prompts assumes that the prompt is fixed for a specific task and all samples in the task share the same prompt. Different from the above methods, our proposed IPL dynamically learns a special prompt for each instance and obtains considerable improvements compared to strong baselines.

Very recently, a contemporaneous work also presents another instance dependent prompt generation approach [Anonymous, 2021], which studies only masked language model on only NLU tasks. In contrast, our IPL model is simple and effective for both unidirectional and bidirectional PLMs on both NLU and NLG tasks.

## 6 Conclusion and Future Work

In this paper, we propose an instance-aware prompt learning method named IPL, which learns a unique prompt for each instance. We find that IPL has the potential to be applied to both unidirectional and bidirectional PLMs on both language understanding and generation tasks. In the few-shot learning SuperGLUE benchmark, IPL outperforms all other models and obtains the new state-of-the-art. Detailed analysis demonstrates that our IPL model can indeed dynamically learn appropriate prompts for various instances.

In the future, we would explore how to generate better instance-aware prompts, and apply the instance-aware method to parameter-efficient tuning for more natural language processing tasks.

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