Input-Tuning: Adapting Unfamiliar Inputs to Frozen Pretrained Models

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Abstract

Recently the prompt-tuning paradigm has attracted significant attention. By only tuning continuous prompts with a frozen pretrained language model (PLM), prompt-tuning takes a step towards deploying a shared frozen PLM to serve numerous downstream tasks. Although prompt-tuning shows good performance on certain natural language understanding (NLU) tasks, its effectiveness on natural language generation (NLG) tasks is still underexplored. In this paper, we argue that one of the factors hindering the development of prompt-tuning on NLG tasks is the unfamiliar inputs (i.e., inputs are linguistically different from the pretraining corpus). For example, our preliminary exploration reveals a large performance gap between prompt-tuning and fine-tuning when unfamiliar inputs occur frequently in NLG tasks. This motivates us to propose **input-tuning**, which fine-tunes both the continuous prompts and the input representations, leading to a more effective way to adapt unfamiliar inputs to frozen PLMs. Our proposed input-tuning is conceptually simple and empirically powerful. Experimental results on seven NLG tasks demonstrate that input-tuning is significantly and consistently better than prompt-tuning. Furthermore, on three of these tasks, input-tuning can achieve a comparable or even better performance than fine-tuning.

1 Introduction

Recently, there has been a surge of interest in **prompt-tuning** (Liu et al., 2021a; Jiang et al., 2020; Shin et al., 2020; Liu et al., 2021c; Lester et al., 2021). Unlike fine-tuning that adapts pretrained language models (PLMs) to downstream tasks by tuning all parameters, prompt-tuning is based on the intuition that tasks can be adapted to a frozen PLM via proper task-specific contexts.
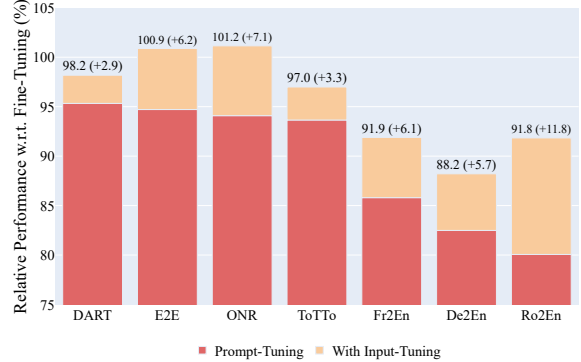

Figure 1: Relative performance (w.r.t. fine-tuning) of prompt-tuning and input-tuning on seven NLG tasks with unfamiliar inputs. The frozen PLM is T5-LARGE (∼770M parameters) (Raffel et al., 2020a). The performance of prompt-tuning lags behind that of fine-tuning. Input-tuning (our method) can close this gap significantly and consistently.

Concretely, for each task, prompt-tuning freezes PLM parameters, but optimizes a small continuous task-specific prompt (i.e., a vector sequence) to be prepended to the input text. Prompt-tuning is appealing, as it takes a step towards deploying a frozen PLM as a common cloud service that can serve many downstream tasks from customers.

The intuition behind prompt-tuning is to cast each downstream task into a language model format that fits the pretraining objective. This leads to the remarkable success of prompt-tuning on natural language understanding (NLU) tasks (Liu et al., 2021c; Lester et al., 2021). However, many tasks, especially natural language generation (NLG) tasks, involve **unfamiliar inputs**, i.e., *the input sequences are linguistically different from the pretraining corpus*. For example, in a logic-to-text task, the input sequences are written in some domain-specific logic expressions (e.g. "Sort(datePublished asc of MusicRecording())[1];") and the output sequences are their natural descriptions (e.g., "Re-
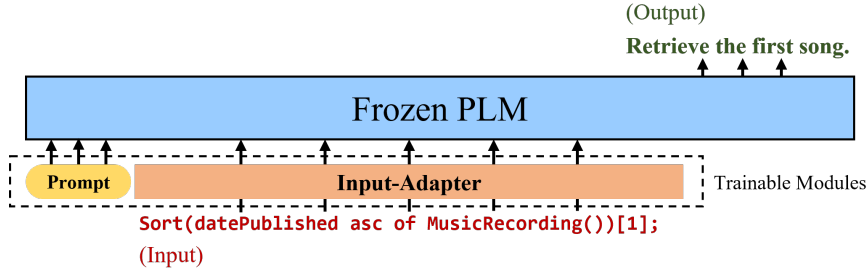

Figure 2: Input-tuning: comparing to prompt-tuning, we propose to add a lightweight trainable module between word embeddings and the bottom layer of the frozen PLM, thus affecting the encoding of unfamiliar inputs more directly and effectively.

trieve the first song"). Moreover, for PLMs pre-trained on English corpus, machine translation tasks with non-English inputs (e.g., French, German, and Romanian) can also be regarded as tasks with unfamiliar inputs. We can hardly cast such inputs to a format that fits the pretraining objective by simply prompting. Therefore, it is natural to ask *whether prompt-tuning can be useful at such tasks*, but this has not yet been discussed in the prior work.

Our preliminary exploration shows that, on NLG tasks with unfamiliar inputs, the performance of prompt-tuning lags far behind that of fine-tuning (Figure 1, detailed in Section 5). Though Lester et al. (2021) reported that, on NLU tasks, prompt-tuning can match the performance of fine-tuning by using giant PLMs (>10 billion parameters), our preliminary results indicate that this success can hardly be replicated on tasks with unfamiliar inputs: for example, on the E2E task, changing the frozen PLM from T5-Large($\sim$770M parameters) to T5-11B only improves the BLEU score from 64.5 to 65.6, while fine-tuning on T5-Large achieves 68.5.

In this paper, we first conduct preliminary exploration to empirically show *how the performance of prompt-tuning is limited by unfamiliar inputs*. In particular, we find that: the gap between prompt-tuning and fine-tuning can be controlled by manually transforming the inputs towards/away the pretraining distribution. Therefore, to adapt unfamiliar inputs to the frozen PLM effectively, not only prompting, but also transforming their surface representations directly, is required.

This finding indicates the limitation of prompt-tuning and the direction to alleviate it, but it still remains challenging to effectively generalize prompt-tuning to tasks with unfamiliar inputs, since it is not easy to find the best way that the unfamiliar

inputs should be transformed. To mitigate this, we propose **input-tuning**, which bridges the gap between prompt-tuning and fine-tuning (Figure 1) by making the transformation learnable. Concretely, we **add a lightweight trainable module between word embeddings and the bottom layer of the PLM, to adjust the encoding of unfamiliar inputs directly** (i.e., the "input-adapter" module in Figure 2). For each task, the soft prompt and the input-adapter are the only two trainable modules, and they are optimized jointly. During inference, each input sequence is encoded by the input-adapter, concatenated to the soft prompt, and then sent to the frozen PLM to generate an output sequence.

Experimental results on seven NLG tasks demonstrate that input-tuning is significantly and consistently better than prompt-tuning. Moreover, on three of these tasks, input-tuning can achieve comparable or even better performance than fine-tuning. We further explore the effectiveness of input-tuning with different backbones, showing that it is applicable with both the encoder-decoder architecture and the auto-regressive language model (Section 6.1). For different data scales, input-tuning stably outperforms prompt-tuning and prefers low-resource scenarios (Section 6.2).

2 Background

2.1 Sequence-to-Sequence Learning

Sequence-to-sequence learning aims to model the conditional probability of the target sequence $\mathbf{y} = \{y_1, ..., y_m\}$ given the source sequence $\mathbf{x} = \{x_1, ..., x_n\}$:

$$P(\mathbf{y}|\mathbf{x}) = \prod_{i=1}^{m} P(y_i|\mathbf{x}, \mathbf{y}_{<i}), \qquad (1)$$

where the factor $P(y_i|\mathbf{x}, \mathbf{y}_{<i})$ can be estimated by a neural model $p_\phi(y_i|\mathbf{x}, \mathbf{y}_{<i})$ parametrized by ϕ. Suppose that p_ϕ is a pretrained language model, either autoregressive language model (such as GPT-2 (Brown et al., 2020b) and UniLM (Dong et al.)) or encoder-decoder model (such as T5 (Raffel et al., 2020a) and BART (Lewis et al., 2020)).

In the *fine-tuning* paradigm, given a train dataset $\mathcal{D}$, the full set of the pretrained weights ϕ_0 are updated by gradient descent methods to optimize the objective:

$$\max_\phi \sum_{(\mathbf{x},\mathbf{y})\in\mathcal{D}} \sum_{i=1}^{|\mathbf{y}|} \log\left(p_\phi(y_i|\mathbf{x}, \mathbf{y}_{<i})\right). \quad (2)$$

2.2 Prompt-Tuning

Brown et al. (2020a) showed that *prompt design* is surprisingly effective at adapting multiple downstream tasks to a frozen GPT-3 model, by prepending a natural language task instruction and a few examples to the task input. Lester et al. (2021) proposed prompt-tuning, in which each prompt is not a text sequence manually designed, but a sequence of continous embeddings that can be optimized by learning from the train dataset $\mathcal{D}$.

Given a PLM p_ϕ and an input sequence $\mathbf{x} = \{x_1, ..., x_n\}$, the first thing p_ϕ does is to embed $\mathbf{x}$ as a matrix $X \in \mathcal{R}^{n\times e}$, where e is the dimension of the embedding space. In prompt-tuning, a soft prompt can also be represented as a matrix $C \in \mathcal{R}^{k\times e}$, where k is a hyperparameter that controls the prompt length. This soft prompt is then concatenated to X, forming a single matrix $[C; X] \in \mathcal{R}^{(k+n)\times e}$. This matrix is feed into the frozen PLM (from the bottom layer of the Transformer architecture) to generate the output sequence $\mathbf{y}$:

$$P(\mathbf{y}|\mathbf{x}) = \prod_{i=1}^{m} p_\phi(y_i|[C; X], \mathbf{y}_{<i}). \quad (3)$$

During training, PLM parameters are frozen (i.e., $\phi \equiv \phi_0$), while the parameters of C (denoted as θ_C) are updated by:

$$\max_{\theta_C} \sum_{(\mathbf{x},\mathbf{y})\in\mathcal{D}} \sum_{i=1}^{|\mathbf{y}|} \log(p_{\phi_0}(y_i|[C; X], \mathbf{y}_{<i})). \quad (4)$$

Existing work uses prompt-tuning to address tasks like SuperGLUE (Lester et al., 2021), while lacking further investigation on its effectiveness for more tasks such as machine translations.
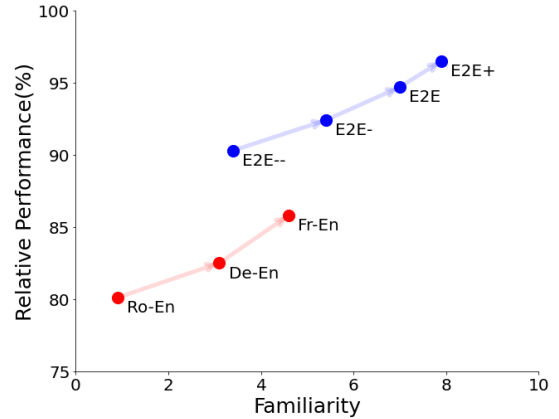

Figure 3: Relative performance and input familiarity of machine translation and table-to-text tasks. It shows the trend that the relative performance of the prompt-tuning rises as the pretrained model's familiarity with the task inputs increases. This trend indicates that alleviating the unfamiliarity by transforming the inputs can help prompt-tuning perform better.

Variant	Input Example
E2E	name[The Punter], food[Indian], priceRange[cheap]
E2E+	name is The Punter, food is Indian, priceRange is cheap.
E2E−	nom[The Punter], nourriture[Indian], gamme de prix[cheap]
E2E−−	nom[Le Punter], nourriture[Indienne], gamme de prix[pas cher]

Table 1: Variants of E2E inputs. The + suffix means that we increase the familiarity by manually transforming the inputs, while − and −− contra.

3 Preliminary Exploration

In this section, we start from an observation that on machine translation tasks there are performance gaps between prompt-tuning and fine-tuning, which are related to unfamiliar inputs (Section 3.1). We further find that this gap can be controlled by manually transforming the inputs (Section 3.2), motivating the idea that we can use a trainable module to learn what is the best way to transform the unfamiliar inputs (Section 3.3).

3.1 Unfamiliar Inputs in Prompt-Tuning

We start by investigating the effectiveness of prompt-tuning on three machine translation tasks: Fr-En, De-En and Ro-En. We use the datasets from WMT 2014 (Bojar et al., 2014) for Fr-En and De-En, and WMT 2016 (Bojar et al., 2016) for Ro-En.

Concretely, we use T5-Large ([Raffel et al., 2020b](#)) as the frozen PLM, and measure the gap between **P**rompt-**T**uning (PT) and **F**ine-**T**uning (FT) based on the **R**elative **P**erformance (RP), which is calculated by:

$$\text{RP} = \frac{\text{BLEU}_{\text{PT}}}{\text{BLEU}_{\text{FT}}}. \quad (5)$$

Experimental results show that, on all machine translation tasks, prompt-tuning can only achieve 85.8% / 82.5% / 80.1% of the fine-tuning performance, respectively. This unexpected phenomena leads to a natural follow-up research question: *where does the gap come from?*

Since T5-Large is mostly pretrained on English natural language corpus, a reasonable speculation to the question is that the frozen PLM lacks sufficient knowledge of how to encode the non-English inputs in these three tasks, leading to the large gap between prompt-tuning and fine-tuning. In other words, *the frozen PLM is unfamiliar with the inputs*. To make it more clear, we quantify the **Familiarity** (denoted by Fam) of a task's inputs to a frozen PLM using the bi-gram frequencies in the pretraining corpus. Concretely, we define the Familiarity of task inputs as:

$$\text{Fam} = \frac{1}{|\mathbf{X}|} \sum_{\mathbf{x} \in \mathbf{X}} \sum_{i=1}^{n-1} \frac{\log \text{BiC}(\mathbf{x}_{i:i+1})}{n-1}, \quad (6)$$

where $\mathbf{x}$ is a token sequence from all inputs $\mathbf{X}$ in the task, and $\text{BiC}(\mathbf{x}_{i:i+1})$ returns the bi-gram counts of $\mathbf{x}_{i:i+1}$. The red points in Figure 3 shows the RP of translation tasks with different input familiarities. It shows the trend that the more familiar with inputs, the higher RP the prompt-tuning achieves, which implies that the performance gap partly comes from the unfamiliarity. Based on this observation, we suppose that **alleviating the unfamiliarity by transforming the inputs can help prompt-tuning perform better.**

3.2 Manually Transforming Inputs

Next step, to evaluate the effectiveness of transforming inputs, we conduct some controllable experiments based on a table-to-text task E2E ([Novikova et al., 2017](#)). The inputs of E2E are synthetic linearized tables, which are easy to manually transform. We consider two kinds of input transformations: more familiar transformation (denote with suffix +) that changes the inputs more

like natural language, and less familiar transformation (denote with suffix − and −−) that makes the bi-gram counts of input lower. Details of these transformations are listed in the Appendix A. Some input examples are shown in Table 1.

As shown in Figure 3 (painted in blue), the task with more familiar inputs (E2E+) achieve better performance than the original task while the tasks with less familiar inputs (E2E− and E2E−−) perform contra. We also conduct another controllable experiment on logic-to-text tasks and observe the similar performances (detailed in Appendix A). This trend is similar to it in machine translation tasks, which assists the speculation before. Furthermore, observing the gain from E2E to E2E+, it indicates that transforming inputs is a promising way to alleviate the unfamiliarity and improve the prompt-tuning.

3.3 Motivation

As discussed before that manually transforming the inputs can benefit the prompt-tuning, but apparently, it is inefficient and error-prone for non-synthetic tasks such as translations. Moreover, separating the transforming processes with prompt-tuning could cause incompatibility between two modules.

Based on these concerns, our motivation is to design a transforming method that meets two requirements: first, it should be universally applicable for different tasks and pretrained backbones. Second, it could be optimized automatically and jointly with prompt-tuning. Therefore, we proposed to **utilize a neural-based adapter to transform the continuous input embeddings**.

4 Input-Tuning

Based on our motivation, we extend the prompt-tuning with a neural-based adapter to transform the input embeddings, namely *input-tuning*. Figure 2 illustrates the basic idea of input-tuning. Given a frozen PLM p_{ϕ_0} and an input sequence $\mathbf{x}$, input-tuning generates the output sequence $\mathbf{y}$ by:

$$P(\mathbf{y}|\mathbf{x}) = \prod_{i=1}^{m} p_{\phi_0}(y_i|\mathcal{F}(\mathbf{x}), \mathbf{y}_{<i}) \quad (7)$$

where $\mathcal{F}(\cdot)$ is a learnable function deciding how $\mathbf{x}$ should be "tuned" to activate p_{ϕ_0} to generate proper $\mathbf{y}$. Prompt-tuning (Equation 4) can be regarded as a special case of input-tuning, where $\mathcal{F}(\cdot)$ is defined
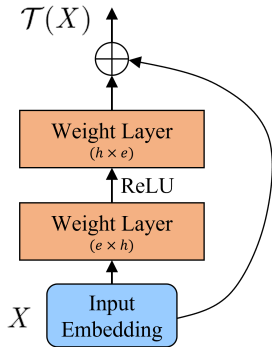
Figure 4: The illustration of our Input-Adapter.

	Data Size	Vocab Size	Input Len (Avg)	Output Len (Avg)
E2E	47.4K	3.0K	30.3	21.7
DART	81.6K	33.2K	30.2	21.1
ToTTo	136.1K	136K	151.3	18.0
ONR	13.7K	1.3K	56.9	9.3
Fr-En	$\sim 2M$	373K	28.8	27.5
De-En	$\sim 2M$	586K	26.2	27.4
Ro-En	$\sim 400K$	169K	26.8	26.8

Table 2: Task statistics.

as the concatenation of C (the soft prompt) and X (the embedding matrix of $\mathbf{x}$).

In this paper, we model $\mathcal{F}(\cdot)$ as:

$$\mathcal{F}(\mathbf{x}) = [C; \mathcal{T}(X)], \qquad (8)$$

$$\mathcal{T}(X)_{i,*} = X + \sigma(X_{i,*}\mathbf{W_1})\mathbf{W_2}, \qquad (9)$$
$$\text{for each } i = 1, ..., n.$$

Here σ is an element-wise nonlinear activation function (ReLU). $\mathbf{W_1}$ and $\mathbf{W_2}$ are learnable matrices. We denote $\mathcal{T}(\cdot)$ as an *input-adapter*, since it plays the role that adapts the surface representations of $\mathbf{x}$ to better utilize the frozen PLM. Figure 4 illustrates this module.

Initialization. We initialize the soft prompt C by randomly picking from pretrained embeddings, as Lester et al. (2021) claimed that it is much better than totally random initialization. For parameters of the input-adapter, we initialize $\mathbf{W_2}$ as a zero matrix so that the $\mathcal{T}(X)$ will be the same with pretrained embeddings at the beginning of training.

Token-wise or Sequence-wise. Input-adapter tunes the surface representation of each token in $\mathbf{x}$ respectively, without taking sequence contexts into consideration (e.g., model $\mathcal{T}(X)$ using RNNs or Transformers). The key reason of this design choice is to prevent the input-adapter dominating the frozen PLM. Concretely, as RNNs and Transformers are already good sequence-to-sequence learners, using them to implement the input-adapter may lead to the result that the sequence-to-sequence task is mainly addressed in the input-adapter while the frozen PLM contributes little. Therefore, we chose a simple token-wise MLP to implement the input-adapter, which is far from sufficient for sequence-to-sequence learning, thus activating the frozen PLM better. Our experimental results also support this design choice (Section 6.3).

5 Experiments

5.1 Experimental Setup

Tasks and Metrics We evaluate on seven NLG tasks: three table-to-text tasks, one logic-to-text task, and three machine translation tasks. Table 2 shows the statistics of these datasets.

The *table-to-text* tasks are: E2E (Novikova et al., 2017), DART (Nan et al., 2020), and ToTTo (Parikh et al., 2020). E2E is relatively simpler than the other two tasks, as it only has 1 domain (i.e., restaurant reviews). DART and ToTTo are both open-domain, using open-domain tables from Wikipedia. ToTTo is the most challenging task among them, as it increases the generalization challenge by reducing the vocabulary overlap between train set and dev/test set.

The *logic-to-text* task is ONR (OverNight-Reverse), which is constructed based on the text-to-logic benchmark Overnight (Wang et al., 2015) (detailed in Appendix B).

The *Machine translation* tasks are: French to English (Fr-En), German to English (De-En) and Romanian to English (Ro-En). We use the parallel corpus from version 7 of Europarl corpus (Koehn et al., 2005) as the training data for all three translation tasks. For Fr-En and De-En, we take WMT newstest2013 newstest2014 (Bojar et al., 2014) as the development sets and test sets, respectively. For Ro-En, we use the development and test sets from WMT 2016 (Bojar et al., 2016).

For every tasks, we report the official evaluation metrics, including BLEU (Papineni et al., 2002), NIST (Belz and Reiter, 2006), METEOR (Lavie and Agarwal, 2007), ROUGE-L (Lin, 2004), CIDEr (Vedantam et al., 2015), TER (Snover et al., 2005), MoverScore (Zhao et al., 2019), BERTScore (Zhang et al., 2019), BLEURT (Sellam et al., 2020) and PARENT (Dhingra et al., 2019).

	E2E					DART						ONR				
	BLEU	NIST	MET	R-L	CIDEr	BLEU	MET	TER↓	Mov	BERT	BLRT	BLEU	NIST	MET	R-L	CIDEr
								T5-Large								
Prompt-Tuning	64.5	8.35	44.1	67.3	2.23	46.9	<u>0.39</u>	0.47	0.51	**0.95**	0.45	65.3	10.10	46.9	78.4	2.76
Input-Tuning	**68.7**	**8.74**	<u>46.1</u>	<u>70.7</u>	2.42	<u>48.3</u>	<u>0.39</u>	<u>0.46</u>	<u>0.52</u>	**0.95**	<u>0.47</u>	**70.2**	**10.50**	<u>49.1</u>	<u>80.6</u>	<u>2.84</u>
Fine-Tuning	68.1	8.67	**46.6**	**71.3**	2.44	**49.2**	0.40	**0.44**	0.53	0.95	0.48	69.4	10.41	**49.4**	**81.4**	**2.87**
								GPT2-Large								
Prompt-Tuning	65.8	8.51	44.4	68.2	2.23	43.5	0.37	0.51	0.48	**0.94**	0.39	64.2	9.71	44.3	75.6	2.62
Input-Tuning	<u>68.2</u>	**8.79**	<u>45.3</u>	**70.2**	<u>2.34</u>	<u>46.4</u>	<u>0.38</u>	<u>0.50</u>	<u>0.49</u>	**0.94**	<u>0.42</u>	**68.4**	**10.01**	**46.9**	**78.5**	**2.75**
Fine-Tuning	**68.5**	8.78	**46.0**	69.9	**2.45**	**47.0**	0.39	0.46	0.51	0.94	0.40	67.0	9.58	45.7	77.6	2.67

Table 3: Results of table-to-text tasks **E2E** (left), **DART** (middle) and logic-to-text task **ONR** (right). The **bold scores** are the best results among all methods, and the <u>underlined scores</u> represent the best results in prompt-tuning and input-tuning. The fine-tuning results of GPT2-Large on E2E and DART are reported by Li and Liang (2021). On all three tasks, our input-tuning significantly outperforms the prompt-tuning. Impressively, it can achieve comparable or even better performance than fine-tuning on these tasks.

	ToTTo (PARENT on Dev Set)		
	Overall	Overlap	Non-Overlap
Prompt-Tuning	56.0	59.3	52.9
Input-Tuning	<u>58.0</u>	<u>61.3</u>	<u>54.7</u>
Fine-Tuning	**59.8**	**63.4**	**56.3**

Table 4: PARENT scores on **ToTTo**, with T5-Large as the backbone. Input-tuning outperforms prompt-tuning, and the relative gains on Overlap and Non-Overlap subsets are on par (2.0 and 1.8, respectively), showing that it maintains a stable generalization ability.

	Machine Translation (BLEU)					
	Fr-En		De-En		Ro-En	
	Dev	Test	Dev	Test	Dev	Test
Prompt-Tuning	26.9	29.6	24.4	24.5	26.7	26.5
Input-Tuning	<u>28.5</u>	<u>31.7</u>	<u>25.9</u>	<u>26.2</u>	<u>31.3</u>	<u>30.4</u>
Fine-Tuning	**30.9**	**34.5**	**29.0**	**29.7**	**34.4**	**33.1**

Table 5: BLEU scores on **Machine Translation** tasks(Fr/De/Ro-En), with T5-Large as the backbone.

Backbones and Hyperparameters We choose T5-Large ($\sim$770M parameters) and GPT2-Large (774M parameters) as our backbones. Our implementation is based on the HuggingFace Transformer models (Wolf et al., 2020). The training hyperparameters mainly include the learning rate (1e-5$\sim$5e-3), weight decay (1e-1 or 1e-2) and learning rate scheduler (linear or constant). The evaluation hyperparameters mainly include the beam size (1 or 5). All experimental results are produced under the same hyperparameter searching strategy except the cited results. The default prompt length is 100 (the best prompt length indicated by Lester et al. (2021)) and the hidden layer dimensions in the input-adapter are two times of the embedding dimensions. The reparameterization trick used by Li and Liang (2021) is applied. More hyperparameter details are listed in the Appendix C.

5.2 Main Results

Table 3, 4 and 5 show the main results on seven NLG tasks. In general, our input-tuning method notably outperforms prompt-tuning on all these tasks.

Moreover, on E2E, DART and ONR tasks (shown in Table 3), input-tuning achieves comparable or even better performance than fine-tuning.

Table-to-Text With an additional lightweight input-adapter, the input-tuning notably outperforms prompt-tuning on three table-to-text tasks including E2E, DART and ToTTo (shown in Table 3 and 4). Surprisingly, it can be comparable or even better than fine-tuning on E2E and DART tasks. For the ToTTo task, input-tuning still outperforms prompt-tuning and slightly lags fine-tuning, and the relative gains on Overlap and Non-Overlap subsets are on par (2.0 and 1.8, respectively), showing that it maintains a stable generalization ability. These results show that a simple input-adapter can bring significant benefits.

Logic-to-Text Unlike table-to-text tasks, the inputs of logic-to-text tasks contain more nested and complex logic forms. On ONR task, the input-tuning also apparently outperforms prompt-tuning, and even surprisingly outperforms fine-tuning (shown in Table 3). These results indicate that the input-adapter can handle different input formats and keep a stable performance.

Machine Translation Compared with table-to-text and logic-to-text, the translation tasks are much more challenging as they contain larger vocabularies and more training data, making them much harder for lightweight models. Table 5 shows that on all three translation tasks, input-tuning significantly closes the gap between prompt-tuning and fine-tuning. It demonstrates that input-tuning consistently outperforms prompt-tuning even on more challenging tasks.

6 Analysis

In this section, we further explore the effectiveness of input-tuning under different settings. Section 6.1 analyzes the performance with different PLM backbones. Section 6.2 explores the different data scale settings. Section 6.3 discusses the different designs of input-tuning. And Section 6.4 shows the performance with different lengths of soft prompts.

6.1 Different Backbones

We evaluate the effectiveness on different backbones from two aspects: backbone architectures (GPT2-Large and T5-Large) and backbone sizes (T5-Small/Base/Large). Note that as the input-adapter only modifies the input embeddings, it can be universally applied to different types of backbones with word embeddings as input.

Backbone Architectures The results in Table 3 show that although the fine-tuning performance of GPT2-Large and T5-Large vary, input-tuning maintains better results than prompt-tuning. It implies the potential of input-tuning to be effective for a variety of model architectures.

Backbone Sizes As shown in Figure 5, the input-tuning stably outperforms prompt-tuning with different sizes of T5 (Small, Base and Large). Furthermore, compared with fine-tuning, the input-tuning benefits more from the increasing of backbone size, indicating that it can be more effective with larger pretrained models.

6.2 Different Data Scales

To explore the impact of data scales, we conduct experiments on different scales of E2E and translation tasks. The experimental results in Figure 6 show that the input-tuning stably performs better than prompt-tuning under different data scales. Compared with fine-tuning, the input-tuning consistently outperforms it in E2E, which is a relative low-resource task compared with translations.
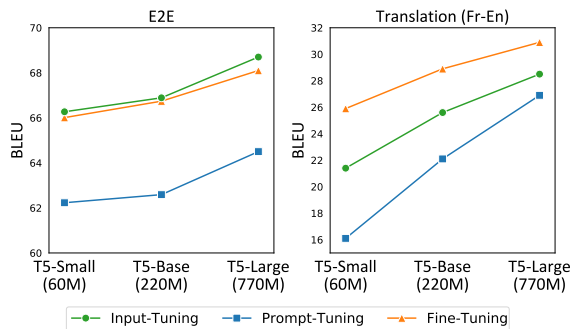

Figure 5: The performance with different backbone sizes (T5-Small/Base/Large) on E2E task and translation task (Fr-En dev set). The input-tuning stably outperforms prompt-tuning and benefits from the increasing of backbone size.
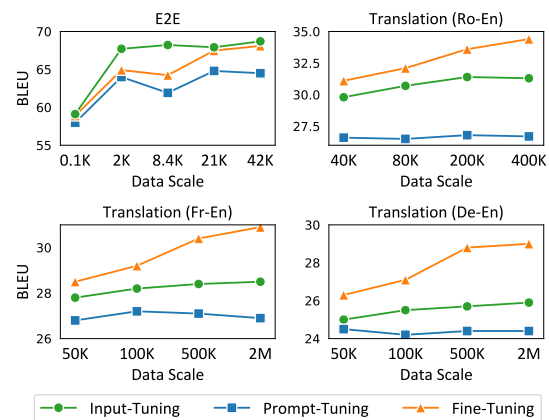

Figure 6: Performance under different data scales on E2E and three translation tasks (dev sets). The input-tuning stably performs better than prompt-tuning and prefers low-resource scenarios.

And for translation tasks, the gaps between input-tuning and fine-tuning are closed with the data scales decreasing. These results indicate that the input-tuning prefers low-resource scenarios.

6.3 Different Designs of Input-Tuning

Besides the original design described in Section 4 (the token-level input-adapter with soft prompts), we consider another two designs: the sequence-wise input-adapter with soft prompts, and the token-level input-adapter without soft prompts. Figure 7 shows the results on four tasks[1].

Sequence-wise Input-Adapter The sequence-wise input-adapter is implemented with a self-attention layer. As shown in Figure 7 (green bars), it always performs worse than the original one with a token-wise input-adapter (blue bars), supporting

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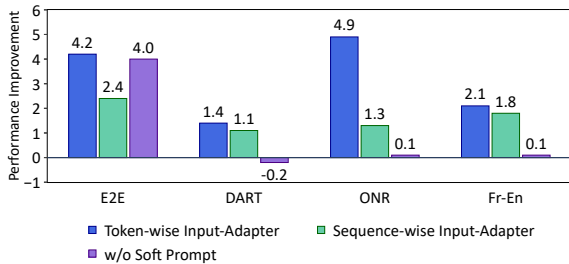[1]The results for more tasks are shown in the Appendix D.

Figure 7: The improvements of input-tuning (w.r.t. prompt-tuning) with different designs. We take BLEU scores for these four tasks. It shows that a simple token-wise input-adapter can activate the frozen PLM better, and the soft prompts are indispensable in input-tuning.
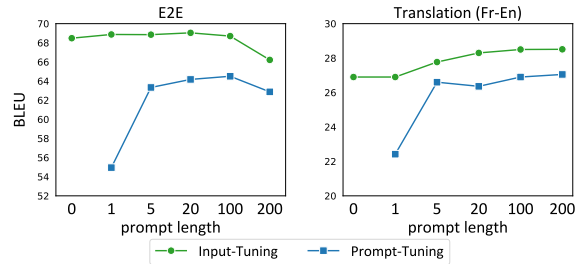

Figure 8: The performance of input-tuning and prompt-tuning with different prompt lengths. The 0 prompt length means that there is only an input-adapter (see Section 6.3). The input-tuning performs better than prompt-tuning with all prompt lengths.

our speculation in Section 4 that a stronger adapter may dominate the pretrained model and lead to the performance loss while a simple and lightweight module can activate the frozen PLM better.

Without Soft Prompts The purple bars in Figure 7 shows the results of input-tuning w/o soft prompts. With only a token-level input-adapter, the input-tuning loses much performance and sometimes even lags behind the prompt-tuning, indicating that soft prompts are indispensable in the input-tuning.

6.4 Different Lengths of Soft Prompts

As soft prompts are important for input-tuning, here we further explore the impact of different prompt lengths. We select prompt lengths from 1 to 200 and conduct experiments on E2E and Fr-En tasks.

As shown in Figure 8, the input-tuning is better than prompt-tuning with all prompt lengths. Moreover, it seems that different tasks prefer different input lengths. For the relative simple task E2E, it shows that a short soft prompt is enough while the longer prompt length may hurt the performance. For the more challenging task Fr-En, both input-tuning and prompt-tuning prefers longer inputs.

7 Related Work

Parameter-Efficient Fine-Tuning Despite the strong ability of large-scale pretrained language models (Radford et al., 2018; Devlin et al., 2019; Liu et al., 2019; Raffel et al., 2020a), tuning hundreds of billions of parameters is extremely time- and space-consuming. Therefore, parameter-efficient fine-tuning recently attracted more attention. There are two series of related works: invasive methods and non-invasive methods. Invasive methods, which are built on a strong assumption that

the inner structure (e.g., self-attention and feed-forward layers) of the PLM can be modified, includes Prefix-Tuning (Li and Liang, 2021), Bit-fit (Ben Zaken et al., 2021), Child-Tuning (Xu et al., 2021), P-Tuning v2 (Liu et al., 2021b), LoRA (Hu et al., 2021), UnifiedSKG (Xie et al., 2022) and Adapter-based models (Rebuffi et al., 2017; Houlsby et al., 2019; Lin et al., 2020; He et al., 2021; Pfeiffer et al., 2021). Non-invasive methods, which only modify input embeddings and regard the inner structure as a black box, mostly are prompting methods (including our Input-Tuning).

Prompting Prompting means prepending instructions or a few examples to the task input and generating the output from the PLM. Recently, various kinds of hard prompt designing and searching methods were proposed (Jiang et al., 2020; Shin et al., 2020; Schick and Schütze, 2020; Gao et al., 2020). To overcome the shortcomings of hand-crafting, some works optimize continuous soft prompts such as prompt-tuning (Lester et al., 2021), P-Tuning (Liu et al., 2021c), Ppt (Gu et al., 2021) and SPoT (Vu et al., 2021). Recently, Sun et al. (2022) and Diao et al. (2022) explored black-box tuning, which trains the prompt without gradient back-propagation. Compared with these work, we are the first to study the effectiveness of soft prompts from the view of task inputs.

8 Conclusion

In this paper, we revealed that input unfamiliarity is an essential ingredient affecting the performance of prompt-tuning, and proposed input-tuning to alleviate this unfamiliarity with a neural-based input-adapter. We conducted experiments on seven NLG tasks with thorough analysis, showing that input-tuning performs stably better than prompt-tuning.

References

Anja Belz and Ehud Reiter. 2006. Comparing automatic and human evaluation of nlg systems. In *11th conference of the european chapter of the association for computational linguistics*.

Elad Ben Zaken, Shauli Ravfogel, and Yoav Goldberg. 2021. Bitfit: Simple parameter-efficient fine-tuning for transformer-based masked language-models. *arXiv e-prints*, pages arXiv–2106.

Ondřej Bojar, Christian Buck, Christian Federmann, Barry Haddow, Philipp Koehn, Johannes Leveling, Christof Monz, Pavel Pecina, Matt Post, Herve Saint-Amand, et al. 2014. Findings of the 2014 workshop on statistical machine translation. In *Proceedings of the ninth workshop on statistical machine translation*, pages 12–58.

Ondřej Bojar, Rajen Chatterjee, Christian Federmann, Yvette Graham, Barry Haddow, Matthias Huck, Antonio Jimeno Yepes, Philipp Koehn, Varvara Logacheva, Christof Monz, et al. 2016. Findings of the 2016 conference on machine translation. In *Proceedings of the First Conference on Machine Translation: Volume 2, Shared Task Papers*, pages 131–198.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020a. Language models are few-shot learners. In *Advances in Neural Information Processing Systems*, volume 33, pages 1877–1901. Curran Associates, Inc.

Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020b. Language models are few-shot learners. *arXiv e-prints*, pages arXiv–2005.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186.

Bhuwan Dhingra, Manaal Faruqui, Ankur Parikh, Ming-Wei Chang, Dipanjan Das, and William W Cohen. 2019. Handling divergent reference texts when evaluating table-to-text generation. *arXiv preprint arXiv:1906.01081*.

Shizhe Diao, Xuechun Li, Yong Lin, Zhichao Huang, and Tong Zhang. 2022. Black-box prompt learning for pre-trained language models. *arXiv preprint arXiv:2201.08531*.

Li Dong, Nan Yang, Wenhui Wang, Furu Wei, Xiaodong Liu, Yu Wang, Jianfeng Gao Ming Zhou, and Hsiao-Wuen Hon. Unified language model pre-training for natural language understanding and generation.

Tianyu Gao, Adam Fisch, and Danqi Chen. 2020. Making pre-trained language models better few-shot learners. *arXiv preprint arXiv:2012.15723*.

Yuxian Gu, Xu Han, Zhiyuan Liu, and Minlie Huang. 2021. Ppt: Pre-trained prompt tuning for few-shot learning. *arXiv preprint arXiv:2109.04332*.

Ruidan He, Linlin Liu, Hai Ye, Qingyu Tan, Bosheng Ding, Liying Cheng, Jia-Wei Low, Lidong Bing, and Luo Si. 2021. On the effectiveness of adapter-based tuning for pretrained language model adaptation. *arXiv preprint arXiv:2106.03164*.

Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin De Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. 2019. Parameter-efficient transfer learning for nlp. In *International Conference on Machine Learning*, pages 2790–2799. PMLR.

Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. 2021. Lora: Low-rank adaptation of large language models. *arXiv preprint arXiv:2106.09685*.

Zhengbao Jiang, Frank F Xu, Jun Araki, and Graham Neubig. 2020. How can we know what

language models know? *Transactions of the Association for Computational Linguistics*, 8:423–438.

Philipp Koehn et al. 2005. Europarl: A parallel corpus for statistical machine translation. In *MT summit*, volume 5, pages 79–86. Citeseer.

Alon Lavie and Abhaya Agarwal. 2007. Meteor: An automatic metric for mt evaluation with high levels of correlation with human judgments. In *Proceedings of the second workshop on statistical machine translation*, pages 228–231.

Brian Lester, Rami Al-Rfou, and Noah Constant. 2021. The power of scale for parameter-efficient prompt tuning.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880, Online. Association for Computational Linguistics.

Xiang Lisa Li and Percy Liang. 2021. Prefix-tuning: Optimizing continuous prompts for generation. *arXiv preprint arXiv:2101.00190*.

Chin-Yew Lin. 2004. Rouge: A package for automatic evaluation of summaries. In *Text summarization branches out*, pages 74–81.

Zhaojiang Lin, Andrea Madotto, and Pascale Fung. 2020. Exploring versatile generative language model via parameter-efficient transfer learning. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings*, pages 441–459.

Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. 2021a. Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. *arXiv preprint arXiv:2107.13586*.

Xiao Liu, Kaixuan Ji, Yicheng Fu, Zhengxiao Du, Zhilin Yang, and Jie Tang. 2021b. P-tuning v2: Prompt tuning can be comparable to fine-tuning universally across scales and tasks. *arXiv preprint arXiv:2110.07602*.

Xiao Liu, Yanan Zheng, Zhengxiao Du, Ming Ding, Yujie Qian, Zhilin Yang, and Jie Tang. 2021c. Gpt understands, too. *arXiv preprint arXiv:2103.10385*.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*.

Linyong Nan, Dragomir Radev, Rui Zhang, Amrit Rau, Abhinand Sivaprasad, Chiachun Hsieh, Xiangru Tang, Aadit Vyas, Neha Verma, Pranav Krishna, et al. 2020. Dart: Open-domain structured data record to text generation. *arXiv preprint arXiv:2007.02871*.

Jekaterina Novikova, Ondřej Dušek, and Verena Rieser. 2017. The e2e dataset: New challenges for end-to-end generation. In *Proceedings of the 18th Annual SIGdial Meeting on Discourse and Dialogue*, pages 201–206.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting of the Association for Computational Linguistics*, pages 311–318.

Ankur Parikh, Xuezhi Wang, Sebastian Gehrmann, Manaal Faruqui, Bhuwan Dhingra, Diyi Yang, and Dipanjan Das. 2020. Totto: A controlled table-to-text generation dataset. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 1173–1186.

Jonas Pfeiffer, Aishwarya Kamath, Andreas Rücklé, Kyunghyun Cho, and Iryna Gurevych. 2021. Adapterfusion: Non-destructive task composition for transfer learning. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 487–503.

Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. 2018. Improving language understanding by generative pre-training.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena,

Yanqi Zhou, Wei Li, and Peter J Liu. 2020a. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21:1–67.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020b. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67.

Sylvestre-Alvise Rebuffi, Hakan Bilen, and Andrea Vedaldi. 2017. Learning multiple visual domains with residual adapters. In *Proceedings of the 31st International Conference on Neural Information Processing Systems*, pages 506–516.

Timo Schick and Hinrich Schütze. 2020. It's not just size that matters: Small language models are also few-shot learners. *arXiv preprint arXiv:2009.07118*.

Thibault Sellam, Dipanjan Das, and Ankur P Parikh. 2020. Bleurt: Learning robust metrics for text generation. *arXiv preprint arXiv:2004.04696*.

Taylor Shin, Yasaman Razeghi, Robert L Logan IV, Eric Wallace, and Sameer Singh. 2020. Autoprompt: Eliciting knowledge from language models with automatically generated prompts. *arXiv preprint arXiv:2010.15980*.

Mathew Snover, Bonnie Dorr, Richard Schwartz, John Makhoul, Linnea Micciulla, and Ralph Weischedel. 2005. A study of translation error rate with targeted human annotation. In *Proceedings of the 7th Conference of the Association for Machine Translation in the Americas (AMTA 06)*, pages 223–231.

Tianxiang Sun, Yunfan Shao, Hong Qian, Xuanjing Huang, and Xipeng Qiu. 2022. Black-box tuning for language-model-as-a-service. *arXiv preprint arXiv:2201.03514*.

Ramakrishna Vedantam, C Lawrence Zitnick, and Devi Parikh. 2015. Cider: Consensus-based image description evaluation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4566–4575.

Tu Vu, Brian Lester, Noah Constant, Rami Al-Rfou, and Daniel Cer. 2021. Spot: Better frozen model adaptation through soft prompt transfer. *arXiv preprint arXiv:2110.07904*.

Yushi Wang, Jonathan Berant, and Percy Liang. 2015. Building a semantic parser overnight. In *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 1332–1342.

Thomas Wolf, Julien Chaumond, Lysandre Debut, Victor Sanh, Clement Delangue, Anthony Moi, Pierric Cistac, Morgan Funtowicz, Joe Davison, Sam Shleifer, et al. 2020. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45.

Tianbao Xie, Chen Henry Wu, Peng Shi, Ruiqi Zhong, Torsten Scholak, Michihiro Yasunaga, Chien-Sheng Wu, Ming Zhong, Pengcheng Yin, Sida I Wang, et al. 2022. Unifiedskg: Unifying and multi-tasking structured knowledge grounding with text-to-text language models. *arXiv preprint arXiv:2201.05966*.

Runxin Xu, Fuli Luo, Zhiyuan Zhang, Chuanqi Tan, Baobao Chang, Songfang Huang, and Fei Huang. 2021. Raise a child in large language model: Towards effective and generalizable fine-tuning. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 9514–9528.

Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q Weinberger, and Yoav Artzi. 2019. Bertscore: Evaluating text generation with bert. *arXiv preprint arXiv:1904.09675*.

Wei Zhao, Maxime Peyrard, Fei Liu, Yang Gao, Christian M Meyer, and Steffen Eger. 2019. Moverscore: Text generation evaluating with contextualized embeddings and earth mover distance. *arXiv preprint arXiv:1909.02622*.

This is the Appendix for the paper: "Input-Tuning: Adapting Unfamiliar Inputs to Frozen Pretrained Models".

A Preliminary Exploration

Here we show more details in our preliminary exploration.

A.1 Manually Transforming Inputs

We take a table-to-text task E2E and logic-to-text task ONR. Details of these tasks are shown in Section 5.1. Here we describe how we transform the inputs of E2E and ONR manually.

E2E+   Replace the left brackets [with is, remove the right brackets, and add a period at the end of the sentence.

E2E−   Translate the attributes into French.

E2E−−   Translate both the attributes and the values into French.

ONR+   We use the canonical utterances for every logic forms.

ONR−   Convert the function names into Chinese Pinyin.

The examples of E2E inputs variants are listed in Table 1, and here we show the variants of ONR inputs in Table 6.

Variant	Input Example
ONR	call listvalue (call getproperty en.person.alice (string birthplace))
ONR+	city that is birthplace of alice and that is birthplace of alice
ONR−	diaoyong lieju (diaoyong dedao en.person.alice (zifuchuan birthplace))

Table 6: Variants of ONR inputs.

A.2 More Controllable Experiments

We list the relative performance of prompt-tuning and input familiarity in Table 7.

Variant	Relative Performance(%)	Familiarity
ONR	94.1	3.2
ONR+	97.1	11.8
ONR−	89.3	1.1

Table 7: Relative performance (w.r.t. fine-tuning) and input familiarity of different ONR variants.

It shows the similar performances with E2E variants that the ONR+, which with more familiar inputs, achieves better performance than original task ONR while ONR− performs contra. These results support our intuition that alleviating the unfamiliarity by transforming the inputs can help prompt-tuning perform better.

B Construction of ONR

In this section, we present how we construct the ONR (**O**ver**N**ight-**R**everse) task based on the text-to-logic benchmark Overnight (Wang et al., 2015).

The original task of Overnight dataset is semantic parsing, which converts natural language inputs into logic forms in 8 different domains. In our experiment, we mix all the domains and swap the input and output (i.e. use logic forms as inputs and natural language sentences as outputs), and merge different NL outputs with the same logic form input as its candidate outputs, in order to compute metrics (such as BLEU) more precisely. We then shuffle and divide them as new train (9030), dev (2262) and test (2390) set, using the original proportion as overnight. For the train set, we divide multiple candidates as multiple training data. For the test set, we use identical logic forms who have 5 candidate corresponding NL labels.

C Hyperparameters

In this section, we list the detailed hyperparameters for input-tuning used in our main experiments. The total training steps are 100K steps, and we save the checkpoints and evaluate for every 10k steps. The length penalty for evaluation is 1.0. The other details are listed in Table 8.

D More Results for Different Designs of Input-Tuning

Here we show the results on all seven tasks for different designs of input-tuning, as a supplementary to Section 6.3.

As shown in Figure 9, the sequence-wise input-adapter consistently performs worse the token-wise input-adapter, and without the soft prompts, the performance of input-tuning always drop. These results enhance that a simple token-wise input-adapter can activate the frozen PLM better, and the soft prompts are indispensable in input-tuning.

Task	Backbone	batch size	learning rate	weight decay	learning rate scheduler	warmup ratio	beam size	no_repeat_ngram_size
E2E	T5-Large	16	5e-4	1e-2	constant	-	1	3
	GPT2-Large	8	1e-3	1e-1	warmup	0.1	5	0
DART	T5-Large	8	5e-5	1e-2	constant	-	5	3
	GPT2-Large	8	5e-4	1e-1	warmup	0.1	1	0
ONR	T5-Large	8	5e-4	1e-2	constant	-	1	3
	GPT2-Large	8	1e-3	1e-1	warmup	0.1	5	0
ToTTo	T5-Large	8	5e-4	1e-2	constant	-	1	3
Fr-En	T5-Large	16	1e-4	1e-2	constant	-	5	0
De-En	T5-Large	16	1e-4	1e-2	constant	-	5	0
Ro-En	T5-Large	16	1e-4	1e-2	constant	-	5	0

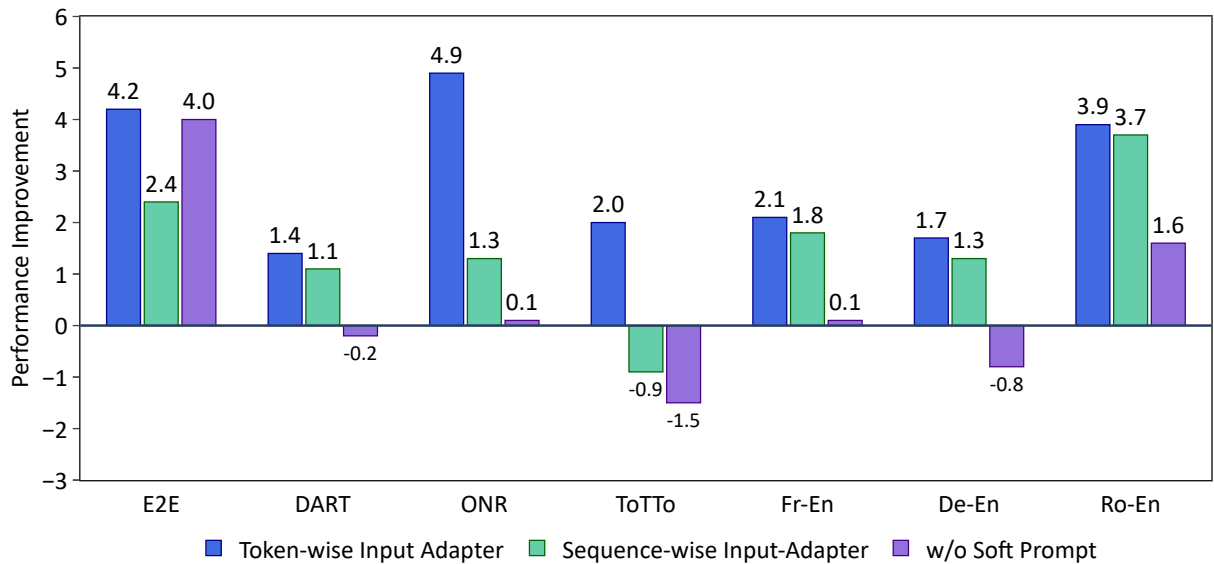Table 8: Hyperparameters for input-tuning in different tasks.

Figure 9: The improvements of input-tuning (w.r.t. prompt-tuning) with different designs. We take the PARENT score for ToTTo and BLEU scores for others.