# On Transferability of Prompt Tuning for Natural Language Understanding

Yusheng Su<sup>1\*</sup>, Xiaozhi Wang<sup>1\*</sup>, Yujia Qin<sup>1</sup>, Chi-Min Chan<sup>1</sup>, Yankai Lin<sup>2</sup>, Zhiyuan Liu<sup>1†</sup>, Peng Li<sup>2</sup>, Juanzi Li<sup>1</sup>, Lei Hou<sup>1</sup>, Maosong Sun<sup>1</sup>, Jie Zhou<sup>2</sup>

<sup>1</sup>Department of Computer Science and Technology, Tsinghua University, Beijing, China <sup>2</sup>Pattern Recognition Center, WeChat AI, Tencent Inc.

yushengsu.thu@gmail.com, wangxz20@mails.tsinghua.edu.cn

#### **Abstract**

Prompt tuning (PT) is a promising parameterefficient method to utilize extremely large pre-trained language models (PLMs), which could achieve comparable performance to fullparameter fine-tuning by only tuning a few soft prompts. However, compared to fine-tuning, PT empirically requires much more training steps. To explore whether we can improve the efficiency of PT by reusing trained soft prompts and sharing learned knowledge, we empirically investigate the transferability of soft prompts across different tasks and models. In *cross-task transfer*, we find that trained soft prompts can well transfer to similar tasks and initialize PT for them to accelerate training and improve performance. Moreover, to explore what factors influence prompts' transferability across tasks, we investigate how to measure the prompt similarity and find that the overlapping rate of activated neurons highly correlates to the transferability. In cross-model transfer, we explore how to project the prompts of a PLM to another PLM and successfully train a kind of projector which can achieve nontrivial transfer performance on similar tasks. However, initializing PT with the projected prompts does not work well, which may be caused by optimization preferences and PLMs' high redundancy. Our findings show that improving PT with knowledge transfer is possible and promising, while prompts' crosstask transferability is generally better than the cross-model transferability.

## 1 Introduction

Pre-trained language models (PLMs), such as BERT (Devlin et al., 2019) and GPT (Radford et al., 2018) have achieved great performance on various natural language processing tasks (Han et al., 2021). Recently, after the success of GPT-3 (Brown et al., 2020), people have found that extremely large

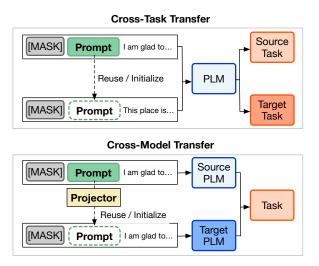


Figure 1: To investigate the prompt transferability, we transfer source prompts to different target tasks (cross-task) and PLMs (cross-model). In these two settings, we explore whether initializing prompts with trained prompts for prompt tuning on the target task accelerates training and improves performance.

PLMs can achieve remarkable natural language understanding (NLU) performance, and various large PLMs are continually developed (Raffel et al., 2020; Zhang et al., 2021; Zeng et al., 2021; Wei et al., 2021; Sun et al., 2021), which contain up to hundreds of billions of parameters.

Considering the extremely large scale of these state-of-the-art PLMs, conventional full-parameter fine-tuning methods adapting PLMs to downstream tasks become computationally unaffordable. Hence various parameter-efficient tuning methods (Houlsby et al., 2019; Ben Zaken et al., 2021; Lester et al., 2021; Li and Liang, 2021; Liu et al., 2021) are explored, among which prompt tuning (PT) has attracted broad research attention. PT prepends some *soft prompts*, which are essentially learnable virtual tokens, into the input sequences and train them through back-propagation while keeping all the PLM parameters fixed. The training objective is to output the tokens indicat-

<sup>\*</sup> The first two authors contributed equally.

<sup>‡</sup> Corresponding author: Z.Liu (liuzy@tsinghua.edu.cn)

ing corresponding labels, i.e., *label tokens*. PT can achieve remarkable NLU performance with only thousands of tunable parameters. Moreover, Lester et al. (2021) have shown that PT becomes more effective when the PLM's scale grows, and can finally reach comparable performance to full-parameter fine-tuning when the PLM have billions of parameters.

Although PT is an effective approach to utilize extremely large PLMs, it requires much more training steps than fine-tuning to reach the convergence (refer to § 3.1), hence it is worthwhile to explore how to improve the efficiency of PT. Intuitively, since soft prompts are the only learnable parameters in PT representing task-specific knowledge conditioned on PLMs to solve tasks, the trained prompts of a task may be helpful to other tasks requiring similar knowledge. Moreover, as different PLMs all learn general language understanding abilities from pre-training, trained prompts conditioned on different PLMs may transfer between PLMs. Hence, transferring learned knowledge to other tasks and PLMs with trained soft prompts may be a promising way to accelerate PT on new tasks and PLMs. To understand basic characteristics and help to develop transfer learning methods for PT, we empirically analyze the transferability of PT across different tasks and models in this paper as shown in Figure 1.

In cross-task transfer, we study whether the soft prompts trained on the same PLM can transfer across different NLU tasks. (1) We investigate the zero-shot transfer performance of soft prompts on 13 NLU tasks, which are divided into four types based on the required language understanding skills. We find that trained soft prompts can directly transfer to similar tasks of the same type and achieve non-trivial performance, but poorly transfer to different-type tasks requiring different NLU abilities. (2) Based on these results, we propose cross-task transferable prompt tuning  $(\mathbf{TPT}_{TASK})$ , which is to start PT with the trained soft prompts of similar tasks as initialization. Experiments show that TPT<sub>TASK</sub> can significantly accelerate training compared to vanilla PT and also achieve a certain performance improvement. (3) We further explore why the prompts can transfer across tasks and what controls their transferability. To this end, we examine how various **prompt sim**ilarity metrics correlate to prompt transferability and find that the overlapping rate of their activated

neurons in the feed-forward layers of PLM can better reflect prompt transferability. This suggests the prompts are essentially stimulating PLM's inner ability distributing among parameters (neurons) to do specific NLU tasks, and the transferability between prompts depends on their similarity in model stimulation rather than embedding similarity, which may inspire the design of future PT transfer methods.

In cross-model transfer, we study the transferability of soft prompts across different PLMs in two settings: (1) transferring between heterogeneous PLMs of the same scale (e.g. BERT<sub>BASE</sub> to RoBERTa<sub>BASE</sub>) and (2) transferring from smaller PLMs to larger homogeneous models (e.g. RoBERTa<sub>BASE</sub> to RoBERTa<sub>LARGE</sub>). We find that directly reusing prompts on target PLMs is either unhelpful, which is shown by experiments, or infeasible, which is due to the inconsistent embedding dimensions of different-size PLMs. (1) Hence, we develop various **prompt projectors** to project the soft prompts trained on a PLM to the semantic space of other PLMs and find that by training a projector with PT on some tasks, the trained projector can successfully project the soft prompts of similar tasks and achieve non-trivial performance. (2) Similar to TPT<sub>TASK</sub>, we propose cross-model transferable prompt tuning (TPT<sub>MODEL</sub>), which is to start PT with the projected prompts of the same task on the target PLM. However, experiments show that  $TPT_{MODEL}$  does not work so well as  $TPT_{TASK}$ . (3) We observe that the activated neurons of projected prompts are **not similar** with prompts originally trained on the target PLM. Considering the PLMs' high redundancy (Aghajanyan et al., 2021), this may indicate that the projected prompts are different solutions to finish tasks conditioning on the target PLM, while the PT does not prefer these solutions and is hard to optimize with them continuously.

In general, our findings and analyses show that improving PT's efficiency with knowledge transfer is possible and promising, and transferring prompts between different PLMs is more challenging than transferring between different tasks on the same PLM. We hope these findings can facilitate further research on transferable and efficient PT.

## 2 Related Work

**Prompt Tuning** Pre-training a PLM on massive data (Radford et al., 2018; Devlin et al., 2018; Yang

et al., 2019; Liu et al., 2019b; Raffel et al., 2020) and then adapting it to downstream tasks have become the typical paradigm for NLP. Conventionally, the adaptation is done with task-oriented finetuning, which optimizes all parameters of PLMs through task-specific supervision. However, with the continual growth of PLM parameters, fullparameter fine-tuning becomes unaffordable for both typical paradigm and model storage. To remedy this, many parameter-efficient tuning methods (Ben Zaken et al., 2021; Houlsby et al., 2019; Li and Liang, 2021; Qin and Eisner, 2021; Lester et al., 2021) have been proposed, which only tune a few parameters and keep most of the PLM parameters frozen. Among these parameter-efficient finetuning variants, prompt tuning has gained much attention, which is motivated by GPT-3 (Brown et al., 2020). It demonstrates remarkable few-shot performance by giving every task a text prompt prepended before the input text and letting the PLM directly generate the answers. Recently, many prompt-based works have emerged, i.e., manuallydesigned (Schick and Schütze, 2021a,b; Mishra et al., 2021) or automatically-searched (Jiang et al., 2020; Shin et al., 2020; Gao et al., 2021) hard prompts, which are discrete tokens but not necessarily human-readable. Furthermore, soft prompt (Li and Liang, 2021; Hambardzumyan et al., 2021; Zhong et al., 2021; Liu et al., 2021) comes out, which are tuneable embeddings rather than tokens in the vocabularies and can be directly trained with task-specific supervision. And Lester et al. (2021) demonstrates that this prompt tuning (PT) method can match the performance of full-parameter finetuning when the PLM size is extremely large. This suggests that PT is promising to utilize extremely large PLMs. However, the much more training steps needed to reach the convergence (§ 3.1) make PT inefficient. In this work, we show that prompt transfer can remedy this and also improve the effectiveness to some extent with knowledge transferring, and empirically analyze the transferability of PT across tasks and models.

**Transferring for PLM** Cross-task transferring, or generally multi-task learning (Ruder, 2017) has been a long-standing way to improve the effectiveness and efficiency of NLP systems. In the PLM era, some works propose to tune the PLMs on intermediate tasks (Phang et al., 2019; Pruksachatkun et al., 2020; Gururangan et al., 2020; Wang et al., 2019a; Vu et al., 2020; Poth et al., 2021) before

fine-tuning on the specific target task and achieve certain benefits. Especially, Vu et al. (2020) empirically analyze the transferability across tasks in this setting. However, these explorations are all for fine-tuning. Prompt Tuning (PT) is a promising way to utilize large PLMs, and we believe that the transferability and transferring methods for PT are worth exploring.

As a prior attempt, Lester et al. (2021) demonstrates that PT's cross-domain transferability for the same task is stronger than fine-tuning. Similar to our work, concurrent work (Vu et al., 2021) demonstrates the cross-task transferability for PT and also proposes to perform cross-task transfer with prompts initialization. Differently, we further analyze prompts through the lens of model stimulation and improve the efficiency of PT with cross-task transfer. Additionally, we also attempt the cross-model transfer of prompt, which is inspired by previous cross-model knowledge transfer works such as Net2Net (Chen et al., 2016), knowledge distillation (Hinton et al., 2015) and knowledge inheritance (Qin et al., 2021a).

## 3 Preliminary

In this section, we introduce the basic knowledge about prompt tuning (PT) (§ 3.1) as well as the downstream tasks (§ 3.2) and models investigated (§ 3.3) in experiments.

### 3.1 Prompt Tuning

In this work, we study the PT methods that are capable of tuning large PLMs (Li and Liang, 2021; Lester et al., 2021; Liu et al., 2021), while freezing the PLM parameters. Considering we focus on NLU abilities, we do not explore the prefixtuning (Li and Liang, 2021) working on generation tasks. PT directly prepends some virtual tokens, i.e., the soft prompts, into the inputs of the PLM to provide knowledge about the downstream tasks. The soft prompts are essentially tuneable embedding vectors, which are trained with the objective of enforcing the PLM to decode tokens indicating the corresponding labels of the inputs, while the PLM's model parameters are kept frozen. The tokens corresponding to labels are dubbed as label tokens.

Formally speaking, given an input sequence  $X = \{x_1, x_2, \dots, x_n\}$ , where  $x_i$  is the token, we first prepend l randomly initialized soft prompts  $P = \{\mathbf{P}_1, \mathbf{P}_2, \dots, \mathbf{P}_l\}$  before them, where  $\mathbf{P}_i \in$ 

 $\mathbb{R}^d$  is an embedding vector and d is the input dimension of the PLM. Before them, we prepend a [MASK] token, which is used to predict the label tokens y. The training objective is to maximize the likelihood of decoding y:

$$\mathcal{L} = p(y|[\texttt{MASK}], P, x_1, \dots, x_n), \tag{1}$$

while only P is learnable. Hence the tuned parameters in PT are extremely fewer than full-parameter fine-tuning, which is friendly for tuning large PLMs.

PT can achieve comparable performance with fine-tuning when the used PLM is extremely large, but the obvious performance gap still exists when the PLM is not so large, and PT also takes more memories than fine-tuning (Mahabadi et al., 2021). Moreover, we empirically find that the speed of convergence of PT is significantly slower than fine-tuning as shown in Figure 2. Hence we argue that efficiency of PT need to be further improved, and knowledge transferring intuitively may help.

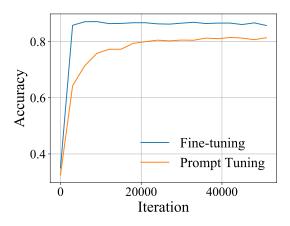


Figure 2: The evaluation accuracies against training steps of fine-tuning and PT for RoBERTa<sub>BASE</sub> on MNLI dataset. On average, PT and fine-tuning respectively spend 2.15s and 1.78s for each step (with 8 V100 GPUs and 16 batch size).

### 3.2 Investigated NLU Tasks

To comprehensively study the transferability of soft prompts across various NLU tasks, we involve 13 diverse tasks, which can be divided into 4 types: (1) Sentiment analysis (SA), including IMDB (Maas et al., 2011), SST-2 (Socher et al., 2013), laptop (Pontiki et al., 2014), restaurant (Pontiki et al., 2014), Movie Rationales (Movie) (Zaidan et al., 2008) and TweetEval (Tweet) (Barbieri et al., 2020); (2) Natural language inference (NLI), including MNLI (Williams et al.,

2018), QNLI (Wang et al., 2019b) and SNLI (Bowman et al., 2015); (3) Ethical judgement (EJ), including deontology (Hendrycks et al., 2021) and justice (Hendrycks et al., 2021); (4) Paraphrase identification (PI), including QQP (Sharma et al., 2019), and MRPC (Dolan and Brockett, 2005). Details of the tasks, used label tokens, and implementations are left in appendix A.1, appendix A.3, and appendix A.2, respectively.

#### 3.3 Investigated Models

To study the cross-model transferability, we investigate two kinds of PLMs: BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019b), which are widely-used for NLU tasks. Specifically, we use RoBERTa<sub>BASE</sub>, RoBERTa<sub>LARGE</sub> and BERT<sub>BASE</sub> checkpoints in the experiments. The RoBERTa<sub>BASE</sub> and BERT<sub>BASE</sub> models consist of 12 Transformer (Vaswani et al., 2017) encoder layers and their embedding dimensions are both 768, while RoBERTa<sub>LARGE</sub> is of 24 Transformer layers and 1024 embedding dimension.

#### 4 Cross-Task Transfer

In this section, we empirically study the cross-task transferability of soft prompts (§ 4.1) and try to improve the effectiveness and efficiency of prompt tuning by utilizing the transferability (§ 4.2), then we explore why can the prompts transfer and what controls the transferability between prompts by analyzing various prompt similarity metrics (§ 4.3). All the experiments in this section are conducted on RoBERTa<sub>BASE</sub>.

## 4.1 Zero-shot Transferability

To study the cross-task transferability, we first examine PT's zero-shot transfer performance, i.e., we conduct PT on a source task, then we directly reuse the trained prompts on other target tasks and evaluate their performances. The results are shown in Figure 3, from which we can observe that: (1) For the tasks within the same type, transferring soft prompts between them can generally perform well and may even outperform vanilla PT on the target dataset, especially when the source task has a larger dataset than the target task (the case of transferring from IMDB to Movie), which demonstrates that it is promising to improve PT's effectiveness and efficiency with knowledge transferring from similar tasks. (2) For the tasks of different types, the transferability of soft prompts between them

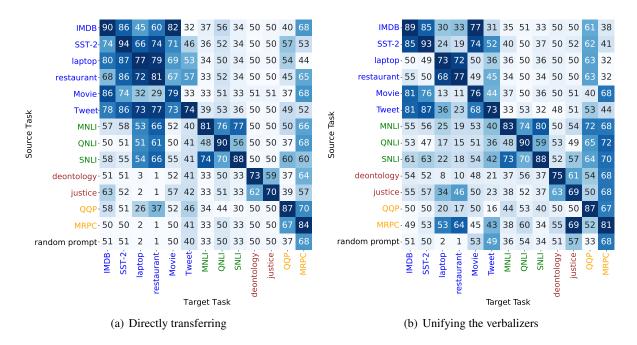


Figure 3: The accuracies on the target tasks (columns) of the soft prompts trained on the source tasks (rows), which demonstrate the zero-shot transfer performances. Colors of the tasks names indicate the task types. Blue: sentiment analysis. Green: natural language inference. Brown: ethical judgement. Orange: paraphrase identification. *Random Prompt* of the last row means the soft prompts are randomly generated without any training.

Task Type		SA					NLI			EJ		PI	
Task	IMDB	SST-2	laptop	restaurant	Movie	Tweet	MNLI	QNLI	SNLI	deontology	justice	QQP	MPRC
Labels	2	2	4	4	2	3	3	2	3	2	2	2	2
Accuracy (PT) (%) Accuracy (TPT <sub>TASK</sub> ) (%)	89.9 <b>90.0</b>	93.8 <b>93.9</b>	<b>77.3</b> 76.6	80.7 <b>83.5</b>	79.2 <b>80.2</b>	<b>74.5</b> 74.2	80.6 83.3	90.5 <b>90.6</b>	<b>88.5</b> 88.1	72.9 <b>76.6</b>	70.0 <b>70.1</b>	86.9 <b>87.5</b>	<b>83.9</b> 82.6
Convergence Time (%) Comparable-result Time (%)	90.6 53.1	65.3 54.5	77.3	28.9 3.3	41.7 1.5	52.3	46.5	94.2 94.2	94.1	75.0 12.4	34.1 2.2	133.0 107.0	57.7

Table 1: Accuracies on 13 NLU tasks of original prompt tuning (**PT**) and prompt tuning with transferring initalization (TPT<sub>TASK</sub>) as well as the convergence time comparisons (the training steps of TPT<sub>TASK</sub> reaching convergence divided by the training steps of **PT**) and comparable-result time comparisons (the training steps of TPT<sub>TASK</sub> achieving comparable performance to **PT** divided by the training steps of **PT**).

is generally poor, and transferring soft prompts only achieve similar performances to the given randomly initialized prompt in many cases. The poor transferability may result from the fact that different-type tasks usually use different label tokens, e.g., entailment and contradict are for NLI tasks while positive and negative are for SA tasks. To exclude this factor, We unify the label tokens of different tasks into the same set of numbers  $(1, 2, \ldots)$  and the results are shown in Figure 3 (b), from which we can observe that the transferability between different-type tasks are generally not improved in this way. This indicates that different-type tasks surely require distinct abilities, which prohibits reusing prompts between them. (3)

The transferability between some tasks are intuitive, such as the best-performing source task for *IMDB* is *Movie*. However, some are counterintuitive like the best source task for *laptop* is *Tweet*. To understand this, it is worthwhile to explore what controls the transferability between prompts, and we will do some preliminary study in § 4.3.

#### 4.2 Transfer with Initialization

To study how to improve the effectiveness and efficiency of PT with cross-task transferring, we explore cross-task transferable prompt tuning  $(TPT_{TASK})$  in this section.  $TPT_{TASK}$  initializes the soft prompts with well-trained soft prompts of similar tasks before starting prompt tuning and observes whether it can accelerate training and improve final

performances.

For the 13 investigated tasks, we start  $TPT_{TASK}$  with trained soft prompts of other tasks that can achieve the best performance in Figure 3 (a). The performance and training time comparisons are shown in Table 1. From the results, we can see  $TPT_{TASK}$  can mostly achieve better or comparable performance to vanilla PT starting from random initialization, which takes fewer training steps to reach the comparable performance and convergence. For the detailed comparisons of training curves, please refer to appendix B.

## 4.3 Exploring Transferability Indicator

Furthermore, we explore why can the soft prompts transfer across tasks and what controls the transferability between them, which may help to shed light on the mechanisms behind the success of PT and help to design transferable PT methods. To this end, we explore various similarity metrics of prompts and examine how well do they align with the zero-shot transfer performance. If a designed similarity metric can well indicate transferability, we can say the factors considered in designing this metric mostly controls the transferability between prompts. Moreover, the prompt similarity metrics can qualify task similarities using the trained soft prompts as task embeddings and may help in designing cross-task transferring methods. As a straightforward example, if we build a prompt warehouse containing trained prompts of diverse tasks, we can retrieve prompts of similar tasks for a new task with a certain similarity metric and better improve PT on the new task with TPT<sub>TASK</sub>. In this work, we explore the following two kinds of metrics.

**Embedding Similarity** In the first type of investigated similarity metrics, we regard the trained soft prompts as only embeddings in the vector space and calculate their similarities with two conventional metrics: *Euclidean similarity* and *cosine similarity*.

Given two groups of trained prompts containing l virtual tokens:  $P^{t_1} = \{\mathbf{P}_1^{t_1}, \dots, \mathbf{P}_l^{t_1}\}$  and  $P^{t_2} = \{\mathbf{P}_1^{t_2}, \dots, \mathbf{P}_l^{t_2}\}$ , which correspond to tasks  $t_1$  and  $t_2$ . Firstly, we concatenate the l prompt token embeddings for each group and get  $l \times d$  dimensional embeddings  $\hat{\mathbf{P}}^{t_1}, \hat{\mathbf{P}}^{t_2}$ , then we compute Euclidean similarity and cosine similarity for them:

Metric	Same Task	Different Task
$E_{concat}$	36.4	0.4
$E_{average}$	27.7	4.2
$C_{ m concat}$	41.1	3.1
$C_{average}$	6.0	2.0
ON (1 - 3 layers)	94.4	52.3
ON (4 - 6 layers)	90.5	41.7
ON (7 - 9 layers)	86.4	35.2
ON (10 - 12 layers)	75.0	28.9
ON (All 12 layers)	87.7	39.9

Table 2: The average values (%) of the 5 similarity metrics for prompt pairs within the same task (trained with 5 different random seeds) and between different tasks. For the ON metric, we take the activation states of layers in different levels into computation. 1 indicates the bottom layer and 12 indicates the top layer.

$$E_{\text{concat}}(P^{t_1}, P^{t_2}) = \frac{1}{1 + \|\hat{\mathbf{P}}^{t_1} - \hat{\mathbf{P}}^{t_2}\|},$$

$$C_{\text{concat}}(P^{t_1}, P^{t_2}) = \frac{\hat{\mathbf{P}}^{t_1} \cdot \hat{\mathbf{P}}^{t_2}}{\|\hat{\mathbf{P}}^{t_1}\| \|\hat{\mathbf{P}}^{t_2}\|}.$$
(2)

Considering that the prompt is position invariant since we do not add position embedding in the Transformer (Vaswani et al., 2017) into the prompt during PT, we further introduce a simple way to make the metrics invariant to token positions. Straightforwardly, we compute Euclidean distances and cosine similarities for every prompt token pairs in the two groups and use the averaged results as the final similarity metrics for the two soft prompts:

$$E_{\text{average}}(P^{t_1}, P^{t_2}) = \frac{1}{1 + \frac{1}{l^2} \sum_{i=1}^{l} \sum_{j=1}^{l} \|\mathbf{P}_i^{t_1} - \mathbf{P}_j^{t_2}\|},$$

$$C_{\text{average}}(P^{t_1}, P^{t_2}) = \sum_{i=1}^{l} \sum_{j=1}^{l} \frac{\mathbf{P}_i^{t_1} \cdot \mathbf{P}_j^{t_2}}{\|\mathbf{P}_i^{t_1}\| \|\mathbf{P}_j^{t_2}\|}.$$
(3)

Model Stimulation Similarity In the second way, we do not regard the soft prompts only as embedding vectors but depict their similarities based on how they *stimulate the PLMs*, i.e., we examine the similarities of how the PLM responses to the two trained soft prompts. Motivated by Mor et al. (2021) and Dai et al. (2021), which both find that the activation of the neurons in the intermediate of feed-forward layers of Transformer models corresponds to specific model behaviors, we propose to use the *overlapping rate of activated neurons* as a similarity metric of soft prompts. Specifically, the feed-forward network FFN(·) in a Trans-

Correlation		SA						NLI		EJ		PI		Overall
Metrics	IMDB	SST-2	laptop	restaurant	Movie	Tweet	MNLI	QNLI	SNLI	deontology	justice	QQP	MPRC	Overall
E <sub>concat</sub>	58.8	47.8	1.1	-0.5	40.7	38.5	-13.2	-2.2	-2.2	51.1	9.9	18.1	14.3	20.2
$E_{average}$	48.4	21.4	-3.3	-6.0	40.7	2.2	-72.0	-41.8	-43.4	32.4	-8.2	-30.2	3.3	-4.4
$C_{concat}$	70.9	45.1	18.1	63.2	48.9	63.2	-19.2	31.3	14.3	38.5	38.5	43.4	15.9	36.3
$C_{average}$	81.3	34.1	91.2	71.4	86.8	30.2	67.6	41.2	58.8	13.7	38.5	45.1	12.6	51.7
ON (1 - 3 layers)	68.1	54.4	63.7	71.4	41.2	38.5	61.0	63.7	68.1	-1.1	36.8	54.9	-12.6	46.8
ON (4 - 6 layers)	79.7	79.1	76.9	70.9	77.5	21.4	42.3	51.1	58.8	50.0	19.8	43.4	15.4	52.8
ON (7 - 9 layers)	69.2	85.2	75.8	63.7	75.8	34.1	75.8	57.7	45.6	51.6	19.8	23.1	11.0	53.0
ON (10 - 12 layers)	81.3	84.6	89.6	80.8	86.8	44.5	86.8	65.4	70.3	56.0	30.8	32.4	33.0	64.8
ON (All 12 layers)	76.9	84.6	88.5	79.1	75.3	22.5	78.0	71.4	62.1	37.4	29.7	44.0	6.0	58.1

Table 3: The Spearman's rank correlation scores (%) between various similarity metrics and zero-shot transfer performances of soft prompts. For the overlapping rate of activated neurons (ON) metric, we also investigate the effect of different levels of layers by only taking the activation states of specific layers into computation. 1 indicates the bottom layer and 12 indicates the top layer.

former (Vaswani et al., 2017) layer is as follows:

$$FFN(\mathbf{x}) = \max(0, \mathbf{x}W_1^{\top} + b_1)W_2 + b_2, \quad (4)$$

where  $\mathbf{x} \in \mathbb{R}^d$  is the input embedding,  $W_1, W_2 \in \mathbb{R}^{d_m \times d}$  are trainable matrices, and  $b_1, b_2$  are bias vectors. The  $\max(\mathbf{x}W_1^T + b_1, 0)$  can be regarded as the non-negative activation values for  $d_m$  hidden neurons (Mor et al., 2021). We then change all the positive elements of  $\max(\mathbf{x}W_1^T + b_1, 0)$  to 1 and get the one-hot activation state vector  $\mathbf{s}$ .

We input sequence  $\{[MASK], p_1, \dots, p_l, <s>\}$ into the PLM, where  $\langle s \rangle$  is the special token indicating the start of sentences. This format is essentially the format of PT inputs but without specific input sentences. For each Transformer layer of PLM, we use the activation state s of the [MASK] position since the [MASK] is used to predict label tokens and hence more task-specific. Then we concatenate the activation states of all the layers in PLM to get the overall PLM activation state:

$$AS(P) = [\mathbf{s}_1; \mathbf{s}_2; ...; \mathbf{s}_L]. \tag{5}$$

We can also only retrieve the activation states of a part of layers in the similarity computation. We calculate the overlapping rate of activated neurons  $ON(P^{t_1}, P^{t_2})$  between the trained soft prompts of task  $t_1$  and  $t_2$  with the cosine similarity:

$$ON(P^{t_1}, P^{t_2}) = \frac{AS(\mathbf{P}^{t_1}) \cdot AS(\mathbf{P}^{t_2})}{\|AS(\mathbf{P}^{t_1})\| \|AS(\mathbf{P}^{t_2})\|}.$$
 (6)

## 4.3.1 Experimental Results

To evaluate the effectiveness of the above similarity metrics of soft prompts, we (1) test whether

the similarity metrics can distinguish the trained prompts of the same tasks and different tasks, and (2) examine whether these metrics align with the zero-shot transfer performance of soft prompts.

We compare the similarity values of the investigated metrics for two trained prompts within the same task (trained with different random seeds) and between different tasks in Table 2. From the results, we can observe that: (1) All the metrics work well to distinguish the prompts of the same task and different tasks. From the perspective of the embedding similarities, this shows the trained soft prompts of different tasks form distinguishable clusters. From the perspective of the model stimulation similarity, this suggests that different tasks really require the soft prompts to stimulate different abilities within the PLM. (2) For the overlapping rate of activated neurons, the differences of tasks tend to be larger at the higher layers. This is consistent with the probing results (Liu et al., 2019a) showing that the higher layers tend to be more task-specific. Details of the overlapping rate of activated neurons are left in appendix C.

Moreover, we evaluate whether the prompt similarity metrics align with the zero-shot transfer performance in Figure 3. Specifically, (a), we compute the Spearman's rank correlation (Spearman, 1987) for each target task between the similarities and zero-shot transfer performance of the various source tasks' prompts. The results are shown in Table 3, from which we observe that: (1) The *overlapping rate of activated neurons* (ON) metric generally works better than all the embedding similarities, which suggests that model stimulation takes a more important position in prompt transferability than embedding distances. We encourage future

works to explore how to better model the stimulation of prompts. (2) Among all the embedding similarity metrics, the two metrics based on Euclidean distances work poorly and even have negative correlations on some tasks. The metrics based on cosine similarities work better and the Caverage metric can achieve comparable performance to the ON metric using bottom layers. However, the ability of C<sub>average</sub> to distinguish different tasks (Table 2) is obviously worse. These results indicate that the properties of the prompt embedding space are tricky and hard to design transferable PT methods based on them. (3) The results of ON using higher model layers are generally better than that using lower layers, which again confirms that the top layers are more task-specific. However, there are also some counterexamples, such as the justice and QQP, which may come from some specific linguistic abilities are required in these tasks and needs careful study.

#### 5 Cross-Model Transfer

In this section, we study the cross-model transferability of soft prompts. In the experiments, we investigate two practical setting: transferring from a PLM to a heterogeneous same-size PLM (BERT<sub>BASE</sub> to RoBERTa<sub>BASE</sub>) and transferring from a smaller PLM to a homogeneous larger PLM (RoBERTa<sub>BASE</sub> to RoBERTa<sub>LARGE</sub>). Directly reusing trained soft prompts between different-size models is infeasible since the embedding dimensions are not consistent and the performance of reusing between heterogeneous same-size PLMs is poor (see the Directly Reuse row in Table 4), which is intuitive since the embedding spaces are different. Hence, we investigate how to project the soft prompts trained on a model to the space of other models (§ 5.1) and see the transferring performance (§ 5.2). Furthermore, similar to § 4.2, we investigate whether we can further improve the effectiveness and efficiency with cross-model transferring initialization (§ 5.3).

#### 5.1 Projecting Prompts to Different Models

In this section, we explore how to project the trained soft prompts of a model to the semantic space of a different model. To this end, we train projectors with various supervisions and examine the effectiveness of different projector training methods. A good way to train the cross-model projectors may need some task-specific supervisions, e.g. par-

allel soft prompts of the two models or supervised data for some tasks, but the trained projector shall be able to generalize to different tasks so that the efficiency for learning the new tasks of PT on the target model could be improved.

Formally speaking, the projector  $\mathbf{Proj}(\cdot)$  is to project the trained soft prompts  $\mathbf{P}^s \in \mathbb{R}^{l \times d_s}$  of the source model to corresponding prompts  $\tilde{\mathbf{P}}^s \in \mathbb{R}^{l \times d_t}$  in the semantic space of the target model, where  $d_s$  and  $d_t$  are the input embedding dimensions for the source model and target model, respectively. In this work, the projector is parameterized with a two-layer perceptron as follows:

$$\tilde{\mathbf{P}}^{s} = \mathbf{Proj}(\mathbf{P}^{s})$$

$$= \text{LayerNorm}(\mathbf{W}_{2}(\tanh(\mathbf{W}_{1}\mathbf{P}^{s} + b_{1})) + b_{2}),$$
(7)

where  $W_1$ ,  $W_2$  are trainable matrices,  $b_1$ ,  $b_2$  are trainable bias terms, tanh is a non-linear activation function, and LayerNorm is Layer Normalization (Ba et al., 2016).

We investigate three types of learning objectives to train the cross-model projector:

**Prompt Mapping** We firstly try to learn cross-model projections by learning the mapping between parallel soft prompts of the same task trained on different PLMs. Given two groups of prompts  $\mathbf{P}^s$ ,  $\mathbf{P}^t$  of the same task, which are trained on the source model and the target model, respectively. The projector will project  $\mathbf{P}^s$  and the training objective is to minimize the  $L_2$  norm:

$$L_p = \|\mathbf{Proj}(\mathbf{P}^s) - \mathbf{P}^t\|_2. \tag{8}$$

**Token Mapping** Since the prompts are virtual tokens prepended to the input tokens, we explore whether the mapping between input token embeddings of two different PLMs can also work for prompt embeddings. Given a token x and its corresponding token embeddings  $\mathbf{x}^s, \mathbf{x}^t$ , which are of the source PLM and target PLM, respectively. We train the projector to minimize the  $L_2$  norm:

$$L_t = \|\mathbf{Proj}(\mathbf{x}^s) - \mathbf{x}^t\|_2,\tag{9}$$

and use all the input tokens in the vocabularies as training samples.

**Task Tuning** Considering the findings in § 4.3 that the transferability of soft prompts relates more to how they stimulate the PLMs rather than their embedding distances, we try to directly tune the

Method				SA				NLI		EJ		PI	
Method	IMDB	SST-2	laptop	restaurant	Movie	Tweet	MNLI	QNLI	SNLI	deontology	justice	QQP	MRPC
PT on RoBERTa <sub>BASE</sub>	89.9	93.8	77.3	80.7	79.2	74.5	80.6	90.5	88.5	72.9	70.0	86.9	83.9
Random Prompt	50.6	50.8	2.3	1.2	50.5	40.5	32.8	50.5	33.3	50.4	50.2	36.8	68.0
Directly Reuse	50.3	51.0	2.5	41.5	49.5	40.8	32.4	50.6	31.5	50.3	50.0	36.8	68.0
Prompt Mapping (IMDB, laptop)	89.7	53.1	75.6	18.3	54.2	24.0	31.2	50.0	33.3	50.6	50.0	36.8	67.2
Prompt Mapping (MNLI)	55.6	51.0	2.5	1.4	53.1	41.1	80.0	50.6	33.3	50.6	50.0	48.3	68.0
Task Tuning (IMDB, laptop)	88.2	82.2	76.3	77.9	73.4	43.6	32.0	47.9	32.8	49.8	49.4	50.2	47.7
Task Tuning (MNLI)	50.9	52.0	11.9	13.1	45.8	18.2	83.3	74.9	80.0	50.4	49.9	36.8	68.1

Table 4: Zero-shot performance of various methods to transfer soft prompts from **BERT**<sub>BASE</sub> to **RoBERTa**<sub>BASE</sub>, including non-projector baselines (PT, randomly generated prompts, directly reuse BERT<sub>BASE</sub> prompts) and projector methods.

Method				SA				NLI		EJ		]	PI
Method	IMDB	SST-2	laptop	restaurant	Movie	Tweet	MNLI	QNLI	SNLI	deontology	justice	QQP	MRPC
PT on RoBERTa <sub>LARGE</sub>	91.8	96.0	78.1	81.7	81.7	76.6	88.5	93.4	90.7	85.6	81.1	89.0	82.7
Random Prompt	50.1	50.2	2.0	2.0	49.5	40.5	32.7	51.0	33.3	50.3	49.9	40.6	61.2
Token Mapping	49.7	54.2	17.2	8.7	49.0	42.0	33.1	50.4	33.1	50.3	50.1	37.2	58.4
Prompt Mapping (IMDB, laptop)	92.1	50.1	77.0	1.4	51.0	37.6	33.1	50.2	32.8	50.4	50.0	62.3	38.3
Prompt Mapping (MNLI)	50.3	51.2	5.2	5.9	51.0	40.6	88.5	49.1	33.2	50.3	50.0	45.1	66.4
Task Tuning (IMDB, laptop)	90.4	76.2	64.2	69.5	79.7	45.0	33.3	50.5	33.1	50.3	50.0	38.5	79.7
Task Tuning (MNLI)	67.7	76.1	28.9	43.7	60.4	49.1	87.1	79.4	84.5	49.7	50.0	36.8	68.5

Table 5: Zero-shot performance of various methods to transfer soft prompts from  $RoBERTa_{BASE}$  to  $RoBERTa_{LARGE}$ , including non-projector baselines (PT, randomly generated prompts) and projector methods.

projected prompts on the target PLM with corresponding tasks and train the projector in this way, which shall learn how to stimulate the target PLM from task tuning. We then see whether the trained projector can generalize to other unseen tasks.

The **Prompt Mapping** and **Task Tuning** methods rely on some tasks (parallel trained soft prompts or training data) to train the projector. In the experiments, we select two representative SA tasks (IMDB and laptop) and a NLI task (MNLI), respectively, for the projector learning. The **Token Mapping** needs the vocabularies for the source and target PLM are aligned, hence we only try it in the  $RoBERTa_{BASE}$  to  $RoBERTa_{LARGE}$  setting.

## 5.2 Transfer Performance

The transferring performance of various projector-learning methods on the setting of from BERT<sub>BASE</sub> to RoBERTa<sub>BASE</sub> and from RoBERTa<sub>BASE</sub> to RoBERTa<sub>LARGE</sub> are shown in Table 4 and Table 5, respectively. We can observe that: (1) Although the input embedding dimensions of BERT<sub>BASE</sub> and RoBERTa<sub>BASE</sub> are consistent, the performance of directly reusing trained soft prompts between them is similar to use randomly generated prompts, which confirms that the gap between the prompt semantic spaces of different models is huge. (2) The

performance of **Token Mapping** method is also near to the random baseline, which suggests that although the soft prompts are fed to PLMs together with the input tokens, they are not in the same embedding space. (3) **Prompt Mapping** works well to transfer the prompts involved in projector training, but falls back to random performance on the unseen tasks, which is not practical. This is consistent with our findings in § 4.3 that the embedding similarities/distances cannot well reflect the transferability between tasks. (4) Task Tuning performs the best and successfully generalize to sametype unseen tasks of the training tasks (e.g. NLI tasks for the projectors trained with MNLI), which indicates the feasibility of designing practical crossmodel transferring methods for PT. Compared to the failures of **Prompt Mapping**, this confirms that analyzing and manipulating prompts from the perspective of model stimulation is more effective. However, the projectors trained with Task Tuning still cannot work for different-type tasks, which urges more advanced transferring methods.

#### **5.3** Transfer with Initialization

Similar to § 4.2, we further study whether the projected soft prompts can initialize PT on the target model and accelerate training as well as improve

Task Type				SA				NLI		EJ		P	I
Task	IMDB	SST-2	laptop	restaurant	Movie	Tweet	MNLI	QNLI	SNLI	deontology	justice	QQP I	MPRC
Accuracy (PT on RoBERTa <sub>BASE</sub> ) (%)	89.9	93.8	77.3	80.7	79.2	74.5	80.6	90.5	88.5	72.9	70.0	86.9	83.9
			Task T	uning (IM	DB, lap	otop)							
Accuracy (TPT <sub>MODEL</sub> ) (%)	89.9	93.6	75.9	81.3	79.6	73.2	81.0	89.9	86.0	74.8	72.8	86.0	76.3
Convergence Time (%)	150.1	81.6	83.3	97.3	43.1	231.0	92.2	130.1	125.0	120.8	131.4	133.3	100.2
Comparable-result Time (%)	125.7	-	-	36.8	43.1	-	51.1	-	-	83.4	108.0	-	-
			Ta	sk Tuning	(MNLI	)							
Accuracy (TPT <sub>MODEL</sub> ) (%)	90.0	94.4	73.3	80.8	67.2	73.2	81.6	90.3	88.5	72.9	52.4	86.0	83.9
Convergence Time (%)	196.0	118.0	371.0	121.1	101.0	375.0	87.7	93.3	95.1	103.0	97.2	120.5	106.1
Comparable-result Time $(\%)$	159.0	55.1	-	102.0	-	-	20.8	-	88.3	93.3	-	-	103.5

Table 6: We report  $\mathbf{PT}$  (RoBERTa<sub>BASE</sub>) and  $\mathbf{TPT}_{\mathbf{MODEL}}$  (from BERT<sub>BASE</sub> to RoBERTa<sub>BASE</sub>) accuracies for 13 NLU tasks, the convergence time comparisons (the training steps of  $\mathbf{TPT}_{\mathbf{MODEL}}$  reaching convergence divided by the training steps of  $\mathbf{PT}$ ), and comparable-result time comparisons (the training steps of  $\mathbf{TPT}_{\mathbf{MODEL}}$  achieving comparable performance to  $\mathbf{PT}$  divided by the training steps of  $\mathbf{PT}$ ).

Projector (Method)	Task	E <sub>concat</sub>	$E_{\rm average}$	$C_{\mathrm{concat}}$	$\mathcal{C}_{\mathrm{average}}$	ON (all 12 layers)
	Pro	ojected Pron	npts / TPT <sub>M</sub>	DDEL Prompts		
Ta ala Tamin a	IMDB	0.3 / 0.3	2.8 / 3.0	2.3 / 9.4	2.2 / 4.1	38.3 / 58.6
Task Tuning	SST2	0.3 / 0.3	2.6 / 2.8	-2.6 / 0. <del>6</del>	-1.1 / 4.3	36.9 / 55.6
(IMDB, laptop)	laptop	0.3 / 0.3	2.7 / 3.2	-0.9 / 4.3	-1.0 / 4. <del>0</del>	40.4 / 53.7
	restaurant	0.3 / 0.3	2.7 / 3.2	-0.7 / <b>3.5</b>	-1.5 / 2.9	36.7 / 57.6
	Movie	0.3 / 0.2	2.8 / 1.8	3.5 / 3.3	1.4 / 1.6	42.0 / 51.1
	Tweet	0.3 / 0.3	2.8 / 2.8	2.0 / 4.1	2.7 / 4.3	45.4 / 61.8
Task Tuning	MNLI	0.1 / 0.1	1.0 / 1.6	-0.3 / 24.0	-0.3 / 10.0	43.1 / 48.7
ė l	QNLI	0.1 / 0.2	1.2 / 2.1	0.9 / 0.2	0.4 / 7.1	41.9 / 56.2
(MNLI)	SNLI	0.1 / 0.1	1.4 / 1.6	-1.0 / -13.1	6.4 / 9.2	37.3 / 49.1
Overall (mean)		0.2 / 0.2	2.2 / 2.5	0.4 / 4.0	1.0 / 5.3	40.2 / 54.7
Average between diff	erent tasks	0.4	4.2	3.1	2.0	39.9
Average between diff	0.4	4.1	2.4	1.8	36.3	
Average between san	36.4	27.7	41.1	6.0	87.7	
Average between san	Average between same-type tasks			30.4	4.8	58.4

Table 7: Values in black are the similarities (%) between soft prompts originally trained on the target PLM (RoBERTa<sub>BASE</sub>) and prompts projected from the source PLM (BERT<sub>BASE</sub>) with two projectors learned with **Task Tuning**; values in blue are the similarities between soft prompts trained on the target PLM and soft prompts trained by  $TPT_{MODEL}$ . *Average between same (or different) tasks* indicates the average values for the similarity metrics between soft prompts of same (or different) tasks (within the 13 investigated tasks).

performances. Based on the results in § 5.2, we propose cross-model transferring prompt tuning, TPT<sub>MODEL</sub>, which adopts the **Task Tuning** projectors to project the soft prompts trained on the source PLM into the target PLM and initialize PT with the projected prompts.

The performance and training time comparisons in the setting of transferring from BERT<sub>BASE</sub> to RoBERTa<sub>BASE</sub> are shown in Table 6. We can observe that: (1) For the tasks within the same type of the tasks used to train projectors, TPT<sub>MODEL</sub> can mostly achieve comparable or slightly better performances with less training steps, which demonstrates that practical cross-model prompt transferring is possible, although the prior methods here

cannot achieve significant advantages. (2) For the tasks of the different type of projector-training tasks,  $TPT_{MODEL}$  typically cannot bring advantages in either performance or training time, which shows that  $TPT_{MODEL}$  is still seriously limited by the quality of prompt projectors.

Generally, the advantages brought by  $TPT_{MODEL}$  are moderate and significantly lower than  $TPT_{TASK}$ . To analyze what influences the cross-model transferability, we observe the similarities between the original prompts trained on the target PLM and the projected prompts with the prompt similarity metrics in § 4.3. The results are shown in Table 7. We can see that for all the tasks measured with all the metrics, the projected prompts are highly

dissimilar with the prompts originally trained on the target PLM, while the projected prompts of projector-training tasks can achieve comparable performance to the originally trained prompts. We guess this indicates that due to the high redundancy of PLMs (Aghajanyan et al., 2021), dissimilar prompts activating different neurons can also stimulate the PLM to do similar jobs, but the optimization dynamics determined by the optimizer and hyperparameters prefers to find similar solutions (Table 2).

#### 6 Discussion

Using multiple source prompts. In both TPT<sub>TASK</sub> and TPT<sub>MODEL</sub>, we only use one source prompt for initialization, which is a prior attempt. Intuitively, mixing up multiple source prompts may achieve further performance and efficiency gain. Actually, concurrent work (Vu et al., 2021) has confirmed this in the cross-task transfer. Future work can explore advanced mixing/ensemble methods for better initialization, and the explored prompt similarity metrics in this paper may help to this end.

Finding better prompt similarity metric. In § 5.3, we find that although the prompts projected from another PLM can achieve comparable performance to prompts originally trained on the target PLM, these two kinds of prompts are highly dissimilar when measured by all the prompt similarity metrics in this paper, including the overlapping rate of activated neurons. This shows that we still need a better prompt similarity metric considering the high redundancy of PLMs and measuring the essential factors of prompts, which needs a deeper understanding on the mechanisms of PLMs. Previous works (Aghajanyan et al., 2021; Qin et al., 2021b) show that various NLP tasks can be reparameterized into similar low-dimensional subspaces conditioning on PLMs, which may help to this end.

**Designing better cross-model prompt projection.** Compared with TPT<sub>TASK</sub>, the results of TPT<sub>MODEL</sub> in this paper are much weaker due to the different characteristics between source and target PLMs and the limited projection methods. In § 5.3, we find our cross-model projection tends to project into the solutions of comparable performance but not those preferred by the optimization process; thus TPT<sub>MODEL</sub> works not as well as TPT<sub>TASK</sub>. And we find that when we remove the

LayerNorm( $\cdot$ ) of Eq. 7 in **Task Tuning**, this phenomenon is even more significant that the learning loss does not decrease when using TPT<sub>MODEL</sub>. For the details, please refer to appendix D. This suggest that we should design better cross-model projection methods to overcome the heterogeneity of different PLMs and different optimization preferences.

## 7 Conclusion

In this paper, we empirically investigate the transferability of prompt tuning across different tasks and models. In the cross-task setting, we find that soft prompts can transfer to similar tasks without training, and using trained soft prompts as initialization can accelerate training and improve effectiveness. We also explore various prompt similarity metrics and show that how the prompts stimulate PLMs are more important than their embedding distances in transferability. In the cross-model setting, we explore various methods to project soft prompts into the space of other models and find that the transferring initialization using projected prompts can only achieve moderate improvements, which may be due to the redundancy of PLMs. We hope the empirical analyses and attempted transferring methods in this work can facilitate further research on PT transferring.

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## A Appendix

#### A.1 Dataset and Task

Sentiment Analysis (SA) Given a sentence, a PLM will classify the emotions in this sentence. We choose IMDB (Maas et al., 2011), SST-2 (Socher et al., 2013), SemEval/laptop (Pontiki et al., 2014), SemEval/restaurant (Pontiki et al., 2014), Movie Rationales (Movie) (Zaidan et al., 2008), and TweetEval (Tweet) (Barbieri et al., 2020) to analyze.

Natural Language Inference (NLI) Given a premise, a PLM determines whether a hypothesis is entailed, contradict, or undetermined. We choose MNLI (Williams et al., 2018), QNLI (Wang et al., 2019b), and SNLI (Bowman et al., 2015) to analyze.

**Ethical Judgement (EJ)** Given a sentence, a PLM judges whether it is ethically acceptable. We choose Ethics/deontology (Hendrycks et al., 2021) and Ethics/justice (Hendrycks et al., 2021) to analyze.

**Paraphrase Identification (PI)** Given a pair of sentences, a PLM judge whether they have similar semantics. We choose QQP (Sharma et al., 2019) and MRPC (Dolan and Brockett, 2005) to analyze.

## A.2 Prompt Tuning Setting

In § 3.1, we introduce PT, whose objective is to maximize the likelihood of decoding the label token when given an input sequence and the corresponding prompt for the task. We choose BERT<sub>BASE</sub> (Devlin et al., 2019), RoBERTa<sub>BASE</sub>, and RoBERTa<sub>LARGE</sub> (Liu et al., 2019b) as the main evaluated PLMs. For each investigated task, the learning rate is 0.001, the optimizer is AdamW, the soft prompt length *l* is 100, and we replace the first token with [MASK], whose embedding is frozen during the prompt tuning. Besides, we do not add the position embeddings and type embeddings into prompts during PT. All the soft prompts are randomly initialized and optimized with Equation 1.

#### A.3 Label Tokens

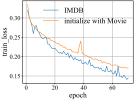
Beside, for all investigated tasks, we provide different label tokens as shown in Table 8.

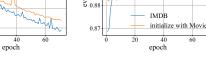
Task	Label Tokens							
Sen	timent Analysis (SA)							
IMDB	positive, negative							
SST-2	positive, negative							
laptop	positive, moderate, negative							
restaurant	positive, moderate, negative							
Movie positive, negative								
Tweet positive, moderate, negative								
Natural 1	Natural Language Inference (NLI)							
MNLI	yes, neutral, no							
QNLI	yes, no							
SNLI	yes, neutral, no							
Eth	nical Judgement (EJ)							
deontology	acceptable, un							
justice	acceptable, un							
Paraphrase Identification (PI)								
QQP	true, false							
MRPC	true, false							

Table 8: Label tokens of 13 tasks for PT.

## B Comparison of PT and $TPT_{TASK}$

To better compare accuracies, convergence time, and comparable-result time of PT (—) and TPT<sub>TASK</sub> (—) for 13 investigated tasks, we plot their training losses and evaluation accuracies during the training process. We find that TPT<sub>TASK</sub> utilizes trained prompts from similar tasks as initialization for prompt tuning (—), which can mostly achieve better or comparable performance to vanilla PT (—) starting from random initialization and take fewer training steps to reach the comparable performance and convergence.





(a) IMDB training loss.

(b) IMDB eval accuracy.

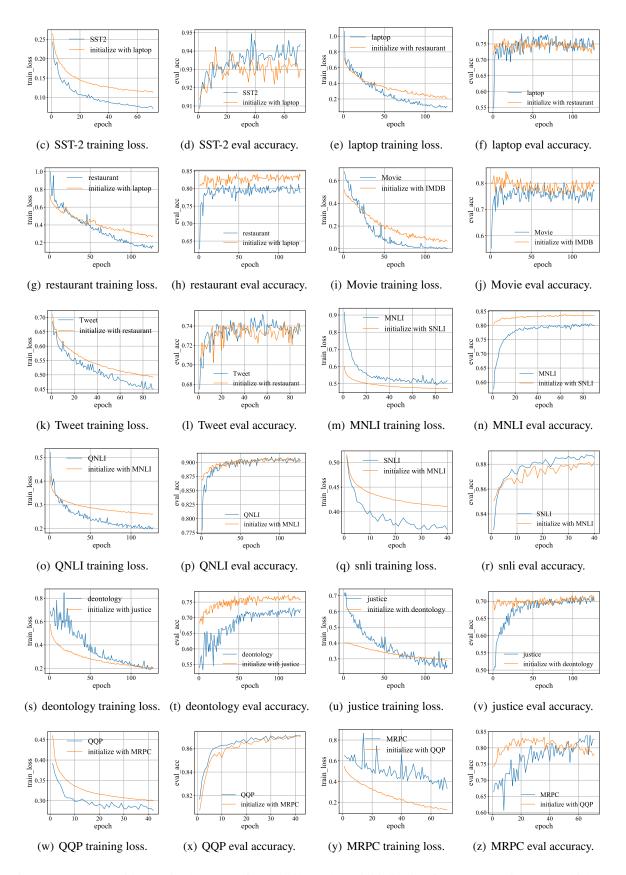


Figure 4:  $TPT_{TASK}$  utilizes trained prompts from similar tasks as initialization for prompt tuning (—), which can mostly achieve better or comparable performance to vanilla PT (—) starting from random initialization and take fewer training steps to reach the comparable performance and convergence.

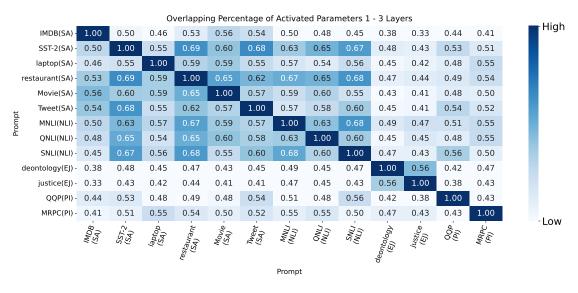


Figure 5: ON in 1 - 3 layers of RoBERTa<sub>BASE</sub>.

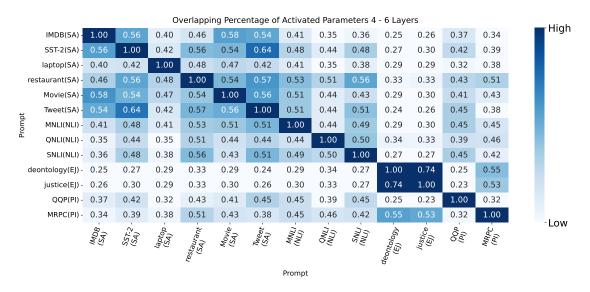


Figure 6: ON in 4 - 6 layers of RoBERTa<sub>BASE</sub>.

## C Overlapping Rates of Activated Neurons in Different Layers

We demonstrate that the overlapping rate of activated neurons, ON, can reflect the similarity between soft prompts.

Here, we measure the similarity between each pair of prompts with ON, which calculates their overlapping rate of activated neurons of RoBERTa<sub>BASE</sub> respectively from 1 to 3 layers (Figure 5), from 4 to 6 layers (Figure 6), from 7 to 9 layers (Figure 7), from 10 to 12 layers (Figure 8), and all 12 layers (Figure 9).

We find that the similarity of prompts for different tasks tends to be smaller at the higher layers. Namely, the activated neurons in the lower layers are common and in higher layers tend to be more

task-specific, which is consistent with the results shown in Liu et al. (2019a).

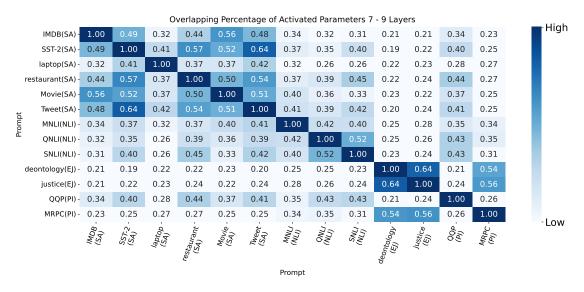


Figure 7: ON in 7 - 9 layers of RoBERTa<sub>BASE</sub>.

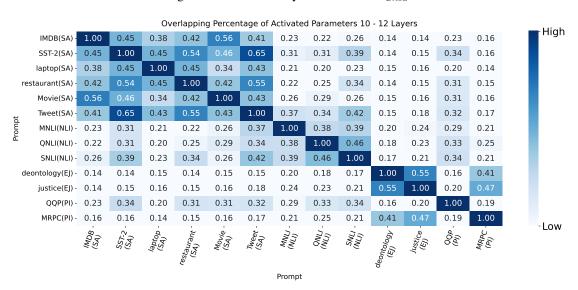


Figure 8: ON in 10 - 12 layers of RoBERTa<sub>BASE</sub>.

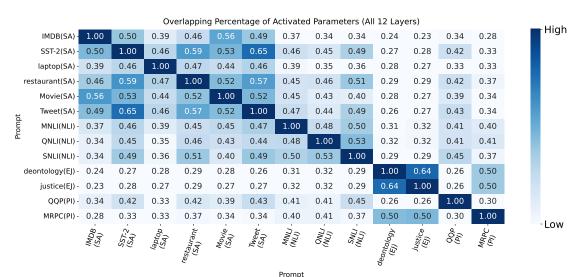


Figure 9: ON in all 12 layers of RoBERTa<sub>BASE</sub>.

Method				SA				NLI		EJ			PI
Method	IMDB	SST-2	laptop	restaurant	Movie	Tweet	MNLI	QNLI	SNLI	deontology	justice	QQP	MRPC
PT on RoBERTa <sub>Base</sub>	89.9	93.8	77.3	80.7	79.2	74.5	80.6	90.5	88.5	72.9	70.0	86.9	83.9
				Witho	ut Laye	rNorm							
Task Tuning (IMDB, laptop)	86.5	84.9	73.4	75.3	76.6	47.7	31.8	52.0	32.9	50.3	50.0	37.6	67.5
Task Tuning (MNLI)	66.6	70.4	53.0	43.8	57.8	47.9	82.4	74.9	78.1	50.4	49.9	45.3	70.1
				With	LayerN	Norm							
Task Tuning (IMDB, laptop)	88.2	82.2	76.3	77.9	73.4	43.6	32.0	47.9	32.8	49.8	49.4	50.2	47.7
Task Tuning (MNLI)	50.9	52.0	11.9	13.1	45.8	18.2	83.3	74.9	80.0	50.4	49.9	36.8	68.1

Table 9: We compare the zero-shot performances of prompts (Prompt<sub>WITHOUT</sub> LN and Prompt<sub>WITH</sub> LN) projected by Task Tuning projectors (without LayerNorm and with LayerNorm) and find that their accuracies are close.

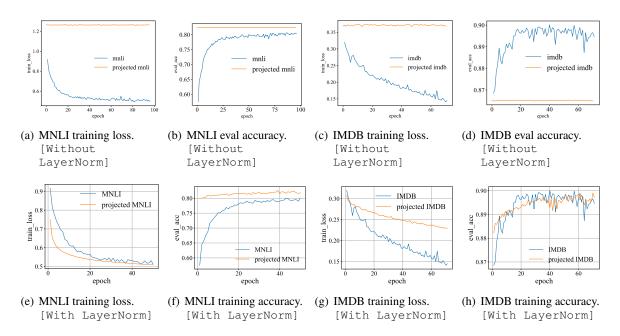


Figure 10: BERT<sub>BASE</sub> to RoBERTa<sub>BASE</sub>: (—) represents vanilla PT. And (—) is  $TPT_{MODEL}$  that utilizes projected prompts as initizations to conduct PT. The projected prompts (Prompt<sub>WITHOUT LN</sub> and Prompt<sub>WITH LN</sub>) respectively come from two different Task Tuning projectors (**without LayerNorm** and **with LayerNorm**). Compared with PT, we find that  $TPT_{MODEL}$  can exploit Prompt<sub>WITH LN</sub> to achieve the similar or better effectiveness and efficiency, but  $TPT_{MODEL}$  hardly uses Prompt<sub>WITHOUT LN</sub> to optimize continuously.

# D Comparison of Task Tuning Projectors with and without the LayerNorm

To design better cross-model projectors, we compare Task Tuning projectors with the LayerNorm ( $Proj_{WITH\;LN}$ ) and Task Tuning projectors without the LayerNorm ( $Proj_{WITH\;OUT\;LN}$ ). In the following experiments, we utilize them to project trained prompts to the target PLM and denote as  $Prompt_{WITH\;LN}$  and  $Prompt_{WITH\;OUT\;LN}$ .

### D.1 Zero-Shot Performance on Target PLM

First, we exploit Proj<sub>WITH LN</sub> and Proj<sub>WITHOUT LN</sub> to project prompts to the target PLM and observe the zero-shot performances on the tasks. As shown in

Table 9, we find that both of the projectors successfully generalize to same-type unseen tasks of the training tasks, and their performances on all of the tasks are close.

# D.2 Accuracy, Convergence Time, and Comparable-Result Time

Second, we leverage projected prompts (Prompt<sub>WITH LN</sub>) and Prompt<sub>WITHOUT LN</sub>) as initialization to conduct  $TPT_{MODEL}$  and respectively compare their accuracies, convergence time, and comparable-result time with PT. As shown in Figure 10, we find that  $TPT_{MODEL}$  can use Prompt<sub>WITH LN</sub> to achieve similar or better effectiveness and efficiency, but  $TPT_{MODEL}$  hardly

Method	Task	E <sub>concat</sub>	$E_{\mathrm{average}}$	$C_{\mathrm{concat}}$	$C_{\mathrm{average}}$	ON (all 12 layers)						
	Without LayerNorm											
Task Tuning	IMDB	$1.0 \times 10^{-5}$	$1.4 \times 10^{-3}$	15.1	5.6	45.7						
(IMDB, laptop)	laptop	$2.4 \times 10^{-4}$	$2.5 \times 10^{-3}$	5.3	5.4	48.1						
(IMDB, Iaptop)	restaurant	$4.0 \times 10^{-4}$	$5.1 \times 10^{-3}$	5.8	4.1	49.8						
Task Tuning	MNLI	$< 10^{-5}$	$< 10^{-5}$	3.2	5.5	35.7						
(MNLI)	SNLI	$< 10^{-5}$	$< 10^{-5}$	4.1	5.3	37.6						
		Wit	h LayerNorm									
Tools Tuning	IMDB	0.3	2.8	2.3	2.2	38.3						
Task Tuning (IMDB, laptop)	laptop	0.3	2.7	-0.9	-1.0	40.4						
(IIVIDB, Iaptop)	restaurant	0.3	2.7	-0.7	-1.5	36.7						
Task Tuning	MNLI	0.1	1.0	-0.3	-0.3	43.1						
(MNLI)	QNLI	0.1	1.2	0.9	0.4	41.9						
(IVIIVLI)	SNLI	0.1	1.4	-1.0	6.4	37.3						
Average between	different tasks	0.4	4.2	3.1	2.0	39.9						

Table 10: Similarities (%) between PT prompts and prompts (Prompt<sub>WITHOUT</sub> LN and Prompt<sub>WITH</sub> LN) projected by Task Tuning projectors (**without LayerNorm and with LayerNorm**). Average between different tasks indicates the average values for the similarity metrics between prompts of 13 tasks introduced in § 3.2.

continue to optimize  $Prompt_{WITHOUT\;LN}$ .

# D.3 Similarities between Original Prompts and Projected Prompts

To analyze influences for initialization of  $Prompt_{WITH\ LN}$  and  $Prompt_{WITHOUT\ LN}$  in the optimization process of  $TPT_{MODEL}$ , we respectively measure the similarity values between PT prompts and projected prompts ( $Prompt_{WITH\ LN}$  and  $Prompt_{WITHOUT\ LN}$ ) for the same tasks with the investigated metrics. As shown in Table 10, we find that both  $Prompt_{WITH\ LN}$  and  $Prompt_{WITHOUT\ LN}$  are dissimilar to PT prompts, and  $Prompt_{WITHOUT\ LN}$  even has significant differences in Euclidean metric values.