FL-Tuning: Layer Tuning for Feed-Forward Network in Transformer

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Abstract

Prompt tuning is an emerging way of adapting pre-trained language models to downstream tasks. However, the existing studies are mainly to add prompts to the input sequence. This way would not work as expected due to the intermediate multi-head self-attention and feed-forward network computation, making model optimization not very smooth. Hence, we propose a novel tuning way called layer tuning, aiming to add learnable parameters in Transformer layers. Specifically, we focus on layer tuning for feed-forward network in the Transformer, namely FL-tuning. It introduces additional units into the hidden layer of each feed-forward network. We conduct extensive experiments on the public CLUE benchmark. The results show that: 1) Our FL-tuning outperforms prompt tuning methods under both full-data and few-shot settings in almost all cases. In particular, it improves accuracy by 17.93% (full-data setting) on WSC 1.0 and F1 by 16.142% (few-shot setting) on CLUENER over P-tuning v2. 2) Our FL-tuning is more stable and converges about 1.17 times faster than P-tuning v2. 3) With only about 3% of Transformer's parameters to be trained, FL-tuning is comparable with fine-tuning on most datasets, and significantly outperforms fine-tuning (e.g., accuracy improved by 12.9% on WSC 1.1) on several datasets. The source codes are available at https://github.com/genggui001/FL-Tuning.

1 Introduction

Pre-trained language models (PLMs), such as ELMo [1] and BERT [2], have become increasingly important in natural language processing. The popular way to accommodate general-purpose PLMs to specific downstream tasks is to FINE TUNE them by updating all the parameters. As a result, it is necessary to store a modified copy of full-size model parameters for each task [3]. However, this would be prohibitively expensive when applying the model to a large number of tasks [4–6].

PROMPT TUNING is an emerging way to adapt PLMs to downstream tasks, which adds prompts to the input sequence and feeds the new input to PLMs in the pre-training task. In this way, all PLM parameters are frozen and only the task-specific prompt is updated. Discrete prompt tuning is the first method that leverages text tokens as the prompt to the original input [7]. For example, in text classification, a common prompt tuning method is to concatenate an input (e.g., “I haven’t published a paper.”) with the prompt “I felt [MASK]” and ask PLMs to fill the masked token with “happy” or “sad”. Since the PLMs are continuous from an optimization point of view, it is difficult to achieve the optimum with discrete prompts [8]. Continuous prompt tuning is thus proposed to replace text
Figure 1: The difference between FL-tuning and prompt tuning. The former introduces learnable parameters to each FFN in the Transformer, while the latter adds tokens/embeddings to the input.

tokens with trainable embeddings, which outperforms discrete prompt tuning on many tasks [6,8,9]. However, the impact of input prompts before the first transformer layer will gradually weaken due to the multiple intermediate layers’ computation [8]. To address this problem, deep prompt tuning [8] is proposed, which takes continuous embeddings as the prompt to the input sequence of each layer in PLMs. Although this method has shown better performance on many tasks, its essence is still only adding a few parameters as prompts to the input. These prompts would not work as expected due to the intermediate multi-head self-attention and feed-forward network computation, making model optimization not very smooth. This situation leads to limited performance gain, unstable training, and slow convergence.

To address the above problem, we propose a novel tuning way, namely LAYER TUNING, for adapting PLMs to downstream tasks. Different from prompt tuning, layer tuning is to add learnable parameters to the Transformer layers with original PLM parameters frozen. Transformer [10] mainly contains two sub-layers: multi-head self-attention and feed-forward network (FFN). In this paper, we mainly focus on Layer Tuning for Feed-forward network in the Transformer, namely FL-tuning. As shown in Figure 1, it aims at introducing additional hidden units into each FFN layer. In other words, FL-tuning expands the dimensions of the weight matrices (W₁ and W₂ in Eq. 1) and bias (b₁) of the linear layers in FFN. The reason for tuning on FFN is that it accounts for about 2/3 of the number of parameters in the Transformer encoder [11], and it is expected to obtain better results. Due to the inconvenience of directly operating on the expanded weight matrices and biases, we split them into fixed and learnable parts. Hence, we can perform independent operations on the two parts to simplify the implementation process. The feasibility of this “split” idea is rigorously proved theoretically in Section 4.2. In addition, we also prove that the influence of the trainable weight matrices and bias on model performance is independent of their positions in the expanded ones. That is, the learnable part can be placed at any position in the expanded weight matrices and bias.

Contributions. The contributions in this paper are summarized as follows:

- To the best of our knowledge, we are the first to propose layer tuning for adapting PLMs to downstream task. The most distinguish characteristic is that it adds learnable parameters in Transformer layers.
- We propose a method of layer tuning for feed-forward network in the Transformer, namely FL-tuning. Our tuning method is more stable and converges faster than P-tuning v2.
- We conduct extensive experiments on 7 downstream tasks and 11 NLU datasets. The results show that our FL-tuning outperforms prompt tuning in almost all cases. In addition, with only about 3% of Transformer’s parameters to be trained, it is comparable with fine-tuning on most datasets, and significantly outperforms fine-tuning on several datasets.

2 Related Work

Prompt tuning adapts PLMs to downstream tasks by adding prompts to the input sequence and has been verified effective in many NLP applications [12,16]. These methods can be divided into three categories. First, discrete prompt tuning directly generates the results without changing the
Discrete prompt tuning leverages text tokens as prompts to adapt PLMs to downstream tasks. For example, to classify the sentiment of S\text-quote-right\text-quote-left="I haven’t published a paper.\text-quote-right\text-quote-right" as happy or sad, we design a prompt “I felt [MASK]” for S. The input embedding for PLMs is defined as:

\[ [e(S), e(I), e(feel), e([MASK])]. \]  

Continuous prompt tuning adds the trainable embeddings to the input ones. Continuing the previous example, the prompt “I felt [MASK]” is replaced with continuous embeddings \([h_0, \ldots, h_l]\), where \(l\) is the prompt length. The input sequence is thus formulated as:

\[ [e(S), h_0, \ldots, h_l, e([MASK])]. \]  

Transformer has been proved to be an effective architecture for PLMs [10]. It is an encoder-decoder structure, which is composed of multi-head self-attention and FFN. Much effort is dedicated to improve the Transformer’s capability [19] and can be divided into three categories. First, some studies attempt to design a novel self-attention architecture in the Transformer [20–24]. Linformer [25] proposes a new self-attention mechanism, which reduces the complexity of self-attention to \(O(n)\) both in time and space. Second, although FFN is just a multi-layer perceptron, it accounts for about \(2/3\) of the number of parameters in the Transformer encoder. Kformer [26] improves the ability of PLMs by incorporating external knowledge into the FFN in the Transformer. Third, in addition to the separate researches on the two sub-layers, there are also many studies to modify the Transformer structure. Fan et al. [19] strength the Transformer with a dynamic mask attention network before the multi-head self-attention. Press et al. [27] study the impact of the combined order of the two sub-layers in the Transformer on model performance. Different from the above work on sub-layers or adding new sub-layers to the Transformer, this paper focuses on introducing hidden units to each FFN layer for PLMs’ tuning.

### 3 Preliminaries

In this section, we briefly review the multi-head self-attention and feed-forward network in the Transformer architecture. Besides, we give the definitions of three kinds of prompt tuning, including discrete prompt tuning, continuous prompt tuning, and deep prompt tuning.

#### 3.1 Transformer

The Transformer model is based on an encoder-decoder structure. Each encoder (decoder) is composed of a stack of identical blocks, containing multi-head self-attention and feed-forward network. These two sub-layers are formulated as follows:

\[
\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V, \quad \text{FFN}(X) = \text{ReLU}(XW_1 + b_1)W_2 + b_2, \quad (1)
\]

where \(X \in \mathbb{R}^{d_a \times d_m}\), \(Q = XW^Q\), \(K = XW^K\), \(V = XW^V\), \(W^Q \in \mathbb{R}^{d_m \times d_k}\), \(W^K \in \mathbb{R}^{d_m \times d_k}\), \(W^V \in \mathbb{R}^{d_m \times d_v}\), \(W_1 \in \mathbb{R}^{d_m \times d_a}\), \(W_2 \in \mathbb{R}^{d_a \times d_m}\) are weight matrices, \(b_1 \in \mathbb{R}^{1 \times d_a}\) and \(b_2 \in \mathbb{R}^{1 \times d_m}\) are bias, and \(\text{ReLU}(x) = \text{max}(0, x)\).

#### 3.2 Prompt tuning

**Discrete prompt tuning** leverages text tokens as prompts to adapt PLMs to downstream tasks. For example, to classify the sentiment of \(S\text-quote-right\text-quote-left="I haven’t published a paper.\text-quote-right\text-quote-right\text-quote-right as happy or sad\text-quote-right\text-quote-right, we design a prompt “I felt [MASK]” for \(S\). The input embedding for PLMs is defined as:

\[ [e(S), e(I), e(feel), e([MASK])]. \]  

**Continuous prompt tuning** adds the trainable embeddings to the input ones. Continuing the previous example, the prompt “I felt [MASK]” is replaced with continuous embeddings \([h_0, \ldots, h_l]\), where \(l\) is the prompt length. The input sequence is thus formulated as:

\[ [e(S), h_0, \ldots, h_l, e([MASK])]. \]  

**Deep prompt tuning** overcomes the limitation of sub-optimal performance in the previous methods. P-tuning [9] introduces continuous embeddings learned by LSTM to the original sequence of input word embeddings. Prefix-tuning [3] designs task-specific trainable prefixes for natural language generation tasks. Third, deep prompt tuning is proposed to solve the challenges of continuous prompt tuning, which are the lack of universality across scales and tasks. P-tuning v2 [8] applies continuous embeddings as the prompts to the input sequence of each layer in PLMs. Unlike the above studies, we aim to propose a novel PLMs’ tuning way, namely layer tuning, which adds learnable parameters to the Transformer layers.
Figure 2: The model architecture of FL-tuning. FL-tuning introduces additional hidden units to each FFN layer, and the units of each layer are independent. The orange circles are hidden units in addFFN, the blue circles are hidden units in original FFN.

**Deep prompt tuning**, also known as P-tuning v2 [8], takes the prefix embeddings as the prompt to the input sequence in each Transformer layer. P-tuning v2 essentially concatenates two matrices $E_0$ and $E_1$ to the key matrix $K$ and the value matrix $V$ respectively in each multi-head attention layer, which is defined as:

$$Attention_{PV^2}(Q, K, V, E_0, E_1) = \text{Softmax} \left( \frac{Q[E_0 \perp K]^T}{\sqrt{d_k}} \right)[E_1 \perp V],$$

(4)

where the operation “$\perp$” means the row-wise concatenation, $E_0$ and $E_1$ are trainable and other parameters are frozen.

### 4 Methodology

In this section, we first introduce the details of FL-tuning. Then, we give the theoretical proofs of its equivalent implementation.

#### 4.1 FL-tuning

In the Transformer [10] architecture, FFN is a multi-layer perceptron with one hidden layer, consisting of two linear transformations with an ReLU activation in their middle [10]. In essence, FL-tuning adds a number of hidden units in each FFN layer, as shown in Figure 2. Note that the added hidden units in different layers are independent to each other. Formally, we change $W_1$ and $W_2$ in Eq. (1) to $[W_1'; W_1]$ and $[W_2' \perp W_2]$ as follows:

$$FFN_{FL}(X) = ReLU(X[W_1': W_1] + [b_1': b_1])[W_2' \perp W_2] + b_2,$$

(5)

where the operations “;” and “$\perp$” stand for the column- and row-wise concatenation, respectively. Only the parameters of $W_1'$, $b_1'$, $W_2'$, and $W_2$ can be trained and all parameters of the Transformer-based PLMs are frozen.

#### 4.2 Implementation

However, it is inconvenient to directly utilize Eq. (5) to implement FL-tuning because the learnable and fixed parameters are mixed in matrices. Therefore, we keep the original FFN hidden layer and add another small FFN hidden layer (referred to as addFFN). The equivalence is established by the following theorem.

**Theorem 1.** In FL-tuning, FFN can be split into:

$$FFN_{FL}(X) = addFFN(X) + FFN(X),$$

(6)

where $addFFN(X) = ReLU(XW_1' + b_1')W_2'$. 

4
we formulate FL-tuning in the infix form as follows:

\[ FFN_{FL}(X) = ReLU([XW'_1 + b'_1 : XW_1 + b_1])[W'_2 \perp W_2] + b_2. \]  

(7)

Let \( H \) be the output of the hidden layer in FFN and \( H' \) be the output of the addFFN’s hidden layer, i.e.,

\[ H = ReLU(XW_1 + b_1), \quad H' = ReLU(XW'_1 + b'_1). \]  

(8)

Eq. (7) can be rewritten as:

\[ FFN_{FL}(X) = [H' : H][W'_2 \perp W_2] + b_2 = H'W'_2 + HW_2 + b_2 = addFFN(X) + FFN(X), \]  

(9)

which proves the theorem.

In the proof of Theorem 1, additional hidden units are introduced into FFN as the prefix (at the beginning of the FFN hidden layer). Alternatively, we also have the choices of the infix (in the middle of the FFN hidden layer) and suffix (at the end of the FFN hidden layer) to add hidden units. However, these three cases are equivalent, as stated in the following theorem.

**Theorem 2.** In FL-tuning, Eq. (6) is not affected by the position of \( addFFN(\cdot) \). That is, Eq. (6) holds regardless of whether \( addFFN(\cdot) \) is prefix, infix, or suffix.

**Proof.** The proof of this theorem is divided into the following three cases:

**Prefix:** In the proof of Theorem 1 we have \( FFN_{FL}(X) = addFFN(X) + FFN(X). \)

**Infix:** In this case, \( W_1, b_1, \) and \( W_2 \) can be split into \([W_{1p} : W_{1s}],[b_{1p} : b_{1s}], \) and \([W_{2p} : W_{2s}]\). Then, we formulate FL-tuning in the infix form as follows:

\[
\begin{align*}
FFN_{FL}(X) &= ReLU(X[W_{1p} : W'_1 : W_{1s}] + [b_{1p} : b'_1 : b_{1s}])[W_{2p} \perp W'_2 \perp W_{2s}] + b_2. \\
&= [H_{1p} : H'] [W_{2p} \perp W'_2 \perp W_{2s}] + b_2 = H_{1p}W_{2p} + H'W'_2 + H_{1s}W_{2s} + b_2 \\
&= H'W'_2 + [H_{1p} : H_{1s}] [W_{2p} \perp W_{2s}] + b_2 = H'W'_2 + HW_2 + b_2 \\
&= addFFN(X) + FFN(X).
\end{align*}
\]  

(10)

**Suffix:** The proof of this case is similar to that of Theorem 1. That is,

\[
\begin{align*}
FFN_{FL}(X) &= ReLU(X[W_1 : W'_1][b_1 : b'_1])[W_2 \perp W'_2] + b_2 \\
&= [H : H'][W_2 \perp W'_2] + b_2 = HW_2 + H'W'_2 + b_2 \\
&= FFN(X) + addFFN(X).
\end{align*}
\]  

(11)

In summary, Eq. (6) is not influenced by the position of \( addFFN(\cdot) \).

\[ \square \]

### 5 Experiments

In this section, we investigate our tuning method over three PLMs and seven NLU tasks. The experimental results and detailed analysis demonstrate the superior performance, stable training, and faster convergence of FL-tuning.

#### 5.1 Experimental Setup

**Backbones.** We perform experiments on three Transformer-based PLMs, including RoBERTa [28], NEZHA [29], and RoFormer [30]. We carefully tune the hyperparameters in experiments based on RoBERTa and apply the optimal ones to NEZHA and RoFormer. Hyperparameters used in fine-tuning, P-tuning v1 [9], P-tuning v2 [8], and FL-tuning over the three PLMs are shown in Table 1.

**Baselines.** We compare our FL-tuning (FL) with fine-tuning (FT), P-tuning v1 (PV1) [9], and P-tuning v2 (PV2) [8]. The prompt length in both PV1 and PV2 are set to 160, and the number of added hidden units of each FFN layer in FL is also pre-defined as 160. FT’s results are obtained by tuning all the Transformer’s parameters without prompts. Results of PV1, PV2, and FL are obtained by freezing the original parameters of the Transformer and only tuning the introduced trainable parameters.
Table 1: Hyperparameters (BS: batch size; SL: sequence length; LR: learning rate; Epo: epoch) used in PLMs' tuning methods on CLUE benchmark and the statistics of CLUE.

| Dataset     | BS | SL | LR  | Epo | BS | SL | LR  | Epo | BS | SL | LR  | Epo | Train | Dev  | Test |
|-------------|----|----|-----|-----|----|----|-----|-----|----|----|-----|-----|-------|------|------|
| IFLYTEK     | 32 | 128| 1e-5| 30  | 128| 128| 6e-4| 40  | 32 | 128| 2e-4| 50  | 32 | 128| 5e-5| 30  |
| TNEWS       | 32 | 128| 1e-5| 40  | 128| 128| 4e-4| 30  | 32 | 128| 1e-3| 80  | 32 | 128| 5e-5| 30  |
| WSC         | 32 | 128| 5e-5| 50  | 128| 128| 6e-4| 20  | 32 | 128| 2e-2| 80  | 32 | 128| 3e-4| 40  |
| AFQMC       | 32 | 128| 1e-5| 15 | 128| 128| 6e-4| 30  | 32 | 128| 8e-3| 30  | 32 | 128| 2e-4| 10  |
| CMNLI       | 32 | 128| 1e-5| 10 | 128| 128| 8e-4| 40  | 32 | 128| 1e-2| 100 | 32 | 128| 5e-4| 30  |
| CSL         | 32 | 128| 1e-5| 30 | 32 | 128| 6e-4| 50  | 32 | 128| 9e-3| 50  | 4  | 512| 3e-2| 50  |
| CLUENER     | 32 | 256| 2e-5| 30 | 32 | 256| 8e-2| 50  | 32 | 256| 1e-4| 30  | 4  | 512| 1e-4| 50  |
| C3          | 16 | 64 | 1e-5| 30 | 128| 64 | 4e-4| 30  | 16 | 64 | 2e-3| 80  | 16 | 64 | 8e-5| 30  |
| CMRC2018    | 16 | 512| 5e-5| 10 | -  | -  | -   | -   | 16 | 512| 3e-2| 50  | 12.5K| 4K |

Table 2: Comparison results of different tuning methods on TC task. We highlight the best of FT, PV1, PV2, and FL in dark gray and use light gray for the next best. If FL outperforms PV2, the improvement over PV2 is reflected in red below. The difference between TNEWS 1.0 and TNEWS 1.1 is that their validation sets are different.

| Dataset     | Text Classification (TC) | NER           | Pronoun Disambiguation (PD) | Name Entity Recognition (NER) |
|-------------|--------------------------|---------------|-------------------------------|-----------------------------|
|             | FT | PV1 | PV2 | FL | FT | PV1 | PV2 | FL | FT | PV1 | PV2 | FL | FT | PV1 | PV2 | FL |
| RoBERTa     | 61.000 | 54.310 | 61.730 | 62.150 | 57.170 | 55.700 | 56.770 | 57.510 | 56.960 | 55.370 | 58.300 | 59.750 |
| NEZHA       | 59.080 | 55.650 | 62.810 | 60.770 | 58.510 | 56.360 | 58.190 | 57.940 | 58.990 | 58.440 | 61.300 | 60.590 |
| RoFormer    | 61.000 | 54.620 | 61.620 | 62.000 | 57.380 | 57.070 | 55.210 | 54.530 | 58.100 | 57.700 | 58.100 | 57.700 |

Datasets. We use NLU text datasets from the CLUE benchmark as experimental data, which is similar to GLUE and SuperGLUE. We select 11 NLU datasets from CLUE for the comparison experiments. The scale of each dataset is shown in Table 1. The selected 11 text datasets are divided into 7 kinds of NLU tasks, including Text Classification (TC), Pronoun Disambiguation (PD), Semantic Similarity (SS), Natural Language Inference (NLI), Keyword Recognition (KR), Name Entity Recognition (NER), and Machine Reading Comprehension (MRC).

Evaluation metrics. We report F1 (%) as the evaluation metric for the NER task and Accuracy (%) for other NLU tasks. All comparison results are obtained after submitting to CLUE and the detailed analysis is based on the parameters of the submitted models.

5.2 Comparison Results Across Tasks

Similar to CLUE, we divide the selected seven kinds of NLU tasks into four categories: Single-Sentence Tasks, Sentence Pair Tasks, Name Entity Recognition Tasks, and Machine Reading Comprehension Tasks.

Single-Sentence Tasks include TC and PD. We adopt the IFLYTEK dataset for long TC, TNEWS for short TC, and WSC for PD. The experimental results on TC and PD tasks are shown in Table 2 and Table 3 respectively. From the table, we observe that FL-tuning outperforms fine-tuning and...
Table 4: Comparison results of different tuning methods on SS, NLI, and KR tasks. FL-tuning is better than prompt tuning methods. Although FT slightly outperforms FL, the number of trainable parameters in FL is only about 3% of Transformer’s parameters.

|                  | Semantic Similarity (SS) | Natural Language Inference (NLI) | Keyword Recognition (KR) |
|------------------|---------------------------|----------------------------------|--------------------------|
|                  | AFQMC                     | CMNLI                            | OCNLI                     |
|                  | PV1                       | PV2                              | FL                        |
|                  | FT                        | FT                               | FT                        |
|                  | FL-Tuning                 | Prompt Tuning                   | Fine-Tuning               |
| RoBERTa          | 72.570                    | 69.850                           | 72.030                    |
| FL               | (80.480)                  | 70.470                           | (79.990)                  |
| FL-Tuning        | 72.900                    | 64.840                           | 72.370                    |
| Prompt Tuning    | (70.020)                  | (2.150)                          |                          |
| Fine-Tuning      | 80.370                    | 80.370                           | 72.800                    |
| RoFormer         | 72.470                    | 72.470                           | 72.370                    |
| FL               | (80.370)                  | 80.370                           | (72.470)                 |
| Prompt Tuning    | 85.330                    | 85.330                           | 84.930                    |
| Fine-Tuning      | (84.930)                  | (0.400)                          |                          |

Table 5: Comparison results of different tuning methods on MRC task. FL significantly outperforms PV2 in almost all cases and is comparable with FT.

|                  | Machine Reading Comprehension (MRC) |
|------------------|-------------------------------------|
|                  | C3                                  | CHID                              |
|                  | PV1                                 | PV2                              |
|                  | FT                                  | FT                               |
|                  | Prompt Tuning                       | Fine-Tuning                       |
| RoBERTa          | 67.650                              | 50.800                           |
| FL               | (67.650)                            | (50.800)                         |
| Prompt Tuning    | 72.550                              | 51.320                           |
| Fine-Tuning      | 87.246                              | 86.759                           |
| RoFormer         | 66.650                              | 53.030                           |
| FL               | (66.650)                            | (53.030)                         |
| Prompt Tuning    | 89.250                              | 86.953                           |
| Fine-Tuning      | (86.953)                            | (3.300)                          |

Table 6: Comparison results of layer/prompt tuning methods under few-shot setting. Our FL-tuning achieves the best results in almost all cases. In particular, it improves F1 of CLUENER by more than 10% on average over PV2.

|                  | TNEWS 1.0 | CMNLI | CLUENER | CHID |
|------------------|-----------|-------|---------|------|
|                  | PV1       | PV2   | FL      |
|                  | PV1       | PV2   | FL      |
|                  | PV1       | PV2   | FL      |
|                  | PV1       | PV2   | FL      |
|                  | PV1       | PV2   | FL      |

prompt tuning in most cases, indicating the effectiveness of our method on TC and PD tasks. In particular, the improvement of NEZHA-based FL-tuning on PD task is very obvious, and its accuracy is 12.76% and 17.93% higher than that of fine-tuning and P-tuning v2. The reason may be that the training dataset of WSC is relatively small and FL-tuning is more suitable for this scenario than other methods. To verify this argument, we supplement the experiments under few-shot settings later in this subsection.

**Sentence Pair Tasks** aim to predict relations between sentence pairs, or abstract-keyword pairs, including SS (AFOMC), NLI (CMNLI and OCNLI), and KR (CSL). Table 4 shows the results on SS, NLI, and KR. According to the results, we conclude that FL-tuning is better than prompt tuning in almost all cases. In particular, it achieves a 2.15% improvement over 78.77% obtained by RoFormer-based PV2. Although FT’s results are slightly better than ours, the number of learnable parameters in FL-tuning is only about 3% of Transformer’s parameters, which greatly reduces the training cost.

**Name Entity Recognition Tasks** experiment on the CLUE Fine-Grain NER (CLUENER) dataset and the results are shown in Table 3. From the table, we observe that FL-tuning performs best among tuning methods in all cases, which further demonstrates the effectiveness of our PLMs’ tuning method.

**Machine Reading Comprehension Tasks** include C3, CHID, and CMRC2018 datasets. The results are shown in Table 5. According to the results, we find that the performance of FL-tuning on MRC tasks is similar to that of Sentence Pair tasks. Although it is not as good as fine-tuning in most cases, it significantly outperforms prompt tuning methods. This verifies that layer tuning is more effective than prompt tuning.
5.3 Detailed Analysis

Next, we take RoBERTa as the backbone to analyze our FL-tuning in detail from the perspectives of convergence, hyperparameter sensitivity as well as the impact of the number and depth of added hidden units on model performance.
Table 7: Comparison results of FL-tuning and MA-tuning (MA) on RoBERTa. It is more effective to realize layer tuning on FFN than multi-head self-attention.

|               | FL-tuning | MA-tuning |
|---------------|-----------|-----------|
| TNEWS         | 60,000    | 57,700    |
| WSC           | 81,240    | 72,990    |
| AFQMC         | 80,920    | 85,030    |
| CMNLI         | 80,570    | 84,400    |
| CSL           | 80,319    | 83,170    |
| CLUENER       | 85,868    | 75,850    |
| C3            | 81,590    | 80,319    |
| CHID          | 62,000    | 57,140    |
| CMRC2018      | 60,000    | 57,140    |

Figure 6: The impact of the depth of hidden units on model performance. The performance of our FL-tuning is positively correlated with the number of added layers. In addition, the deeper the layer of hidden units, the better the model performance.

**Faster convergence and more stable training.** We compare our FL-tuning with PV2 in terms of convergence speed and training stability. The results on WSC, OCNLI, CLUENER, and CMRC2018 are shown in Figure [3](#). From the results, we observe that the loss value of FL-tuning decreases faster than that of PV2, which demonstrates that the former is better than the latter in terms of convergence speed. We further record their running time and find that our FL-tuning converges about 1.17 times faster than PV2 on average. In addition, the loss curve of FL-tuning is flatter than that of PV2 during the training process, indicating that FL-tuning is more stable.

**Hyperparameter insensitive.** The prediction results of deep models are often sensitive to hyper-parameters, especially the learning rate. Even two learning rates with a small gap would make a great difference in predictions. Hence, we analyze the impact of different learning rates on model performance. The results on WSC and CLUENER datasets are reported in Figure [4](#). From the results, we find that in our FL-tuning, the results obtained with different learning rates are more concentrated, while the results are more scattered in PV2. This verifies that our model is more insensitive to the learning rate than PV2.

**The number of hidden units.** The number of added hidden units is an influential hyperparameter for our FL-tuning. We adjust the values to analyze its impact on the model performance. The results on four datasets are shown in Figure [5](#). The model performance improves with the increase of the number of hidden units on CLUENER, while there is no apparent regularity on the other three datasets. As a result, the optimal value of the number of hidden units varies from task to task.

**Depth of hidden units.** To analyze the influence of adding hidden units to different layers on model performance, we select \( k \) layers in both ascending and descending order to introduce hidden units. The results on TNEWS, WSC, OCNLI, and CLUENER are shown in Figure [6](#). According to the results, we observe that the performance of our FL-tuning is not only positively correlated to the number of added layers, but also related to the layer in which the added hidden units are located. The deeper the layer, the better the model performance.

5.4 Discussion

In the Transformer, there are mainly two sub-layers: multi-head self-attention and FFN. The idea of FL-tuning can also be transferred to self-attention. Thus, we perform layer tuning on multi-head self-attention called MA-tuning to compare its performance with FL-tuning. That is, we increase the hidden size of the matrices in multi-head self-attention. The comparison results are listed in Table [7](#). We find that FL-tuning slightly outperforms MA-tuning in most cases. The possible reason is that, as mentioned in the Introduction, FFN occupies about 2/3 of the number of parameters in the model and tuning it may perform better. In addition, the results also show the feasibility of layer tuning on self-attention and FFN at the same time. Hence, we will implement this idea in the future and further analyze its possible optimal combination.
6 Conclusion

In this paper, we propose a novel tuning way, namely layer tuning, to accommodate PLMs to downstream tasks, which aims to add learnable parameters to the Transformer layers. Specifically, we mainly focus on layer tuning on FFN called FL-tuning in the Transformer. It introduces additional units into the hidden layer of each FFN. We conduct extensive experiments on the CLUE benchmark and the results show that: 1) With only about 3% of Transformer’s parameters to be trained, our FL-tuning is comparable with fine-tuning on most datasets, and significantly outperforms fine-tuning on several datasets. 2) FL-tuning is better than prompt tuning methods under both full-data and few-shot settings in almost all cases. 3) FL-tuning is more stable and converges about 1.17 times faster than P-tuning v2.

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