Parameter-Efficient Tuning on Layer Normalization for Pre-trained Language Models

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Abstract

Given the magnitude of the current Pre-trained Language Models (PLMs), conventional fine-tuning becomes increasingly challenging, therefore parameter-efficient tuning is now the focus of cutting-edge research. For PLMs to accomplish transferability, prior techniques in this field added tunable adapters into Multi-Head Attention (MHA) or/and Feed-Forward Network (FFN) of Transformer blocks. However, the ability of Layer Normalization (LayerNorm) for parameter-efficient tuning is disregarded while being a crucial component of Transformer architecture. In this paper, we first propose LN-tuning, which is time-efficient and performs much better than baselines with less than 0.1% tunable parameters by tuning the gain and bias term of the LayerNorm module with only 0.03% parameters. As we continue to research the unified framework of combining LN-tuning with earlier techniques, we discover that: (1) SOTA performance is achieved by the unified framework of combining prefix-tuning, which is one of the adapter-based techniques using MHA, and LN-tuning. (2) While unified frameworks that tune MHA and LayerNorm simultaneously can increase performance, those that simultaneously tune FFN and LayerNorm will have the opposite effect. Further, LN-tuning is better understood by an ablation investigation and a visualization experiment of the bias and gain terms.

1 Introduction

Natural language processing (NLP) is presently dominated by the transfer learning from Pre-trained Language Models (PLMs) paradigm (Devlin et al., 2019; Han et al., 2021), which produces superior results in many tasks (Qiu et al., 2020; Peters et al., 2018; Devlin et al., 2019). The typical method used by PLMs to integrate the information they gained during the pre-training stage into downstream tasks is fine-tuning. A copy of the model needs to be retrained and saved for each downstream operation, which could be expensive given the enormous size of modern PLMs. To address the aforementioned issue, parameter-efficient tuning techniques have been proposed, which only modify a small subset of the pre-trained parameters and freeze the majority of them. To make measurable progress in this area, a lot of work has been done. Ziegler et al.; Houlsby et al.; Pfeiffer et al.; He et al. propose several adapter techniques that insert trainable bottleneck layers, i.e., learnable down and up projections into the Feed-forward Network layer of each PLM block. Prefix-tuning (Li and Liang, 2021), P-tuning v2 (Qin and Eisner, 2021), and deep prompt tuning are used in MHA to optimize MLP networks and achieve continuous prefix prompt. More recently, research efforts have been made to create a unified framework that simultaneously tunes the representations of MHA and FFN, including those of the MAM adapter (He et al., 2021a) and UniPELT (Mao et al., 2022). Prefix-tuning is essentially a form of adapter-based method that is effective in MHA, as noted by MAM adapter. By integrating adapter-based approaches that operate on both MHA and FFN, they are able to attain SOTA performance. It is clear from this that earlier approaches in this area included tunable adapters to the MHA or/and FFN of Transformer blocks to provide parameter-efficient tuning. Nevertheless, the power of LayerNorm for parameter-efficient tuning is overlooked while being a crucial component of Transformer-based PLMs. Following the normalization of mean and variance, the gain and bias terms are applied for affine transformation on each input neuron in LayerNorm, acting as a fine-grained adaptive module on the data (Ba et al., 2016). In earlier techniques, these modules are trained on a sizable general corpus and unsupervised tasks but left unchanged when adapted into a downstream dataset of a particular domain and
supervised tasks, causing an unreasonable transformation since the gap from both the data and the task is quite large between pre-training and fine-tuning stage. In this research, we provide a straightforward but efficient technique called LN-tuning with the learnable gain and bias term of LayerNorm to close the aforementioned gaps. Following are some examples of our contribution:

- We propose LN-tuning, which first explores the potential of LayerNorm for parameter-efficient tuning, achieving comparable performance to prior approaches with a very small number of parameters and a very high time efficiency.

- Prefix-tuning combined with LN-tuning leads to SOTA performance, outperforming MAM, the adapter-based unified framework that tunes MHA and FFN simultaneously.

- We empirically discover that while tuning both MHA and LayerNorm inside a single framework can enhance performance, doing the same with FFN and LayerNorm can actually worsen it.

- LN-tuning is better understood thanks to the ablation study of terms, layers, and modules, as well as the visualization experiment of the gain and bias term.

2 Preliminaries: Parameter-Efficient Tuning

2.1 Existing Approaches

The common parameter-efficient tuning techniques fall into three categories: those only tunes FFN of PLMs, those only tunes MHA of PLMs, those tunes MHA and FFN simultaneously in a unified framework.

Parallel Adapters insert a trainable bottleneck after FFN of each Transformer block, which is indeed a special FFN with down projection and up projection and open the magic box of parameter-efficient tuning for PLMs. Further researches (Pfeiffer et al., 2021, 2020) studied variants of adapters in different positions. Among them, Scaled Sequential Adapter (He et al., 2021a) is shown to have the best performance empirically.

Prefix-tuning (Li and Liang, 2021) and P-tuning v2 (Liu et al., 2022) are proposed to optimize additional past key values in the MHA of each Transformer block, which work as virtual tokens to supply task-specific prompts for PLMs. By learning the whole prefix net in training and only saving past key values obtained from this net for inference, prompt tuning goes a notable step further for parameter-efficient tuning by working in MHA.

The recent unified works, MAM adapter and UniPELT are proposed to combine prefix-tuning and adapter module, tuning the MHA and FFN of each Transformer block simultaneously. Those unified frameworks show empirical improvement compared with non-unified methods, with more tunable parameters and more infeasible tunable layers.

In addition, there are also several other parameter-efficient methods. BitFit only tunes bias vectors of Transformer parameters. Diff-pruning (Guo et al., 2021) learns a sparse parameter update vector. Yang et al. use three learnable vectors to achieve transferability for Natural Language Understanding tasks, which we name 3V for brevity of reference.

2.2 Discussion

By tuning MHA and/or FFN of PLMs, earlier techniques in this field were able to produce parameter-efficient results. However, as a key component of Transformer-based PLMs, the potential of LayerNorm for parameter-efficient tuning is ignored. Is it possible to apply a new tuning technique to PLMs’ LayerNorm by tuning a few parameters? Only unfreezing its own parameters while keeping other PLM parameters frozen can function properly since each LayerNorm module has inherent scale and shift operations. This is what we refer to as LN-tuning.

3 Method

3.1 LN-Tuning

Layer normalization (LayerNorm) is a technique to normalize the distributions of intermediate layers. It enables smoother gradients, faster training, and better generalization accuracy (Xu et al., 2019). As Eq. 1 shows, LayerNorm involves two stages: (1) normalize \( x \) by mean and variance (2) forward by the scale and shift operations consisting of the gain term \( g \) and bias term \( b \), respectively.

Our proposed LN-Tuning keeps parameters in the gain term (for scale operation) and bias term (for shift operation) trainable, which are initialized
from the pre-training stage, while fixing other parameters of PLMs.

\[
\text{LayerNorm}(x) = \frac{g}{\sigma} \odot (x - \mu) + b
\]  

(1)

where

\[
\mu = \frac{1}{H} \sum_{i=1}^{H} x_i \quad \sigma = \sqrt{\frac{1}{H} \sum_{i=1}^{H} (x_i - \mu)^2}
\]

### 3.2 Combine LN-Tuning and Previous Methods

LN-tuning can also be combined with other parameter-efficient to work as a unified framework. We explore five methods:

1. Scaled Parallel Adapter with FFN + LN-tuning
2. Sequential Adapter after FFN + LN-tuning
3. Sequential Adapter after MHA + LN-tuning
4. Prefix-tuning + LN-tuning
5. BitFit + LN-tuning

More details about four different adapter-based variants, i.e., the above methods (1) to (4), can be found in appendix A.

### 4 Experiments

We validate the effectiveness of the proposed method on 11 benchmark datasets and seven types of downstream tasks, including both NLU and NLG ones, with the presence of six state-of-the-art baselines.

#### 4.1 General Setup

**Task Setup.** To evaluate the proposed LN-tuning comprehensively, we conduct cross-task, cross-PLM-architecture, and cross-PLM-scale experiments. For cross-task validation, we conduct both NLU and NLG tasks. Specifically, for NLU tasks, we choose seven type datasets: (1) **Named-Entity Recognition (NER)**, including CoNLL2004 (Carreras and Màrquez, 2004) and Twitter (Derczynski et al., 2016); (2) **Natural Language Inference (NLI)**, including SNLI (Bowman et al., 2015) and CB (Wang et al., 2019a); (3) **Paraphrase Identification (PI)**, including SICK (Marelli et al., 2014); (4) **Sentiment Analysis (SA)**, including SST-2 (Wang et al., 2019b); (5) **Question Answering (QA)**, including CSQA (Talmor et al., 2019) and SocIQA (Sap et al., 2019); (6) **Table-to-Text Generation**, including E2E (Novikova et al., 2017) and DART (Nan et al., 2021); (7) **Dialogue Summarization**, including Samsum (Gliwa et al., 2019).

The cross-PLM-architecture validation requires approaches to be verified on both encoder-only (BERT (Devlin et al., 2019)) and decoder-only (GPT-2 (Radford et al., 2019)) Transformer architecture. The cross-PLM-scale validation requires approaches to be verified on PLMs of different scales. Specifically, the same experiments for NLU are conducted on both BERT$_{\text{base}}$ ² and BERT$_{\text{large}}$ ³, while GPT-2$_{\text{medium}}$ ⁴ is for NLG.

**Baseline Methods.** We compare our methods with six state-of-the-art tuning methods including full-tuning, scaled parallel adapter-tuning (Pfeiffer et al., 2021; He et al., 2021a), prefix-tuning (Liu et al., 2022), MAM adapter (He et al., 2021a), BitFit (Zaken et al., 2022) and 3V⁵ (Yang et al., 2022). For brevity, we agree to use adapter, prefix, MAM to represent scaled parallel adapter-tuning, prefix-tuning, and MAM Adapter respectively in all tables of this paper.

We align the tunable amount of additional parame-

² https://huggingface.co/bert-base-uncased
³ https://huggingface.co/bert-large-uncased
⁴ https://huggingface.co/gpt2-medium
⁵ Since it uses three trainable vectors to achieve parameter-efficient tuning and the orginal paper didn’t name their method, we name it 3V in our paper for clarit and brevity. Also, we carefully write the code of this method ourselves according to the details described in original paper because they haven’t release their code yet.
ters of different methods to ensure a fair comparison, which is accomplished by setting hyperparameters. Specifically, for prefix-tuning, the hyperparameter to be adjusted is its prefix length $l$, where we set $l = 16$ for BERT\textsubscript{base}, $l = 24$ for BERT\textsubscript{large}, and $l = 16$ for GPT-2\textsubscript{medium}. For adapter, we adjust the intermediate dimension $d_{b}$, where we set $d_{b} = 16$ for BERT\textsubscript{base}, $d_{b} = 24$ for BERT\textsubscript{large}, $d_{b} = 16$ for GPT-2\textsubscript{medium}. For MAM adapter, we adjust the both, keeping $d_{b} = l = 8$ for BERT\textsubscript{base}, $d_{b} = 16, l = 8$ for BERT\textsubscript{large}, and $d_{b} = 8, l = 8$ for GPT-2\textsubscript{medium}.

**Implementation Details.** We conduct experiments on two NVIDIA GeForce RTX 3090 GPUs. The results are evaluated by different measures as suggested by different tasks. To reduce the interference of randomness, we repeat the experiments for three times and the average scores (for NLU) or the rank (for NLG) is returned as results. According to the recorded experience (Houlsby et al., 2019; Pfeiffer et al., 2020; Li and Liang, 2021; He et al., 2021a), the common hyper-parameters are adjusted according to the statistical characteristics of datasets.

For NLU tasks, we set the training epoch 30, with an early stopping strategy of 10 non-decrease validation loss. The batch size setting can be found in Table 5 of Appendix B. For LN-tuning, we adjust the learning rate from the priority order in $\{1e^{-2}, 1e^{-3}, 2e^{-4}\}$ 6. We adjust the learning rate from the priority order in $\{1e^{-3}, 2e^{-4}\}$ for other methods.

For NLG tasks, we set the training epoch 20. The batch size setting can be found in Table 6 of Appendix B, and the learning rate is 2e-4 for all methods. The E2E dataset contains about 50K examples whose average output length is 22.9. We use the official evaluation script 8 to calculate BLEU, METEOR, and TER (Snover et al., 2005). We use GPT-2\textsubscript{medium} (Radford et al., 2019) as the experimental PLM, where the max generation length is set to $[35, 35, 45]$ for [E2E, Samsum, DART], respectively.

### 4.2 Main Results

In Table 1, we present the comparison results for the NLU tasks on BERT\textsubscript{large} and BERT\textsubscript{base}. It is clear from this that full-tuning and MAM adapter may typically achieve superior performance. Better performance is expected because more recently introduced parameters and multiple PLM modules need to be tuned. Compared to other earlier approaches, 3V and BitFit performs the poorest with less parameters. Under the tunable parameter alignment setting, the performance of prefix tuning and adapter tuning is comparable to one another.

The performance of LN-tuning is then examined. Comparing approaches whereas the ratio of the tunable parameters is more significant than 0.3%, LN-tuning is inferior to them by tuning only 0.03%–0.04% of parameters. By using almost half the tunable parameters of BitFit, LN-tuning performs much better than BitFit. LN-tuning outperforms 3V in terms of performance and is also applicable to a wider variety of NLP tasks than 3V, including QA tasks for NLU and NLG tasks.

With a few limited differences, the methods’ overall performance in NLG tasks is similar to that in NLU tasks. First, prefix-tuning outperforms MAM adapter. Second, our LN-tuning exhibits a performance closer to that of adapter-based approaches, such as adapter and MAM adapter, compared to the NLU task.

### 4.3 Efficiency Analysis

**Setup.** In order to compare the training and inference time efficiency between our method and earlier ones, we generate statistics from running logs. Then, in comparison to Full-Tuning (FT), we report the relative training and inference times. This includes the average time costs for three NLG datasets for GPT-2 and eight NLU datasets for BERT. The time cost of FT is normalized to 100.

**Result.** As shown in Fig. 2, our proposed LN-tuning takes the least time in all PLM architectures.

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6We empirically find that LN-tuning needs larger learning rate than other approaches in some datasets.

7https://github.com/tuetschek/e2e-metrics

8https://github.com/Yale-LILY/dart
for training process. LN-tuning, along with BitFit and FT, costs the similar least time for inference process as expected. The above results on both training and inference show the significant superiority of our method in time efficiency comparing previous adapter-based methods.

In Fig. 2(a), all parameter-efficient methods require training times that are less than 90% of those of FT in BERT\textsubscript{base} and less than 80% of those of FT in BERT\textsubscript{large}, demonstrating that parameter-efficient methods can train PLMs of greater scales more quickly. From Fig. 2(a), Fig. 2(b) and Fig. 2(c), we can observe that parameter-efficient methods show higher time efficiency in training in NLU tasks than in NLU tasks comparing with FT. However, whether in training or inference, MAM adapter typically has the lowest time efficiency, demonstrating that the unified methods of both tuning MHA and FFN require a significant investment in computational resources despite being able to produce better performance. Further, adapter-tuning shows higher time efficiency than prefix-tuning in training and inference, except for the NLG inference process.

### 4.4 Unified Framework

**Setup.** Since LN-tuning operates in LayerNorm, the question of whether it may be combined with earlier parameter-efficient methods working in MHA or/and FFN to operate as a unified framework and achieve further performance improvement arises naturally. In this section, we explore the unified framework combining LN-Tuning with five approaches, as illustrated in Sec. 3.2, which...
can be divided into four types according to tunable modules: (1) MHA only (2) FFN only (3) MHA and FFN simultaneously (4) BitFit. For the experiment, we employ the variable BERT_{large}.

**Result.** As shown in Table 3, among Prefix+LN and Sequential Adapter (MHA) + LN, which are unified methods of combining methods working in MHA with LN-tuning, perform significantly better than the original single ones. Notably, the Prefix+LN even outperformed MAM Adapter, which is naturally Prefix + Scaled Parallel Adapter (FFN), in terms of SOTA performance. However, the unified methods which combine adapter-based methods working in FFN with LN-tuning get a performance decrease. Empirically, this can be concluded that LN-tuning can combine with adapter-based methods working in MHA to improve further but will decrease performance if combined with those working in FFN. This explains why the performance of the LN + MAM Adapter is so comparable to that of the MAM Adapter, which is the result of performance enhancement brought on by prefix + LN and performance degradation brought on by scaled parallel adapter (FFN) + LN. This is so because the Prefix + Scaled Parallel Adapter (FFN) is
| Ablation Type | Method      | CN04 | Twitter | SICK | SNLI | SST2 | CB  | CSQA | SociQA | Avg  |
|---------------|-------------|------|---------|------|------|------|-----|------|--------|------|
| Term          | Full*       | 80.2 | 77.2    | 84.9 | 84.0 | 91.9 | 74.1| 60.5 | 63.2   | 77.0 |
|               | Only Gain   | 69.5 | 69.5    | 76.3 | 80.9 | 91.6 | 71.4| 53.3 | 57.9   | 71.3 |
|               | Only Bias   | 79.8 | 72.6    | 77.0 | 81.2 | 91.8 | 73.2| 55.8 | 60.9   | 74.0 |
|               | Only FFN    | 77.3 | 76.5    | 82.2 | 81.9 | 92.6 | 72.8| 55.6 | 61.0   | 75.0 |
|               | Only MHA    | 75.8 | 77.4    | 82.0 | 81.6 | 92.2 | 72.3| 56.2 | 58.8   | 74.6 |
| Layer         | Only Layer 1-12 | 73.2 | 75.1    | 82.4 | 78.4 | 91.8 | 73.1| 51.7 | 56.4   | 72.8 |
|               | Only Layer 13-24 | 73.8 | 75.7    | 82.4 | 78.6 | 93.2 | 72.9| 53.8 | 56.6   | 73.4 |

| BERT-Base     | Full*       | 79.8 | 76.4    | 81.0 | 83.3 | 91.4 | 70.2| 57.9 | 59.1   | 74.9 |
|               | Only Gain   | 72.9 | 68.8    | 67.5 | 76.7 | 87.7 | 73.2| 50.0 | 52.9   | 68.7 |
|               | Only Bias   | 76.5 | 67.8    | 77.5 | 76.3 | 89.7 | 71.4| 51.1 | 53.4   | 70.5 |
|               | Only FFN    | 79.1 | 76.6    | 81.5 | 77.0 | 91.6 | 76.2| 53.3 | 53.8   | 73.6 |
| Module        | Only MHA    | 78.4 | 76.5    | 81.8 | 77.2 | 91.2 | 75.0| 52.6 | 54.0   | 73.3 |
| Layer         | Only Layer 1-6 | 78.2 | 76.0    | 67.9 | 74.1 | 90.7 | 74.4| 50.8 | 50.6   | 70.3 |
|               | Only Layer 7-12 | 71.3 | 74.9    | 68.2 | 73.9 | 90.8 | 73.8| 50.3 | 50.3   | 69.2 |

Table 4: Results of ablation study about terms, layers and modules with BERT\textsubscript{large} and BERT\textsubscript{base}. *We use italic font to show results of the full LN-tuning, which is as a standard for comparison.

4.5 Ablation Study

Setup. To explore whether LN-tuning may be enhanced to be more parameter-efficient, we undertake an ablation study from three aspects: terms, modules, and layers. Specifically, for terms, we only keep one option of the gain or the bias term trainable. For layers, we keep vectors of LayerNorm of only the half layers close to input or output trainable, i.e. from layer 1 to 12 or from 13 to 24, if using BERT\textsubscript{large}. The same way is for using BERT\textsubscript{base}. For modules, since there are two LayerNorm modules in each block of Transformer, where one is after MHA and the other is after FFN, we keep vectors trainable of only one module in each Transformer block. We use both BERT\textsubscript{large} and BERT\textsubscript{base} for the experiment in this section.

Result. As shown in Table 4, comparing to full LN-tuning method, all ablated techniques obtain a performance drop, which validates no extraneous components for LN-tuning. Further, the influence of layers seems more critical than that of modules due to a larger performance decrease comparing ablated layer methods and ablated module methods. For term ablation type, the method with only the bias term performs better than that with only the gain term, whether in BERT\textsubscript{large} or BERT\textsubscript{base}, which indicates that the bias term plays a more critical role than the gain term in LN-tuning. The added MHA learnable module looks more relevant for module ablation type than the added FFN learnable module. For layer ablation type, the layers adjacent to input seems to be more important than that close to output in BERT\textsubscript{base}, however, the outcome is the opposite for BERT\textsubscript{large}. This shows that the importance of layers is quite different in different size of PLMs in LN-tuning and those layers close to output can play a more significant role in larger size of PLMs.

4.6 Visualization of Gain and Bias Term.

Setup. We visualize the change of the gain and bias term on each layer of PLMs to give a further understanding about LN-tuning. Specifically, following BitFit, we use $\frac{1}{\dim(t)} \| t_0 - t_f \|_1$ to measure the amount of change for terms, where $t$ represents the gain term $g$ or the bias term $b$ of LayerNorm, which means the average absolute change, across its dimensions, between the initial LM values $t_0$ and its fine-tuned values $t_f$. We choose five datasets which covers all type of NLU tasks in Sec. 4.1 and use BERT\textsubscript{large} for the experiment.

Result. As shown in Fig. 3, there can be obsered that the terms of layers close to the output, i.e. layer 15 to 24, changes more than those close to input, whether the gain or bias. Meanwhile, in those layers close to output, the gain term change more than bias term (This doesn’t mean that the gain term is more important than the bias term in essentially what the MAM Adapter is. Finally, the unified framework of BitFit + LN displays a performance boost, which highlights the advantages of our LN-tuning in high combination compatibility with earlier approaches to get better performance.
Figure 3: Change in gain and bias term on five type of NLU tasks. ‘Gain MHA’ means the gain term of LayerNorm module after MHA in each layer of PLMs, and so forth for other labels of Y-axis.

LN-tuning). Comparing results between tasks, the task complexity and the dataset scale may affect the extent of terms’ change. Firstly, comparing SST-2 and the other two datasets of binary classification tasks, there is a greater change in terms of LN-tuning. This may be because that there are larger solution spaces (greater task complexity) for the QA (CSQA) and NER (Twitter) task than binary classification tasks such as sentiment analysis (SST-2), Paraphrase Identification (SICK) or Natural Language Inference (CB) task. There needs greater variation in the terms of LN-tuning in CSQA and Twitter dataset. Secondly, the order of term variation in binary classification tasks is SST-2 > SICK > CB, which is the same as the order of their data scale: SST-2 (67,349 items) > SICK (4,439 items) > CB (250 items). A reasonable explanation for this different degree of variation is that larger data sizes require a more significant term variation to accommodate a variety of data samples from a wider range of domains.

5 Related Work

Parameter-Efficient Tuning for PLMs. Given the large-scale size of current PLMs, it is infeasible to train and store complete copies of large PLMs for each downstream task. Parameter-efficient tuning methods are proposed to deal with it by efficiently tuning PLMs with few trainable parameters. Existing approaches include Adapter (Houlsby et al., 2019; He et al., 2021b; Pfeiffer et al., 2021, 2020) which tunes FFN only, prompt tuning (Li and Liang, 2021; Liu et al., 2022) which tunes MHA only. Unified Frameworks(He et al., 2021a; Mao et al., 2022), which tunes both simultaneously, and other solutions like BitFit (Zaken et al., 2022) and Diff-pruning (Guo et al., 2021). Our LN-Tuning, which can achieve comparable performance with fewer parameters and high time efficiency, first establishes the significance of LayerNorm for parameter-efficient tuning of PLMs in comparison to these parameter-efficient studies. Additionally, SOTA performance is attained by the combined framework of prefix-tuning and LN-tuning, which takes lightweight tuning of PLMs to a higher level of parameter efficiency.

Feed-forward Network. Our work also has a connection to the Feed-forward Network (FFN). The scale and shift operation in LN-tuning is a unique, sped-up FFN that only conducts projection on a single neuron, as opposed to linear aggregation between input layer neurons. By training a very small number of sets of parameters, our approach can efficiently transfer PLMs to downstream tasks. Previous research overlooked this streamlined FFN. By putting it to use in parameter-efficient tuning for PLMs, we are the first to discover its potent transferability.

6 Conclusions

In this paper, we first propose LN-Tuning, which only tunes the bias and gain term of LayerNorm to enable parameter-efficient transferring for PLMs. Later, we investigate a unified framework for merging LN-tuning with earlier parameter-efficient techniques and discover that SOTA performance can be achieved by combining prefix-tuning with LN-tuning. We also draw the empirical conclusion that while tuning MHA and LayerNorm in a single framework will increase performance, doing the same for FFN and LayerNorm would result in worse performance. Finally, the ablation study of terms, layers, and modules, as well as the visualization experiment of the gain and bias term further understand LN-tuning.
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A Adapter-based Variants.

Fig. 4 displays the four different adapter-based variants shown in Sect. 3.2 and used in Sect. 4.4. The $W_{\text{down}}$ and $W_{\text{up}}$ matrices are tunable modules in each adapter.

B Batch Size Settings

The detailed batch size settings for NLU and NLG tasks are displayed in the Table 5 and able 6 respectively. In order to conduct a fair comparison, we make full use of the GPUs’ VRAM capacity and work to make sure the batch size parameters for each approach are identical. We decrease the value of batch size to prevent a ”CUDA Out of Memory” problem because full-tuning and MAM Adapter have more tunable parameters.

| Methods | CN04 | Twitter | SICK | SNLI | SST2 | CB | CSQA | SociQA |
|---------|------|---------|------|------|------|----|------|--------|
| FT      | 128  | 128     | 512  | 512  | 256  | 48 | 48   | 48     |
| MAM     | 128  | 128     | 512  | 512  | 392  | 64 | 64   | 48     |
| Others  | 128  | 128     | 512  | 512  | 392  | 64 | 64   | 64     |

Table 5: Batch size setting for NLU tasks.

| Method | Samsum | E2E | WebNLG |
|--------|--------|-----|--------|
| FT     | 32     | 48  | 40     |
| Others | 36     | 96  | 84     |

Table 6: Batch size setting for NLG tasks.

C Supplementary Experiment of Prefix+LN

On both NLU and NLG tasks, we contrast the prior method for achieving SOTA performance with Prefix+LN. On NLG tasks, the unified prefix+LN technique outperforms prefix-tuning on most measures with an increase of just 0.03% tunable parameters, as shown in Table 7. Prefix+LN outperforms MAM Adapter on NLU tasks in Table 8. This is true for both scales of BERT models with about just half tunable parameters, especially on BERT$\text{large}$, which demonstrates the promise of prefix+LN for parameter-efficient tuning of large scale PLMs.

D Future Work

While prefix-tuning and LN-tuning operate together to attain SOTA performance and LN-tuning has a high time efficiency with very few tunable parameters, there are still worthwhile areas for additional research. First, take note that the LN-tuning approach for tuning gain and bias term is a novel tuning technique that can be used after any PLM output vector. Exist any undiscovered techniques to perform SOTA by only learnable modules in LN-tuning? Further investigation can be done in future work to determine why the unified framework of integrating LN-tuning and Prefix-tuning (MHA+LN) can perform better than earlier adapter-based techniques (MHA+FFN).
Table 7: The performance comparison between Prefix-tuning and Prefix-tuning+LN-tuning on NLG tasks. Even thought prefix-tuning achieve the best performance on NLU tasks over methods shown in Table 1, our prefix-tuning+LN-tuning can obtain further performance improvement than prefix-tuning only.

| Method       | #Para. | E2E          | Samsum       | WebNLG       |
|--------------|--------|--------------|--------------|--------------|
|              |        | BLEU NIST MET R-L CIDEr | BLEU MET TER R-L | Mover BERT BLEURT |
| Prefix       | 0.13%  | 65.27 8.55 43.70 68.27 2.37 | 43.70 19.97 40.83 | 38.87 0.33 0.54 0.65 0.93 0.38 |
| Prefix+LN    | 0.16%  | 65.24 8.57 43.75 68.43 2.39 | 43.88 20.03 41.07 | 39.16 0.34 0.54 0.65 0.93 0.38 |

Table 8: The performance comparison between MAM Adapter and Prefix-tuning+LN-tuning on NLU tasks. Even thought MAM achieves the best performance on NLU tasks over methods shown in Table 2, our prefix-tuning+LN-tuning can still outperform it.

| Method       | #Para. | CN04 | Twitter | SICK | SNLI | SST-2 | CB | CSQA | SocIQA | Avg. |
|--------------|--------|------|---------|------|------|-------|----|------|--------|------|
|              |        |      |         |      |      |       |    |      |        |      |
| BERT-Large   |        |      |         |      |      |       |    |      |        |      |
| MAM          | 0.66%  | 83.0 | **78.1** | 86.6 | 85.2 | 93.1  | 77.6| 63.2 | 65.5   | 79.0 |
| Prefix+LN    | 0.36%  | **84.2** | 77.2    | **86.6** | **85.4** | **93.8** | **81.2** | **64.0** | **65.5** | **79.8** |
| BERT-Base    |        |      |         |      |      |       |    |      |        |      |
| MAM          | 0.56%  | 80.3 | **76.3** | **84.8** | 84.5 | 91.6  | 73.8| 60.4 | 61.8   | 76.7 |
| Prefix+LN    | 0.32%  | **80.7** | **76.1** | **84.5** | **84.6** | **91.9** | **74.1** | **60.6** | **61.7** | **76.8** |