

# LORA-FA: MEMORY-EFFICIENT LOW-RANK ADAPTATION FOR LARGE LANGUAGE MODELS FINE-TUNING

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## ABSTRACT

The low-rank adaptation (LoRA) method can largely reduce the amount of trainable parameters for fine-tuning large language models (LLMs), however, it still requires expensive activation memory to update low-rank weights. Reducing the number of LoRA layers or using activation recomputation could harm the fine-tuning performance or increase the computational overhead. In this work, we present LoRA-FA, a memory-efficient fine-tuning method that reduces the activation memory without performance degradation and expensive recomputation. LoRA-FA chooses to freeze the projection-down weight of  $A$  and update the projection-up weight of  $B$  in each LoRA layer. It ensures the change of model weight reside in a low-rank space during LLMs fine-tuning, while eliminating the requirement to store full-rank input activations. We conduct extensive experiments across multiple model types (RoBERTa, T5, LLaMA) and model scales. Our results show that LoRA-FA can always achieve close fine-tuning accuracy across different tasks compared to full parameter fine-tuning and LoRA. Furthermore, LoRA-FA can reduce the overall memory cost by up to  $1.4\times$  compared to LoRA.

## 1 INTRODUCTION

Large language models (LLMs) have become a cornerstone of natural language processing (Brown et al., 2020; Touvron et al., 2023a; OpenAI, 2023; Anil et al., 2023), and fine-tuning pre-trained LLMs has been shown very effective to improve their performance in various downstream tasks (Liu et al., 2019; Wei et al., 2021) and to enable them to align with human intents (Ouyang et al., 2022; Bai et al., 2022). However, fine-tuning LLMs with full parameter is prohibitively expensive, for example, fine-tuning a LLaMA-65B (Touvron et al., 2023a) model with AdamW (Loshchilov & Hutter, 2017) requires more than 1TB of GPU memory to store model parameter, gradient, and optimizer states (Rajbhandari et al., 2020).

To reduce the memory of full-parameter fine-tuning, parameter-efficient fine-tuning (PEFT) methods are proposed to update only a small fraction of parameters, such as adapter weights (Houlsby et al., 2019; Hu et al., 2022) and prompt weights (Li & Liang, 2021; Lester et al., 2021). Among these methods, LoRA (Hu et al., 2022) has shown to achieve comparable performance than full-parameter fine-tuning, and it has been widely used in many applications (Dettmers et al., 2023).

Specifically, LoRA adds a parallel low-rank adapter besides the weight of a linear layer, as shown in Figure 1(b), where  $W$  is the pre-trained weight,  $A$  and  $B$  are low-rank weights. Because LoRA freezes  $W$  and only updates smaller matrices  $A$  and  $B$ , its memory overhead for trainable parameter and corresponding gradient and optimizer states can be largely reduced, compared to full-parameter fine-tuning as shown in Figure 1(a), which can be regarded as updating  $W$  and freezing  $A$  and  $B$ . Furthermore, LoRA introduces no additional inference latency by merging the value of  $AB$  into  $W$ .

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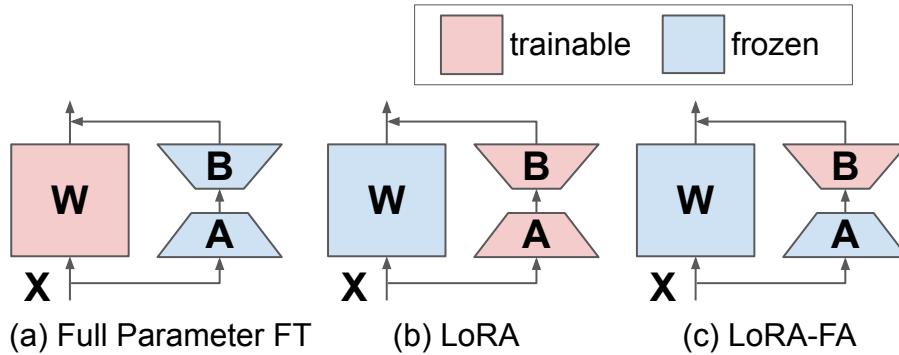


Figure 1: The illustration of (a) full-parameter fine-tuning (FT), (b) LoRA, and (c) LoRA-FA.

However, LoRA still has limitations as it requires expensive activation memory consumption in LoRA layers. This is because the large input activation of  $X$  needs to be stored during the feed-forward pass, and used to construct the gradient of  $A$  during the back-propagation pass. It means LoRA cannot reduce the activation memory cost compared to full-parameter fine-tuning. For example, fine-tuning a LLaMA-65B with input sequence length of 2048 and batch size of 4 requires more than 50GB of activation memory (in 16-bit format) in all LoRA layers. To address it, existing methods select a part of linear layers for LoRA fine-tuning (Hu et al., 2022) or use activation re-computation (Chen et al., 2016), which however could affect fine-tuning performance or efficiency.

In this work, we propose LoRA with Frozen-A (LoRA-FA), which can largely reduce the activation memory footprint of LoRA without adding any computational overhead. Specifically, LoRA-FA chooses to freeze both pretrained weight of  $W$  and projection-down weight of  $A$ , and only update projection-up weight of  $B$ , as shown in Figure 1(c). By doing so, we only need to compute the gradient of  $B$ , which requires storing a much smaller input of  $AX$  during the feed-forward pass. Assume that  $W \in \mathbb{R}^{d \times d}$ ,  $A \in \mathbb{R}^{d \times r}$ , and  $B \in \mathbb{R}^{r \times d}$ , the projection-down weight of  $A$  has mapped a  $d$ -dimensional input of  $X$  into an  $r$ -dimensional input of  $XA$ . As we have  $r \ll d$ , the activation memory requirement for LoRA-FA can be significantly reduced. For example, LoRA-FA (with a rank size of  $r = 4$ ) can reduce the activation memory in a linear layer of LLaMA-65B (with a hidden dimension of  $d = 8192$ ) by 2048 times compared to full-parameter fine-tuning. At the same time, LoRA-FA reduces the amount of trainable parameters from  $d^2$  to  $dr$  by 2048 times.

We initialize  $A$  randomly from a normal distribution (which is typically a rank- $r$  matrix) and initialize  $B$  as zero. It ensures that the pretrained models with LoRA-FA modules will not change the model prediction before we start fine-tuning. During the model adaptation, LoRA-FA will fix  $A$  and update  $B$  to improve the model performance, and it implies that the change of model weight i.e.  $\Delta W = AB$  is residing in a low-rank space, defined by the column space of the initialized  $A$ . Empirically, our experimental results show that LoRA-FA is sufficient to fine-tune LLMs. In addition, LoRA-FA does not change feed-forward and back-propagation computations of LoRA (except skipping the gradient calculation of  $A$ ), thus, it will not increase the computational overhead during the fine-tuning phase. During the inference, similar to LoRA, it can merge low-rank weights by adding  $AB$  into  $W$ , introducing no extra inference latency compared to a fully fine-tuned model.

We conduct extensive experiments across many model types and scales. We finetune RoBERTa (Liu et al., 2019) on natural language understanding tasks, T5 (Raffel et al., 2020) on machine translation tasks, and LLaMA (Touvron et al., 2023a) on MMLU (Hendrycks et al., 2021) benchmarks. We find that our LoRA-FA can achieve very close model accuracy across many tasks compared to full-parameter fine-tuning (FT) and LoRA. In terms of memory overhead, our LoRA-FA can reduce the overall memory cost by up to  $2\times$  and  $1.4\times$ , compared to full-parameter fine-tuning and LoRA, respectively. For example, LoRA-FA reduced the memory footprint from 56GB to 27.5GB for fine-tuning a LLaMA-7B model. It means we can use a lower resource budget (e.g., cheaper GPU services with smaller memory size) to achieve the same fine-tuning performance. Besides, we study the effects of hyper-parameters, and our results show that LoRA-FA is robust to hyper-parameters.

In summary, LoRA-FA has several key advantages: 1) it is memory-efficient by reducing the amount of trainable parameters and activations, 2) it does not increase the computational overhead during the fine-tuning stage, and the latency overhead during the inference stage, and 3) it achieves similar model performance across many models and tasks compared to full-parameter fine-tuning.

## 2 BACKGROUND

### 2.1 LARGE LANGUAGE MODELS

We focus on transformer-based large language models (LLMs). The transformer model was first proposed in (Vaswani et al., 2017) for machine translation task. Later, different transformer models have been used in language modelling (i.e., pre-training), and the pre-trained models are adapted to many downstream tasks (Kenton & Toutanova, 2019; Raffel et al., 2020; Brown et al., 2020).

Take decoder-only GPT (Brown et al., 2020) model as an example, it consists of  $L$  stacked transformer blocks, and each block has two sub-modules: multi-head attention (MHA) and feed-forward network (FFN). In MHA, three linear layers transform the input into query, key, and value, they are fed into the self-attention for interaction, and the attention output is sent to another linear layer. In FFN, we have two linear layers and a GeLU activation function between them. For MHA and FFN, layernorm and residual connection are applied to improve model performance. In LLMs, the weights in these linear layers generally account for the majority of the model parameters and are responsible for most of the compute flops.

### 2.2 LOW-RANK ADAPTATION

As fine-tuning LLMs with full parameter is very expensive, parameter-efficient fine-tuning methods particularly LoRA (Hu et al., 2022) are proposed to update only a small fraction of model parameters to alleviate the memory overhead, while achieving comparable performance of fine-tuning LLMs. Specifically, LoRA adds a low-rank adaptor besides the weight of a linear layer as follows:

$$Y = XW + \alpha XAB, \quad (1)$$

where  $W \in \mathbb{R}^{d_{in} \times d_{out}}$  is the pre-trained weight,  $d_{in}$  is the input dimension, and  $d_{out}$  is the output dimension. We omit the bias term as it does not affect our analysis.  $X \in \mathbb{R}^{b \times s \times d_{in}}$  and  $Y \in \mathbb{R}^{b \times s \times d_{out}}$  are input and output tensors, respectively,  $b$  is the batch size and  $s$  is the sequence length. For the LoRA part,  $A \in \mathbb{R}^{d_{in} \times r}$  is the projection-down weight, and  $B \in \mathbb{R}^{r \times d_{out}}$  is the projection-up weight,  $r$  is the rank size, and  $\alpha > 0$  is a hyper-parameter (which is typically set as  $1/r$ ).

For a transformer model, such as GPT (Brown et al., 2020), we typically have  $d_{in} = d_{out} = d$  for four linear layers in MHA, and  $d_{in} = d, d_{out} = 4d$  (or  $d_{in} = 4d, d_{out} = d$ ) for the first (or second) linear layer in FFN<sup>1</sup>, where  $d$  is the hidden dimension. By default, we add LoRA modules into all linear layers in transformer blocks to enhance the fine-tuning performance (Zhang et al., 2023b).

**Memory complexity.** For full-parameter fine-tuning, we need to update the weight of  $W$  in a linear layer, which has  $d_{in} \times d_{out}$  elements, and the total number of weight parameters for a GPT-type model is given by  $n = 12d^2L$ <sup>2</sup>. For LoRA, we only update two low-rank matrices, having  $(d_{in} + d_{out})r$  elements, and the total number of LoRA parameters for a GPT is  $n_r = 18drL$ . Thus, LoRA can largely reduce the number of trainable parameters if rank size  $r$  is much smaller than  $d$ .

Now consider the 16-bit mixed-precision training setting, full-parameter fine-tuning takes  $2n$  bytes for the model weight, and  $14n$  bytes for the gradient and optimizer states (32-bit AdamW's states and parameter copy) (Rajbhandari et al., 2020), while LoRA takes  $2n$  bytes for the model weight, and  $16n_r$  bytes for adaptor related weight, gradient, and optimizer states. It means that LoRA can reduce this part of memory overhead by about 8 times if we have  $n_r \ll n$  (or  $r \ll d$ ).

However, the situation is quite different when comparing the activation memory overhead. The full-parameter fine-tuning needs to store the input of  $X$  to compute the gradient of  $W$ , while LoRA needs to store the input of  $X$  to compute the gradient of  $A$ , as well as the low-rank input of  $XA$  to compute the gradient of  $B$ . Specifically, LoRA and full-parameter fine-tuning take  $14bsdL + 8bsrL$  bytes and

<sup>1</sup>The expand dimension is  $8d/3$  for LLaMA models by using SwiGLU function (Touvron et al., 2023a).

<sup>2</sup>The total number of full parameters shall be larger as we do not include embeddings, biases, and so on.

$14bsdL$  bytes of activations (in 16-bit), respectively. Besides, both of them will consume activation memory in other components such as attention, GeLU, and layernorm (Korthikanti et al., 2023). Therefore, LoRA is not able to reduce (and even increase) the activation memory cost compared to full-parameter fine-tuning, which unfortunately becomes a new memory bottleneck.

**Challenges of reducing activation memory.** There are two ways to reduce the activation memory cost of LoRA. First, we can add LoRA modules to a small number of linear layers, such as query and value projections in a Transformer model (Hu et al., 2022), therefore, other frozen linear layers without LoRA do not need to store their input activations. However, this method could affect the fine-tuning task performance (Dettmers et al., 2023), and it also introduces the difficulty of selecting which layers to fine-tune with LoRA (Zhang et al., 2023b). Second, activation recomputation (Chen et al., 2016; Korthikanti et al., 2023) has been proposed to checkpoint the only the input of each transformer block during the feed-forward pass, and recompute other necessary activations starting from this checkpoint during the back-propagation pass. However, activation recomputation has very expensive recomputation cost, which introduces around 1/3 of total computing flops.

### 3 LORA-FA METHOD

First of all, we present the design of LoRA-FA method, interpret it from a low-rank model adaptation perspective, and analyze its benefit in reducing the memory overhead. Second, we show that LoRA-FA can be integrated into other memory optimization techniques to enhance its utilization. Third, we discuss the relation between LoRA-FA and gradient compression.

#### 3.1 LORA WITH FROZEN-A

The LoRA method updates two low-rank matrices  $A$  and  $B$ , and uses  $AB$  as the change of a pre-trained and frozen weight  $W$  of a linear layer, i.e.,  $W + \alpha\Delta W = W + \alpha AB$ . As we discussed before, LoRA does not update  $W$  directly and it can largely reduce the amount of trainable parameters, but it still requires very expensive activation memory.

To address it, we propose LoRA with Frozen-A (LoRA-FA), which freezes both  $W$  and  $A$ , and updates  $B$  only during the fine-tuning process. Specifically, we initialize  $A$  randomly from a normal distribution, which generally gives a rank- $r$  matrix, and we initialize  $B$  as zero, so  $\Delta W = AB$  remains zero and the model prediction is not affected before we start fine-tuning.

**Low-rank model adaptation.** During the fine-tuning process, as shown in Figure 1(c), we freeze the initialized  $A$  and the pre-trained  $W$ , and update the projection-up weight  $B$ . Thus, the change of weight during model adaptation will be constrained in a low-rank space as follows:

$$\Delta W = AB = Q\bar{B} = \sum_{i=1}^r Q_{:,i}\bar{B}_{i,:}, \quad (2)$$

where  $A = QR$  is the QR decomposition of  $A$ , and the  $r$  columns of  $Q$ , i.e.,  $Q_{:,i}$  for  $i = 1, \dots, r$ , are orthogonal unit vectors, when  $A$  is a rank- $r$  matrix. We denote  $\bar{B} = RB$ , and derive that  $\Delta W_{:,j} = \sum_{i=1}^r \bar{B}_{ij}Q_{:,i}$ , so any column of  $\Delta W$  is a combination of  $k$  orthogonal vectors. In other words, the change of weight resides in a low-rank space, defined by the column space of  $A$ .

**Memory complexity.** We study the memory complexity of LoRA-FA in details. For a LoRA-FA module, it only computes the gradient of  $B$ , which has  $d_{out} \times r$  elements. In a GPT-type model, the total trainable parameters is  $n_r/2 = 9drL$ , i.e., half the amount of trainable parameters in LoRA. Thus, the memory cost for model weight and adaptor related states is  $2n + 8n_r$  bytes in 16-bit mixed-precision training. More importantly, in terms of activation memory, LoRA-FA only store the low-rank input of  $X A$  to calculate the gradient of  $B$ , which takes  $8bsrL$  bytes of activations (in 16-bit) for all LoRA-FA modules. Compared to full-parameter fine-tuning, LoRA-FA is memory-efficient by significantly reducing the amount of trainable parameters and input activations.

#### 3.2 COMBINATION WITH MEMORY OPTIMIZATIONS

LoRA-FA can be naturally combined with advanced memory optimization approaches, such as weight quantization (Dettmers et al., 2023), weight sharding (Rajbhandari et al., 2020), and selective activation recomputation (Korthikanti et al., 2023).

**Weight quantization.** As discussed before, the memory cost for model weight in 16-bit format is  $2n$ , where  $n$  is the number of model parameters. For example, the model weight memory cost is 130GB for a LLaMA-65B model, which cannot be held in one NVIDIA A100 (80GB) GPU. In LoRA-FA, as the model weights are frozen during fine-tuning, we can quantize them into lower bit width to reduce the model weight memory overhead without affecting the fine-tuning performance. For example, 8-bit (Dettmers et al., 2022a) and 4-bit quantization methods (Dettmers et al., 2023) can be combined with LoRA-FA to reduce the model weight memory by 2 and even 4 times.

**Weight sharding.** When training a LLM on multiple GPUs with data parallelism, weight sharding or ZeRO stage-3 (Rajbhandari et al., 2020) technique can be combined with LoRA-FA to shard the model weight into different GPUs, so that the per-GPU memory cost is reduced by the number of GPUs. Different from using ZeRO stage-3 in full-parameter fine-tuning, we only shard the model weights and all-gather them to support the feed-forward and back-propagation computations, without sharding the adaptor related weights and their gradients and optimizer states. However, weight sharding has introduced expensive weight gathering communication cost in LoRA-FA, while data parallelism only communicates a small amount gradients for trainable parameters.

**Selective activation recomputation.** The activation memory overhead exists in other components of a transformer model, such as attention, layernorm, GeLU, and dropout (Korthikanti et al., 2023). To address it, we can use full activation recomputation to store the input of each transformer block. However, it will disable the memory advantage of LoRA-FA over LoRA, as there is no need to store the inputs of LoRA layers with full activation recomputation. To balance the activation cost and recomputation cost, we instead use selective activation recomputation to recompute only a fraction of model components. For example, FlashAttention (Dao et al., 2022) can eliminate the memory cost of attention softmax outputs and accelerate the attention computations with less HBM accesses. Besides, we can recompute the dropout by storing the random generator state to get the exact mask.

### 3.3 RELATION TO GRADIENT COMPRESSION

We discuss the relation between LoRA-FA and low-rank gradient compression (Vogels et al., 2019; Zhang et al., 2023a). Given a LoRA-FA layer (we omit  $\alpha$  for simplicity), i.e.,  $Y = XW + XAB$ , the gradient of  $B$  is computed by

$$dB = A^T X^T dY = A^T dW. \quad (3)$$

The change of  $B$  with one update step of vanilla SGD is  $\Delta B = -\eta dB$ , where  $\eta$  is the learning rate, so the change of  $W$  with frozen  $A$  is  $\Delta W = A\Delta B = -\eta A A^T dW$ , and  $dW$  is the gradient of  $W$ .

This implies that LoRA-FA is equivalent to a low-rank gradient compression method for full-parameter fine-tuning, in which the calculated weight gradient is compressed by  $A^T dW$  (to reduce the gradient communication overhead in the context of gradient compression), and then it is uncompressed by  $A(A^T dW)$ . Because  $A$  is initialized from a normal distribution, we have  $\mathbb{E}[AA^T dW] = \mathbb{E}[AA^T]dW = rdW$ , which (almost) gives an unbiased gradient compression.

However, the gradient compression has no advantages over LoRA-FA for fine-tuning LLMs, because it still updates the full parameter with large memory overhead, while LoRA-FA with a small amount of trainable weights can also enjoy the reduced gradient communication in a data parallelism setting. Besides, these two methods become different when applying adaptive methods such as AdamW.

## 4 EXPERIMENTS

### 4.1 FINE-TUNING PERFORMANCE

We evaluate the fine-tuning performance of three approaches: full-parameter fine-tuning (FT), LoRA (Hu et al., 2022) and LoRA-FA on different model types and model scales. Our experiments cover a wide range of tasks, from natural language understanding (NLU) to machine translation (MT) and natural language generation (NLG). Specifically, we evaluate on the GLUE (Wang et al., 2019) benchmark for RoBERTa-base and RoBERTa-large models (Liu et al., 2019), the WMT16 En-Ro translation for T5-small, T5-base, and T5-large models (Raffel et al., 2020), and the MMLU (Hendrycks et al., 2021) for LLaMA models (Touvron et al., 2023a). We follow the setups of prior

works (Hu et al., 2022; Dettmers et al., 2023), and we conduct hyper-parameters tuning for each experiment, including the learning rate of  $\eta$  in  $\{5 \times 10^{-5}, 6 \times 10^{-5}, \dots, 1 \times 10^{-4}, 2 \times 10^{-4}, \dots, 5 \times 10^{-3}\}$ , and the LoRA rank of  $r$  in  $\{1, 2, 4, 8, 16, 32, 64, 128\}$ . We report the best performance for a fair comparison, and the impact of hyper-parameters has been studied in Section 4.3. Due to the limited budget, we conduct our experiments on different devices: we use NVIDIA Turing RTX2080Ti for small-sized RoBERTa models, NVIDIA Ada RTX4090 for medium-sized T5 models, and NVIDIA Ampere A100 for large-sized LLaMA models.

#### 4.1.1 ROBERTA BASE/LARGE

The RoBERTa (Liu et al., 2019) is an encoder-only model built on BERT (Devlin et al., 2019) and it uses a different fine-tuning scheme, together with the removing of next-sentence training objective. It performs quite well on NLU tasks with a rather small model scale compared to LLMs. We hence take the pre-trained RoBERTa-base with 125 millions of parameters and RoBERTa-large with 355 millions of parameters to evaluate the fine-tuning performance on GLUE. We mainly replicate the result of Transformers (Wolf et al., 2020) and (Dettmers et al., 2023) according to their setup. Before conducting all the experiments, we first carry out a hyper-parameter search on a signal MRPC task to get optimal hyper-parameter settings, which are used in other experiments. We use the batch size of 64 for fine-tuning RoBERTa-base, and the batch size of 32 for fine-tuning RoBERTa-large. We use the sequence length of 128 for fine-tuning both models. The result is presented in Table 1.

Table 1: Fine-tuning RoBERTa-base (RoB-B) and RoBERTa-large (RoB-L) models on the GLUE benchmark. We report the Matthews correlation for COLA, Pearson correlation for STS-B, averaged matched and mismatched accuracy for MNLI, and accuracy for other tasks. Higher is better for all metrics. We also report the number of trainable parameters (# TPs) for each method.

Model & Method	# TPs	MRPC	COLA	QNLI	RTE	SST-2	STS-B	MNLI	QQP	Avg.
RoB-B (FT)	118.9M	<b>90.1</b>	60	<b>92.5</b>	67.1	<b>94.8</b>	89.4	<b>87.4</b>	<b>90.5</b>	84.0
RoB-B (LoRA)	2.4M	89.5	<b>63.6</b>	90.5	67.5	94	<b>90.1</b>	86.8	89.8	<b>84.5</b>
RoB-B (LoRA-FA)	1.8M	90	<b>63.6</b>	<b>92.5</b>	<b>67.9</b>	<b>94.8</b>	89.6	86.8	90.1	84.4
RoB-L (FT)	338.9M	90.1	67.8	94.2	86	96.1	<b>92</b>	<b>90.2</b>	<b>91.1</b>	88.4
RoB-L (LoRA)	5.4M	<b>90.2</b>	<b>68</b>	<b>94.4</b>	<b>86.3</b>	<b>96.2</b>	91.9	90	<b>91.1</b>	<b>88.5</b>
RoB-L (LoRA-FA)	3.7M	90	<b>68</b>	<b>94.4</b>	86.1	96	<b>92</b>	90.1	<b>91.1</b>	<b>88.5</b>

The Table 1 shows that both LoRA and LoRA-FA have a smaller trainable parameter group compared to full-parameter fine-tuning, with LoRA-FA further reducing the scale. For example, LoRA-FA takes only 1.5% of full parameters in fine-tuning RoBERTa-base, while LoRA takes 2%. With such a small scale of parameter group, LoRA-FA can still achieve close (and even better) results of full-parameter fine-tuning. Specifically, LoRA-FA leads the best on COLA, QNLI, RTE, SST-2 when fine-tuning RoBERTa-base, and on COLA, RTE, QQP when fine-tuning RoBERTa-large. LoRA-FA gets a average accuracy of 84.4% in fine-tuning RoBERTa-base, and 88.5% in fine-tuning RoBERTa-large, which proves that LoRA-FA is capable of fine-tuning RoBERTa on multile tasks.

#### 4.1.2 T5 SMALL/BASE/LARGE

T5 (Raffel et al., 2020) is an encoder-decoder model pre-trained on a multi-task mixture of unsupervised and supervised tasks. T5 works well on various of tasks by prepending a prefix to the input corresponding to each task, e.g., for translation tasks: *translate English to Romanian*. T5 comes in 5 sizes: T5-small (60M), T5-base (220M), T5-large (770M), T5-3B, T5-11B. We use the size of small, base, and large of T5 models to evaluate the performance of full-parameter fine-tuning, LoRA and LoRA-FA on WMT16 En-Ro translation tasks. The evaluation metric includes BLEU and RougeL. We use the batch size of 64 for fine-tuning T5-small, 32 for fine-tuning T5-base, and 16 for fine-tuning T5-large. The result is presented in Table 2.

As indicated in Table 2, when compared to full-parameter fine-tuning, LoRA-FA exhibits a reduced trainable parameter size. This reduction is quantified as 0.35% for T5-small, 0.28% for T5-base, and

Table 2: Fine-tuning T5-small, T5-base, and T5-large models with three approaches on the WMT16 En-Ro dataset. We report BLEU and ROUGE-L scores. Higher is better for all metrics.

Model & Method	# Trainable Parameters	BLEU	ROUGE-L
T5-small (FT)	57.7M	<b>28.7</b>	<b>40.1</b>
T5-small (LoRA)	0.4M	27	39.6
T5-small (LoRA-FA)	0.2M	27	39.7
T5-base (FT)	212.6M	33.4	42.6
T5-base (LoRA)	1.3M	32.8	<b>43.2</b>
T5-base (LoRA-FA)	0.6M	<b>33.5</b>	42.8
T5-large (FT)	703.5M	36.9	49
T5-large (LoRA)	4.5M	<b>37</b>	<b>49.1</b>
T5-large (LoRA-FA)	2.25M	<b>37</b>	49

0.32% for T5-large, respectively. Surprisingly, we find that LoRA-FA leads the board when fine-tuning T5-base and T5-large. It shows that LoRA-FA is suitable for fine-tuning relatively large T5 models such as T5-base and T5-large. Besides, LoRA-FA can achieve the same performance in fine-tuning a small model such as T5-small compared to LoRA, but both of them perform slightly worse than full-parameter fine-tuning. This may be because LoRA and LoRA-FA’s small parameter group could not handle the fine-tuning dataset when applied to a small size base model, e.g., T5-small who has only 57.7M parameters. There is more of interest to apply LoRA-FA into large models.

#### 4.1.3 LLAMA

The fine-tuning result on RoBERTa and T5 illustrate that LoRA-FA can be a competitive alternative to full-parameter fine-tuning and LoRA on NLU and MT tasks. We further evaluate if LoRA-FA still prevails on larger decoder-based NLG models, such as LLaMA-7B. The LLaMA (Touvron et al., 2023a) models are open-source large language models developed by Meta AI. They come in sizes ranging from 7B to 65B parameters and were trained on between 1T and 1.4T tokens, establishing the basis of language understanding and generation abilities. To make them follow instructions, we fine-tune a LLaMA-7B model on Alpaca (Taori et al., 2023) and FLAN v2 (Wei et al., 2021) instruction datasets. Due to the massive scale of FLAN v2, we randomly sample a split that contains 50k training data according to (Dettmers et al., 2023). This split keeps a similar size with Alpaca (52k training samples). Following prior works (Touvron et al., 2023a; Dettmers et al., 2023), we evaluate the average 5-shot performance of fine-tuned LLaMA models on MMLU benchmarks (Hendrycks et al., 2021), which cover 57 tasks including elementary mathematics, US history, computer science, law, etc. We use the batch size of 32 for fine-tuning LLaMA-7B. The result is presented in Table 3.

Table 3: Average 5-shot MMLU accuracy comparison for LLaMA-7B models fine-tuned with three approaches on two different datasets: Alpaca and FLAN v2. Higher is better for accuracy metric. We report the absolute performance improvements over the base LLaMA-7B model in parentheses.

Model & Method	# Trainable Parameters	5-shot MMLU Accuracy
LLaMA-7b-Alpaca (FT)	6426.3M	<b>37.6 (+2.5)</b>
LLaMA-7b-Alpaca (LoRA)	152.5M	37.2 (+2.1)
LLaMA-7b-Alpaca (LoRA-FA)	83M	37.4 (+2.3)
LLaMA-7b-FLANv2 (FT)	6426.3M	<b>45.2 (+10.1)</b>
LLaMA-7b-FLANv2 (LoRA)	152.5M	43.9 (+8.8)
LLaMA-7b-FLANv2 (LoRA-FA)	83M	44 (+8.9)

The Table 3 shows that the parameter group of LoRA-FA takes only 1.3% of full-parameter fine-tuning. Full-parameter fine-tuning leads the board for both Alpaca and FLAN v2, due to its strength of the largest parameter group. Meanwhile, LoRA-FA achieves the competitive performance using only 83 millions of trainable parameters, and it performs better than LoRA in our evaluations. This shows that LoRA-FA is capable of fine-tuning LLaMA with much less trainable parameters, and can target similar and even better performance than LoRA. Furthermore, the absolute performance improvements (e.g., 10.1% with FLAN v2) over base model validate the importance of instruction tuning, and FLAN v2 is more useful than Alpaca to improve the problem solving power of LLMs.

#### 4.1.4 CONVERGENCE PERFORMANCE

Due to the less trainable parameters LoRA-FA uses than full-parameter fine-tuning and LoRA, we provide an analysis on convergence performance to see whether it has an impact on convergence speed. We report the convergence results of fine-tuning RoBERTa-base on COLA and SST2 datasets as two examples in Figure 2, and the results on other tasks are very similar. The experiments are conducted on 4x A100 40GB, we use a per-device batch size of 320, and sequence length of 128.

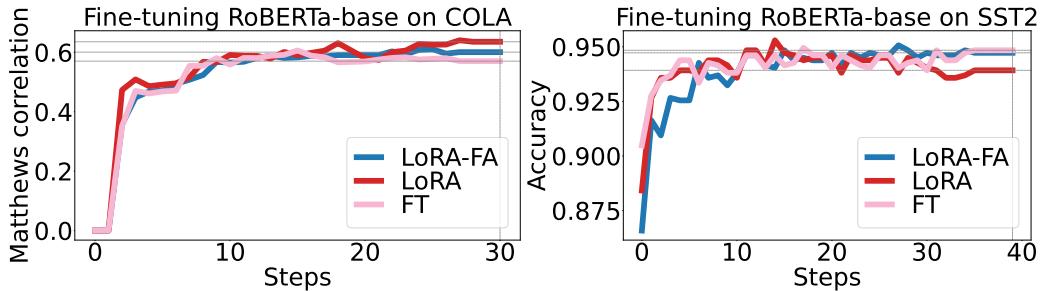


Figure 2: Convergence comparison among full-parameter fine-tuning (FT), LoRA, and LoRA-FA for the RoBERTa-base model on COLA and SST-2 datasets.

Fine-tuning with LoRA-FA does not show any downgrade to convergence speed under suitable hyper-parameter settings according to Figure 2. At the earlier stage (e.g., < 10 steps) of fine-tuning, LoRA and LoRA-FA could converge slower than full-parameter fine-tuning, but they can all reach the target after several short steps. Overall, our result shows that LoRA-FA has a similar convergence performance compared to full-parameter fine-tuning and LoRA.

#### 4.2 MEMORY EFFICIENCY

LoRA-FA can save a considerable amount of GPU memory usage by reducing the number of trainable parameters and the activation memory compared to full-parameter fine-tuning. We hence give an analysis on the GPU memory cost of 3 approaches (full-parameter fine-tuning, LoRA, LoRA-FA) in fine-tuning RoBERTa-base/large, T5-small/base/large, LLaMA-7B models. For hyper-parameter settings, we use the batch size of 128 for fine-tuning T5-small, 64 for RoBERTa-base, RoBERTa-large and T5-base, 32 for T5-large and 1 for LLaMA-7B. For LoRA and LoRA-FA, we compare the memory usage under the rank size with the best accuracy performance. The experiment is run on a single A100 GPU (40GB). The result is present in Table 4.

The Table 4 shows that LoRA-FA can significantly reduce the GPU memory usage during fine-tuning. Compared to LoRA, LoRA-FA has an average of 3GB memory saving in fine-tuning RoBERTa-base, 4 to 7GB memory saving in fine-tuning T5-base, T5-large, RoBERTa-large, and 2GB memory saving in fine-tuning LLaMA-7B, while full-parameter fine-tuning has caused out of memory in fine-tuning LLaMA-7B. These results have validated our analysis in Section 2.2, that activation memory overhead can be largely reduced when applying LoRA-FA to LLMs. We will study the combination of LoRA-FA with other memory optimizations in our future version.

We further give an analysis of the relationship between the GPU memory footprint and the rank of LoRA and LoRA-FA in fine-tuning RoBERTa-large and LLaMA-7B models. We use the batch size of 64 and sequence length of 128 for RoBERTa-large, batch size of 32 and max source/target length

Table 4: The peak GPU memory (Mem) usage in GB of three fine-tuning approaches for fine-tuning RoBERTa, T5 and LLaMA models.

Model & Method	Rank	Mem	Model & Method	Rank	Mem
RoBERTa-base (FT)	-	9.6	RoBERTa-large (FT)	-	23.1
RoBERTa-base (LoRA)	8	9.2	RoBERTa-large (LoRA)	8	22.5
RoBERTa-base (LoRA-FA)	8	6.9	RoBERTa-large (LoRA-FA)	8	15.7
T5-small (FT)	-	30.7	T5-base (FT)	-	35.7
T5-small (LoRA)	8	29.4	T5-base (LoRA)	8	32.1
T5-small (LoRA-FA)	8	25.5	T5-base (LoRA-FA)	8	25.3
T5-large (FT)	-	40.4	LLaMA-7B (FT)	-	OOM
T5-large (LoRA)	16	34.3	LLaMA-7B (LoRA)	64	29.4
T5-large (LoRA-FA)	16	27.6	LLaMA-7B (LoRA-FA)	64	27.5

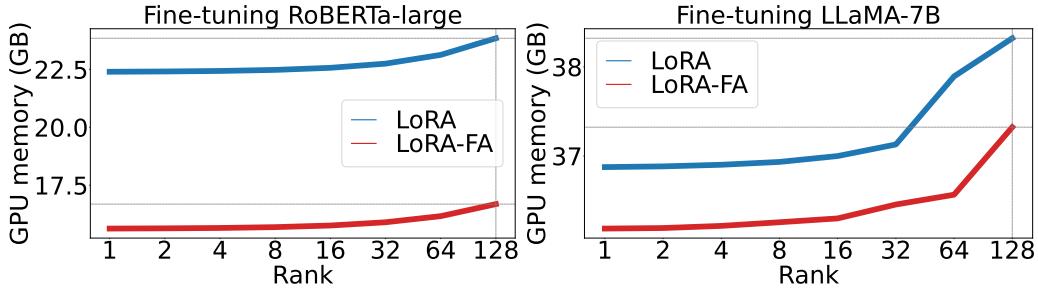


Figure 3: GPU memory footprint (GB) comparison under different rank sizes for fine-tuning RoBERTa-large and LLaMA-7B models with LoRA and LoRA-FA.

of 128 for LLaMA-7B. As shown in Figure 3, LoRA takes more GPU memory than LoRA-FA among all ranks in fine-tuning both models, with a average gap of 5GB in fine-tuning RoBERTa-large, and 1GB in fine-tuning LLaMA-7B. The memory footprint remains steady along ranks, which suggests that LoRA-FA can increase rank painlessly from 1 to 128 to achieve better performance without causing OOM.

#### 4.3 HYPER-PARAMETER STUDY

LoRA-FA has shown its power in the performance of fine-tuning LLM according to the result above, as it can achieve the close accuracy in time yet has a good memory efficiency runtime. To validate the robustness to hyper-parameter of LoRA-FA, we further conduct a hyper-parameter study about the correlation between rank  $r$  and learning rate  $\eta$  on LoRA-FA. We compare the performance of LoRA and LoRA-FA in fine-tuning RoBERTa-base on MRPC under a vast range of ranks and learning rates. We use the batch size of 64, and sequence length of 128. Result is present in Figure 4, demonstrating that LoRA and LoRA-FA exhibit similar hyper-parameter space, while LoRA has a slight wider range when  $r$  and  $\eta$  are around 2 and 5e-5 simultaneously. Both approaches have shown the same pattern that there is a negative correlation between rank  $r$  and learning rate  $\eta$  with regard to fine-tuning performance, i.e., when rank is going higher, the learning rate should be appropriately reduced to maintain the performance.

## 5 RELATED WORK

**Supervised Fine-tuning.** A pre-trained LLM has a good understanding to human corpus. It can generate texts by continuing the input sequence, or generate the word that has been masked inside

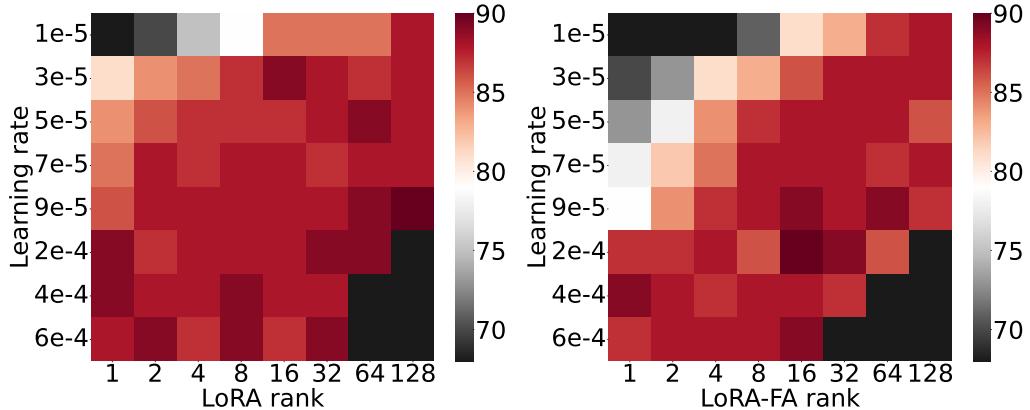


Figure 4: Fine-tuning performance comparison between LoRA and LoRA-FA under different ranks and learning rates for the RoBERTa-base model on the MRPC dataset.

the sequence, thus it can be used for various tasks after fine-tuning. Adding a prediction head to a encoder-only model(Devlin et al., 2019; Liu et al., 2019; He et al., 2020), then fine-tuning the model on a dataset with human annotations is a common way for NLU tasks, such as COLA(Warstadt et al., 2019), SST2(Socher et al., 2013), MNLI(Kim et al., 2019) from GLUE benchmark(Wang et al., 2019). LLM can also be used for text-to-text tasks such as translation, and the encoder-decoder structure is needed in such models, including T5(Raffel et al., 2020), mT5(Xue et al., 2021), ByT5(Xue et al., 2022), UMT5(Chung et al., 2023), etc. However, these fine-tuning methods mainly focus on one task (i.e., single-task specialization), which means they can't handle various human instructions (i.e., multi-task generalization). To make LLMs follow instructions, they are fine-tuned on one or more instruction datasets, such as Alpaca(Taori et al., 2023), Self-instruct(Wang et al., 2022a), UnnaturalInstruction(Honovich et al., 2022), SuperNaturalInstructions(Wang et al., 2022b), and FLAN v2(Wei et al., 2021), which consist of paired instruction-output values. This fine-tuning method is called instruction tuning. Many recent instruction-tuned models include InstructGPT(Ouyang et al., 2022), Llama 2(Touvron et al., 2023b), Guanaco(Dettmers et al., 2023), Vicuna(Chiang et al., 2023), Falcon(Almazrouei et al., 2023), FLAN-T5(Chung et al., 2022), and they have achieved a great performance in understanding general knowledge across a wide variety of fields from Open-LLM Leaderboard(Edward et al., 2023; Gao et al., 2021; Clark et al., 2018; Zellers et al., 2019; Hendrycks et al., 2021; Lin et al., 2022). In our work, we show that LoRA-FA is able to fine-tune different kinds of models, including encoder-only, encoder-decoder and decoder-only models.

**Parameter-Efficient Fine-tuning.** With the plethora of LLMs being released, models get larger and larger, and full-parameter fine-tuning becomes infeasible to train them on consumer hardware. Parameter-Efficient Fine-tuning (PEFT) approaches are meant to address this problem to reduce the number of trainable parameters by various methods while maintaining performance. For example, Prefix tuning(Li & Liang, 2021) adds prefix parameters to the hidden states in every layer of the model. Prompt tuning(Lester et al., 2021; Liu et al., 2021; Gu et al., 2022) uses template to reconstruct prompt, and only updates parameters related to prompt understanding. IA3(Liu et al., 2022) injects learned vectors to the attention and feed-forward modules. BitFit(Ben Zaken et al., 2022) only updates the bias of the model. LoRA(Hu et al., 2022) adds low-rank adapters as a bypass to linear layers. Among all, LoRA is more often employed to fine-tune LLMs for new tasks, and many recent approaches based on LoRA have been proposed. QLoRA(Dettmers et al., 2023) fine-tunes a quantized model with LoRA. ReLoRA(Lialin et al., 2023) applies a warm-up strategy with LoRA for pre-training. LoraHub(Huang et al., 2023) proposes a strategy to automatically construct LoRA modules for a model in fine-tuning with diverse given tasks. GLoRA(Chavan et al., 2023) adds an additional prompt module to the model, and injects vectors to rescale the weight and bias. In contrast, LoRA-FA has shown its strength in memory usage while preserving performance compared to LoRA when fine-tuning LLMs . We will compare to more PEFT approaches in our future work.

**Memory-efficient Training.** To load or train LLMs onto hardware more efficiently and scalably, many memory-efficient training approaches have been proposed. ZeRO(Rajbhandari et al., 2020)

partitions the parameters, gradients and optimizer states equally across all GPUs, and each GPU has a single partition which is also referred to as a shard. At the computing stage, each GPU builds up each layer’s weight by asking participating GPUs to send the information it’s lacking. Similarly, FSDP(Zhao et al., 2023) shards all of these states across data parallel workers, and it can optionally offload the sharded model parameters to CPUs. Activation recomputation(Korthikanti et al., 2023; Jain et al., 2020; Smith et al., 2022), also known as gradient checkpointing, is used to save memory during the forward pass by recomputing intermediate activations just-in-time during the backward pass. Offloading(Ren et al., 2021; Shoeybi et al., 2020) is a technique to offload the weights or states to CPU and only load them to GPU when needed. Quantization(Dettmers et al., 2023; Jacob et al., 2017; Dettmers et al., 2022b) concentrates to quantize the parameters and gradients into low-bit representations, such as 8-bit floating point or integer, 4-bit floating point or integer, or even 1-bit data type. LoRA-FA shows an advantage for reducing trainable parameters and activation memory in fine-tuning LLMs, and it can be combined with above memory-efficient training approaches.

## 6 CONCLUSION

In this work, we proposed a new PEFT method LoRA-FA, which requires much less memory footprint by reducing the trainable parameters and the activation memory cost. We conducted extensive experiments to show that LoRA-FA could achieve similar fine-tuning performance compared to two strong baselines: full-parameter fine-tuning and LoRA. Meanwhile, LoRA-FA reduced up to 13GB GPU memory footprint compared to other methods without any recomputation. We hope that our method can help the community to explore the potential of LLMs adaptation with low resources.

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