BiLoRA: A Bi-level Optimization Framework for Low-Rank Adapters

Anonymous authors
Paper under double-blind review

Abstract

Low-rank adaptations (LoRA) are widely employed for fine-tuning large-scale pretrained models in downstream tasks, by learning low-rank incremental matrices. LoRA and its variants such as AdaLoRA train an entire low-rank incremental matrix on a single training dataset, which often leads to overfitting to training data and inferior generalization on test data. To address this problem, we propose a bi-level optimization (BLO) based method for alleviating overfitting. Our method parameterizes a low-rank incremental matrix in a pseudo singular value decomposition form, and separates the training of pseudo singular vectors and values onto different data subsets in different optimization problems. This separation alleviates the risk of overfitting to a single dataset and improves generalization on other data. Specifically, in the lower level of our BLO formulation, we train the pseudo singular vectors on a subset of the training data. In the upper level, we learn the pseudo singular values on the other subset of the training data. The two levels of optimization problems are mutually dependent on each other and solved jointly. On ten datasets from natural language understanding and generation tasks and on various popular large pretrained models, our method achieves significantly better performance than LoRA, AdaLoRA, and other fine-tuning baseline methods with similar amounts of trainable parameters.

1 Introduction

Large language models (LLMs) have achieved excellent performance across various natural language processing tasks (Devlin et al., 2018; He et al., 2020; Radford et al., 2019; Brown et al., 2020). The prevalent paradigm for leveraging large language models in application development involves pretraining on large-scale data and subsequently fine-tuning the pretrained model on specific downstream tasks. With the ever-increasing size of large language models, full fine-tuning (Qiu et al., 2020) them on various downstream tasks can cause significant computation costs. In addition, the large number of parameters in pre-trained models may make the fine-tuning process more prone to overfitting (Karimi Mahabadi et al., 2021). Researchers have proposed multiple fine-tuning methods to address these issues. These methods, aiming to reduce the parameter count during fine-tuning while maintaining performance, can be collectively referred to as Parameter-Efficient Fine-Tuning (PEFT) methods (Houlsby et al., 2019; Ding et al., 2023; Mao et al., 2021).

Low-Rank Adaptation (LoRA) (Hu et al., 2021) is one of the important methods for PEFT. Different from adapter tuning (Houlsby et al., 2019; Rebuffi et al., 2017; Pfeiffer et al., 2020), LoRA does not add small neural modules to the pre-trained model. LoRA takes inspiration from Li et al. (2018); Aghajanyan et al. (2020) which show that well trained over-parameterized models actually exist within a space characterized by a low intrinsic dimension. It introduces incremental updates named low-rank adapters to frozen pre-trained weights and parameterizes them in the form of the product of two much smaller matrices. For $h = W_0x$, the modified forward pass yields: $h = W_0x + \Delta Wx = W_0x + BAx$, where $\Delta W \in \mathbb{R}^{d\times k}$, $A \in \mathbb{R}^{d\times r}$, $B \in \mathbb{R}^{r\times k}$ and $r \ll min\{d, k\}$. With much less trainable parameters, LoRA achieves comparable or even better performance than full fine-tuning and other adaptation methods (Hu et al., 2021).

LoRA sets the rank of incremental matrices at different layers to be the same, without considering the fact that pretrained weight matrices in different layers have varying importance for a downstream task. A more important weight matrix should be finetuned more, with a larger number of weight parameters (equivalently, a larger rank) in its incremental matrix. To address this issue, AdaLoRA (Zhang et al., 2023) sets different ranks for incremental matrices at different layers adaptively according to layers' importance. It parameterizes a low-rank incremental matrix ΔW as $\Delta W = P \Lambda Q$ to mimic SVD. With regularization to enforce the orthogonality of P and Q, Λ can be approximately considered as a singular value matrix. AdaLoRA uses singular values and vectors to compute important scores for determining how to set layer-specific ranks.

One limitation of AdaLoRA is that it learns pseudo singular vectors in $\{P, Q\}$ and pseudo singular values in Λ simultaneously by minimizing the fine-tuning loss on a single training dataset. This often results in overfitting to the training data and unsatisfactory generalization on test data. Particularly, Λ determines the number of learnable parameters and the contribution of each rank-1 update matrix (outer product of two pseudo singular vectors) in ΔW. Learning Λ by minimizing a single dataset's training loss can easily render these contributions and parameter amounts tailored to this dataset, leading to inferior generalization performance on other data.

To address this problem, we propose a bi-level optimization (BLO) based method to learn $\{P, Q\}$ and Λ on different subsets of the training data. A BLO formulation (Sinha et al., 2017) consists of two levels of nested optimization problems. The optimal variables in the lower level are the inputs of the objective function in the upper level. The non-optimal variables in the upper level are the inputs of the objective function in the lower level. In the lower level of our formulation, we train $\{P, Q\}$ by minimizing a fine-tuning loss on a subset S of the training dataset D while tentatively fixing Λ. The optimally learned $\{P^*(\Lambda), Q^*(\Lambda)\}$ are functionals of Λ. In the upper level, we validate $\{P^*(\Lambda), Q^*(\Lambda)\}$ on the rest of the training data $D \backslash S$. The validation loss is a function of Λ and we learn Λ by minimizing this loss. By separating the learning of $\{P, Q\}$ and Λ onto different data subsets in different optimization problems, our method can effectively alleviate overfitting to a single dataset and improve generalization performance to other datasets.

Our contributions can be summarized as follows:

- We propose a novel bi-level optimization based method to alleviate overfitting in LoRA and its variants. Different from previous methods which learn an entire incremental matrix on a single dataset, our method separates the learning of parameter subsets onto different datasets in different optimization problems which are tightly coupled. In this way, our method can effectively alleviate overfitting to a single dataset.
- We demonstrate the effectiveness of our method on ten datasets in both natural language understanding and generation tasks and on various pretrained large models including RoBERTa, DeBERTa, and GPT2. Compared with LoRA, AdaLoRA and other popular fine-tuning methods, our method achieves significantly better performance with similar amounts of trainable parameters.

2 Related Work

Low-Rank Adaptation. Li et al. (2018) and Aghajanyan et al. (2020) demonstrate that widely-used pre-trained models possess a very low intrinsic dimension and it is possible to achieve comparable fine-tuning performance by utilizing a reparameterization with reduced dimensionality. This inspires low-rank adapters to be introduced for fine-tuning. LoRA introduces incremental updates to frozen pre-trained weights as low-rank adapters (Hu et al., 2021). By parameterizing the low-rank adapter as the product of two low-rank matrices, LoRA greatly reduces trainable parameters while maintaining or even improving the performance over full fine-tuning. Multiple methods have been proposed to improve the time/memory efficiency and performance of low-rank adapters based on LoRA. DyLoRA (Valipour et al., 2022) trains low-rank adapter blocks for multiple ranks by sorting the learned representations dynamically during training. QLoRA (Dettmers et al., 2023) introduces multiple strategies to reduce memory footprint for low-rank adapters, lowering the memory barrier for training LLMs. LoraHub (Huang et al., 2023) is designed to facilitate the efficient combination of LoRA modules trained on various tasks using only a few examples from a new task. AdaLoRA (Zhang et al., 2023) allocates the parameter budget adaptively according to the importance of modules to improve the fine-tuning performance in specific budget settings. It parameterizes the incremental updates in the form of singular value decomposition and iteratively prunes singular values in correspondence to their importance scores during training. Different from these existing methods which train all the parameters in incremental updates on a single training dataset and therefore often lead to overfitting, our method (based on the SVD reparameterization of incremental updates) separately train singular values and singular vectors in two different optimization levels, which effectively alleviates the risk of overfitting to a single dataset.

Bi-level Optimization (BLO). BLO has gained much attention for formulating various machine learning methods including meta-learning (Finn et al., 2017; Rajeswaran et al., 2019), hyperparameter optimization (Franceschi et al., 2017; Lorraine et al., 2020), neural architecture search (Liu et al., 2018; Zhang et al., 2021), reinforcement learning (Rajeswaran et al., 2020), to name a few. In addition to applying BLO to various machine learning problems, various algorithms have been proposed to address this specific form of optimization problem, including zeroth-order methods like Bayesian optimization (Cui & Bai, 2019), first-order algorithms based on hypergradients (Pearlmutter & Siskind, 2008; Lorraine et al., 2020), etc. Gradient-based BLO is efficient for scaling up to high-dimensional problems with a large number of trainable parameters. We expand the application scenarios of gradient-based BLO and build an efficient training framework to improve the generalization performance of low-rank adapters.

3 METHODS

We propose BiLoRA (Figure 1), a novel low-rank adapter training framework based on bi-level optimization. Similar to AdaLoRA, incremental matrices in our method are parameterized in a pseudo SVD form with learnable pseudo singular vectors $\mathcal{V}$ and pseudo singular values $\mathcal{E}$. We split the training dataset into two non-overlapping subsets D_1 and D_2. In the lower level, we train $\mathcal{V}$ on D_1 while fixing $\mathcal{E}$. The optimal solution $\mathcal{V}^*(\mathcal{E})$ (which is a functional of $\mathcal{E}$) is fed into the upper level. In the upper level, we train $\mathcal{E}$ on the dataset D_2. The updated $\mathcal{E}$ is fed into the lower level. The two levels of optimization problems are solved iteratively until convergence.

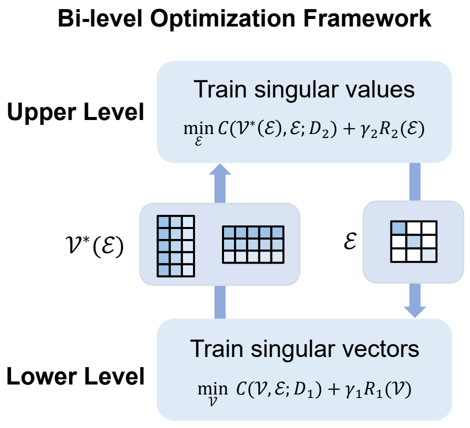

Bi-level Optimization Framework
Upper Level
Train singular values
$\min_{\mathcal{E}} C(\mathcal{V}^*(\mathcal{E}),\mathcal{E};D_2)+\gamma_2 R_2(\mathcal{E})$
$\mathcal{V}^*(\mathcal{E})$
$\mathcal{E}$
Lower Level
Train singular vectors
$\min_{\mathcal{V}} C(\mathcal{V},\mathcal{E};D_1)+\gamma_1 R_1(\mathcal{V})$

Figure 1: The proposed BiLoRA method.

3.1 PARAMETERIZATION OF LOW-RANK INCREMENTAL MATRICES

Following (Zhang et al., 2023), we parameterize the low-rank incremental matrix ΔW as $\Delta W = P\Lambda Q$ which mimics SVD. The diagonal matrix Λ contains *pseudo singular values* and the approximately orthogonal matrices P and Q represent *pseudo left/right singular vectors*. We use k to index the incremental matrix, i.e., $\Delta W_k = P_k\Lambda_k Q_k$ for $k = 1, ..., n$, where n is the number of low-rank adapters. We denote the i-th singular value of ΔW_k as $\lambda_{k,i}$ and the rank of low-rank adapters as r. We further denote the parameter sets as $\mathcal{P} = \{P_k\}_{k=1}^n$, $\mathcal{E} = \{\Lambda_k\}_{k=1}^n$, $\mathcal{Q} = \{Q_k\}_{k=1}^n$, and $\mathcal{V} = \{\mathcal{P}, \mathcal{Q}\}$. To encourage P_k and Q_k to be approximately orthogonal, we use the following regularizer as in AdaLoRA (Zhang et al., 2023):

$$R_1 = \sum_{k=1}^{n} (\|P_k^T P_k - I\|_F^2 + \|Q_k Q_k^T - I\|_F^2), \tag{1}$$

where I is an identity matrix and $\|\cdot\|_F$ denotes the Frobenius norm.

Parameterization of Pseudo Singular Values. We parameterize the pseudo singular values in Λ in three specific forms.

- **Real-Value**: All pseudo singular values are real-valued without any constraints.
- **Softmax**: Given a real vector v, we apply the softmax operation to it. $softmax(v)$ are used as the pseudo singular values. These values add up to one and represent the contributions of their corresponding singular vector pairs.

- **Approximately Binary**: Given a real vector v, we apply element-wise sigmoid to it to transform the values in v into $(0, 1)$. Then we use an element-wise entropy regularizer to encourage the values in $sigmoid(v)$ are close to either zero or one. The regularizer is defined as:
$$R_2(\mathcal{E}) = \sum_{k=1}^{n} \sum_{i=1}^{r} \lambda_{k,i} \log \lambda_{k,i} + (1 - \lambda_{k,i}) \log(1 - \lambda_{k,i}). \tag{2}$$
This setting automatically assigns either a high or low importance to each singular vector pair with the corresponding singular value as zero or one, effectively serving as an automatic rank selection mechanism.

3.2 A Bi-level Optimization Framework

Our method is based on bi-level optimization, where pseudo singular vector matrices $\mathcal{V}$ and their corresponding pseudo singular value matrices $\mathcal{E}$ are set as trainable parameters for the lower and upper level respectively.

Lower Level. In the lower level, we perform LoRA fine-tuning of a pre-trained model by minimizing a loss C defined on the first dataset D_1 and low-rank incremental matrices $\{\Delta W_k\}_{k=1}^{n}$. Calculating C involves the forward pass for each input example x: $W_0 x + \Delta W x = W_0 x + P \Lambda Q x$, where W_0 is a weight matrix in the pretrained model. R_1 in Eq.(1) is applied to promote the approximate orthogonality of P and Q. The overall training objective is $L_1 = C(\mathcal{V}, \mathcal{E}; D_1) + \gamma_1 R_1(\mathcal{V})$, where γ_1 is a tradeoff parameter. In this level, we only train $\mathcal{V}$, while keeping $\mathcal{E}$ tentatively fixed. $\mathcal{E}$ will be updated in the upper level. In the end, the lower level amounts to solving the following problem:
$$\mathcal{V}^*(\mathcal{E}) = \arg\min_{\mathcal{V}} \; C(\mathcal{V}, \mathcal{E}; D_1) + \gamma_1 R_1(\mathcal{V}). \tag{3}$$
$\mathcal{V}^*(\mathcal{E})$ denotes that the optimal solution $\mathcal{V}^*$ depends on $\mathcal{E}$ since $\mathcal{V}^*$ depends on C which depends on $\mathcal{E}$.

Upper Level. In the upper level, we validate the fine-tuned model where the incremental matrices are parameterized by the optimally learned $\mathcal{V}^*(\mathcal{E})$ and unlearned pseudo singular values in $\mathcal{E}$, on the second dataset D_2. This results in a validation loss $C(\mathcal{V}^*(\mathcal{E}), \mathcal{E}, D_2)$, which is a function of $\mathcal{E}$. We learn $\mathcal{E}$ by minimizing this loss. Optionally, we use the regularizer R_2 in Eq.(2) to encourage the pseudo singular values in $\mathcal{E}$ to be approximately binary. The overall objective function is $L_2 = C(\mathcal{V}^*(\mathcal{E}), \mathcal{E}; D_2) + \gamma_2 R_2(\mathcal{E})$, where γ_2 is a tradeoff parameter. This level amounts to solving the following optimization problem:
$$\min_{\mathcal{E}} \; C(\mathcal{V}^*(\mathcal{E}), \mathcal{E}; D_2) + \gamma_2 R_2(\mathcal{E}). \tag{4}$$

A Bi-level Optimization Framework.

Integrating these two interdependent levels of optimization problems, we have the following bi-level optimization framework:
$$\begin{aligned} &\text{Upper Level:} && \min_{\mathcal{E}} \; C(\mathcal{V}^*(\mathcal{E}), \mathcal{E}; D_2) + \gamma_2 R_2(\mathcal{E}) \\ &\text{Lower Level:} && s.t. \; \mathcal{V}^*(\mathcal{E}) = \arg\min_{\mathcal{V}} \; C(\mathcal{V}, \mathcal{E}; D_1) + \gamma_1 R_1(\mathcal{V}) \end{aligned}$$

Note that these two levels of optimization problems are mutually dependent on each other. The output of the lower level, which is $\mathcal{V}^*(\mathcal{E})$, is the input of the upper level. The optimization variable $\mathcal{E}$ in the upper level is the input of the lower level. By solving these two interconnected problems jointly, we can learn the pseudo singular vectors and values end-to-end.

Optimization Algorithm. We utilize a gradient-based optimization algorithm (Choe et al., 2022) to solve this bi-level optimization problem. Our overall optimization algorithm is summarized in Algorithm 1. Specifically, in the lower level, we perform gradient descent for a preset number of steps T_1 on the pseudo singular vector matrices $\mathcal{V}$ to approximate the optimal solution $\mathcal{V}^*(\mathcal{E})$. With the initial $\mathcal{V}$ as $\mathcal{V}^{(0)}$ and learning rate η_1, the gradient descent steps can be formulated as:
$$\mathcal{V}^{(t)} = \mathcal{V}^{(t-1)} - \eta_1 \frac{dL_1}{d\mathcal{V}^{(t-1)}}, \text{ for } t = 1, 2, 3, ..., T_1.$$

Table 1: RoBERTa$_{\text{base/large}}$ (R$_{\text{b/l}}$) with different adaptation methods on the GLUE benchmark. We report the average result of five runs with different random seeds. Higher is better for all metrics. Numbers except BiLoRA are published in prior works. $*$ indicates model already adapted to MNLI when adapting to MRPC, RTE, and STS-B, while † indicates model started as pre-trained when adapting to all datasets.

Method	Params	MNLI	SST-2	MRPC	CoLA	QNLI	QQP	RTE	STS-B	Avg.
R$_b$(FT)	125.0M	87.6	94.8	90.2	63.6	92.8	**91.9**	78.7	91.2	86.4
R$_b$(BitFit)	0.1M	84.7	93.7	**92.7**	62.0	91.8	84.0	81.5	90.8	85.2
R$_b$(Adpt^D)	0.3M	$87.1_{\pm.0}$	$94.2_{\pm.1}$	$88.5_{\pm1.1}$	$60.8_{\pm.4}$	$93.1_{\pm.1}$	$90.2_{\pm.0}$	$71.5_{\pm2.7}$	$89.7_{\pm.3}$	84.4
R$_b$(Adpt^D)	0.9M	$87.3_{\pm.1}$	$94.7_{\pm.3}$	$88.4_{\pm.1}$	$62.6_{\pm.9}$	$93.0_{\pm.2}$	$90.6_{\pm.0}$	$75.9_{\pm2.2}$	$90.3_{\pm.1}$	85.4
R$_b$(LoRA)*	0.3M	$87.5_{\pm.3}$	**$95.1_{\pm.2}$**	$89.7_{\pm.7}$	$63.4_{\pm1.2}$	**$93.3_{\pm.3}$**	$90.8_{\pm.1}$	$86.6_{\pm.7}$	$91.5_{\pm.2}$	87.2
R$_b$(BiLoRA)*	0.3M	**$87.9_{\pm.2}$**	**$95.1_{\pm.2}$**	$91.7_{\pm.5}$	**$64.8_{\pm.6}$**	**$93.3_{\pm.2}$**	$91.4_{\pm.2}$	**$87.2_{\pm.4}$**	**$91.7_{\pm.2}$**	**87.9**
R$_l$(FT)*	355.0M	90.2	96.4	90.9	68.0	94.7	**92.2**	86.6	92.4	88.9
R$_l$(LoRA)*	0.8M	**$90.6_{\pm.2}$**	$96.2_{\pm.5}$	$90.9_{\pm1.2}$	$68.2_{\pm1.9}$	$94.9_{\pm.3}$	$91.6_{\pm.1}$	$87.4_{\pm2.5}$	**$92.6_{\pm.2}$**	89.0
R$_l$(BiLoRA)*	0.8M	**$90.6_{\pm.3}$**	**$96.7_{\pm.4}$**	**$92.6_{\pm1.4}$**	**$69.2_{\pm1.6}$**	**$95.0_{\pm.1}$**	$92.0_{\pm.1}$	**$89.5_{\pm1.1}$**	**$92.6_{\pm.8}$**	**89.8**
R$_l$(Adpt^P)†	3.0M	$90.2_{\pm.3}$	$96.1_{\pm.3}$	$90.2_{\pm.7}$	$68.3_{\pm1.0}$	$94.8_{\pm.2}$	$91.9_{\pm.1}$	$83.8_{\pm2.9}$	$92.1_{\pm.7}$	88.4
R$_l$(Adpt^P)†	0.8M	$90.5_{\pm.3}$	$96.6_{\pm.2}$	$89.7_{\pm1.2}$	$67.8_{\pm2.5}$	$94.8_{\pm.3}$	$91.7_{\pm.2}$	$80.1_{\pm2.9}$	$91.9_{\pm.4}$	87.9
R$_l$(Adpt^H)†	6.0M	$89.9_{\pm.5}$	$96.2_{\pm.3}$	$88.7_{\pm2.9}$	$66.5_{\pm4.4}$	$94.7_{\pm.2}$	**$92.1_{\pm.1}$**	$83.4_{\pm1.1}$	$91.0_{\pm1.7}$	87.8
R$_l$(Adpt^H)†	0.8M	$90.3_{\pm.3}$	$96.3_{\pm.5}$	$87.7_{\pm1.7}$	$66.3_{\pm2.0}$	$94.7_{\pm.2}$	$91.5_{\pm.1}$	$72.9_{\pm2.9}$	$91.5_{\pm.5}$	86.4
R$_l$(LoRA)†	0.8M	**$90.6_{\pm.2}$**	$96.2_{\pm.5}$	$90.2_{\pm1.0}$	$68.2_{\pm1.9}$	$94.8_{\pm.3}$	$91.6_{\pm.2}$	$85.2_{\pm1.1}$	$92.3_{\pm.5}$	88.6
R$_l$(BiLoRA)†	0.8M	**$90.6_{\pm.3}$**	**$96.7_{\pm.4}$**	**$92.2_{\pm1.0}$**	**$69.2_{\pm1.6}$**	**$95.0_{\pm.1}$**	$92.0_{\pm.1}$	**$87.4_{\pm1.0}$**	**$92.6_{\pm.8}$**	**89.5**

We plug $\mathcal{V}^*(\mathcal{E}) \approx \mathcal{V}^{(T_1)}$ into the overall objective function in the upper level and get an approximate objective $\widehat{L}_2 = C(\mathcal{V}^{(T_1)}, \mathcal{E}; D_2) + \gamma_2 R_2(\mathcal{E})$. We perform gradient descent for a preset number of steps T_2 on the pseudo singular values in $\mathcal{E}$ to minimize $\widehat{L}_2$. With the initial $\mathcal{E}$ as $\mathcal{E}^{(0)}$ and learning rate η_2, the gradient descent steps can be formulated as:

$$\mathcal{E}^{(t)} = \mathcal{E}^{(t-1)} - \eta_2 \frac{d\widehat{L}_2}{d\mathcal{E}^{(t-1)}}, \text{ for } t = 1, 2, 3, ..., T_2.$$

These steps constitute one global optimization step. We take iterative global steps between the lower level and upper level to solve this bi-level optimization problem until converge. Specifically, following the chain rule, the hypergradient for the upper level can be calculated as:

$$\frac{d\widehat{L}_2}{d\mathcal{E}} = \frac{\partial \widehat{L}_2}{\partial \mathcal{E}} + \frac{\partial \mathcal{V}^{(T_1)}}{\partial \mathcal{E}} \times \frac{\partial \widehat{L}_2}{\partial \mathcal{V}^{(T_1)}}.$$

Algorithm 1 BiLoRA

```
1: Input: Datasets $D_1$, $D_2$; unroll steps $T_1$, $T_2$; learning rates $\eta_1$, $\eta_2$.
2: In a Global Step do
3:     for $t = 1, 2, 3, ..., T_1$ do
4:         Sample a minibatch $B_1^{(t)}$ from $D_1$
5:         Compute $\frac{dL_1}{d\mathcal{V}^{(t-1)}}$ on $B_1^{(t)}$ and update $\mathcal{V}^{(t)} = \mathcal{V}^{(t-1)} - \eta_1 \frac{dL_1}{d\mathcal{V}^{(t-1)}}$
6:     for $t = 1, 2, 3, ..., T_2$ do
7:         Sample a minibatch $B_2^{(t)}$ from $D_2$
8:         Compute $\frac{d\widehat{L}_2}{d\mathcal{E}^{(t-1)}} = \frac{\partial \widehat{L}_2}{\partial \mathcal{E}^{(t-1)}} + \frac{\partial \mathcal{V}^{(T_1)}}{\partial \mathcal{E}^{(t-1)}} \times \frac{\partial \widehat{L}_2}{\partial \mathcal{V}^{(T_1)}}$ and update $\mathcal{E}^{(t)} = \mathcal{E}^{(t-1)} - \eta_2 \frac{d\widehat{L}_2}{d\mathcal{E}^{(t-1)}}$
9: end this step
```

4 Experiments

We evaluated the downstream performance of BiLoRA on RoBERTa (Liu et al., 2019), DeBERTa (He et al., 2020) and GPT-2 (Radford et al., 2019), and compared with LoRA (Hu et al., 2021), AdaLoRA (Zhang et al., 2023), and other baselines. Our experiments covered a wide range of tasks, from natural language understanding (NLU) to generation (NLG). Specifically, we evaluated

Table 2: DeBERTa-v3-base (D_{v3}) with different adaptation methods, on the GLUE benchmark. We report the average result of five runs with different random seeds. Higher is better. * indicates numbers published in prior works. BiLoRA outperforms FT, LoRA, AdaLoRA, and other adaptation methods with equal or less parameters.

Method	Params	MNLI	SST-2	MRPC	CoLA	QNLI	QQP	RTE	STS-B	Avg.
D_{v3}(FT)*	184.0M	90.01	95.63	89.46	69.19	94.03	92.40	83.75	91.60	88.09
D_{v3}(Adpt^H)*	0.6M	90.18	95.30	89.22	67.87	93.76	91.65	85.56	91.30	87.93
D_{v3}(Adpt^P)*	0.6M	90.22	95.53	89.22	69.48	93.98	91.62	84.12	91.52	88.04
D_{v3}(LoRA)*	0.3M	90.34	94.95	89.71	68.71	94.03	91.61	85.56	91.68	88.15
D_{v3}(AdaLoRA)*	0.3M	90.68	95.80	90.44	70.04	**94.49**	91.78	87.36	91.63	88.86
D_{v3}(BiLoRA)	0.3M	**90.81**	**96.02**	**91.42**	**70.52**	94.25	**91.82**	**88.45**	**91.96**	**89.41**

RoBERTa and DeBERTa on the GLUE benchmark (Wang et al., 2018) and GPT-2 on the E2E NLG challenge (Novikova et al., 2017). We used DeBERTa-xxlarge(1.5B) to evaluate the scaling-up performance of our method. We used NVIDIA A100 for all experiments.

4.1 Baselines

We compared with the same baselines as LoRA and AdaLoRA, and used the reported results in previous work. Additionally, we also took LoRA and AdaLoRA as our baselines to evaluate the effectiveness of our method.

Full Fine-Tuning (FT) is a frequently employed method for adaptation. The model is initialized with pre-trained weights and biases and all model parameters are subjected to gradient updates. We also included a simple variant reported in prior work on GPT-2 (Li & Liang, 2021), which only adapts the last two layers while freezing others.

Bias-only or BitFit (Zaken et al., 2021) is an effective PEFT method which only trains the bias vectors while freezing everything else in the pre-trained model.

Prefix-embedding tuning (PreEmbed) introduces specialized tokens within the input tokens, featuring trainable word embeddings that typically do not belong to the model's vocabulary (Li & Liang, 2021).

Prefix-layer tuning (PreLayer) learns the activations after every Transformer layer by replacing the activations computed from previous layers with trainable parameters. This method can be seen as an extension to prefix-embedding tuning.

Adapter tuning (Houlsby et al., 2019) inserts layer-adapters between neural modules such as the MLP module or the self-attention module. We used four types of adapters as in LoRA (Hu et al., 2021): **Adapter$^{\mathbf{L}}$** with the adapter layer applied only after the MLP module and after a LayerNorm (Lin et al., 2020), **Adapter$^{\mathbf{D}}$** with some adapter layers dropped for increasing efficiency (Rücklé et al., 2020). **Adapter$^{\mathbf{H}}$** incorporates two fully connected layers within an adapter layer, with nonlinearity in between (Houlsby et al., 2019). **Adapter$^{\mathbf{P}}$** (Pfeiffer et al., 2020) is similar to **Adapter$^{\mathbf{L}}$**, but introduces a novel two-stage transfer learning strategy to combine the knowledge from multiple source tasks.

LoRA (Hu et al., 2021) adds trainable incremental update matrices to pretrained weight matrices. Following the experimental settings of LoRA, we applied BiLoRA to W_q and W_v matrices (the query and value weight matrices in the self-attention module) for a fair comparison.

AdaLoRA (Zhang et al., 2023) proposes SVD-based adaptation and rank-allocation based on LoRA, which formulates the incremental matrices in the form of singular value decomposition and allocates rank budget based on importance scores.

4.2 Natural Language Understanding

For natural language understanding (NLU) tasks, we conducted experiments on the General Language Understanding Evaluation (GLUE) benchmark for RoBERTa and DeBERTa. Please see Appendix A for more details on the models and datasets we use.

Table 3: GPT-2 medium (M) and large (L) with different adaptation methods on the E2E NLG Challenge. For all metrics, higher is better. * indicates numbers published in prior works. We keep the same experimental settings as different adaptation baselines for a fair comparison.

Model&Method	Params	BLEU	NIST	MET	ROUGE-L	CIDEr
GPT-2 M(FT)*	354.92M	68.2	8.62	46.2	71.0	2.47
GPT-2 M(Adpt^{L})*	0.37M	66.3	8.41	45.0	69.8	2.40
GPT-2 M(Adpt^{L})*	11.09M	68.9	8.71	46.1	71.3	2.47
GPT-2 M(Adpt^{H})*	11.09M	$67.3_{\pm.6}$	$8.50_{\pm.07}$	$46.0_{\pm.2}$	$70.7_{\pm.2}$	$2.44_{\pm.01}$
GPT-2 M(FT^{Top2})*	25.19M	68.1	8.59	46.0	70.8	2.41
GPT-2 M(PreLayer)*	0.35M	69.7	8.81	46.1	71.4	2.49
GPT-2 M(LoRA)*	0.35M	$70.4_{\pm.1}$	$8.85_{\pm.02}$	$46.8_{\pm.2}$	$71.8_{\pm.1}$	$2.53_{\pm.02}$
GPT-2 M(BiLoRA)	0.35M	**70.5**$_{\pm.4}$	**$8.86_{\pm.03}$**	**46.9**$_{\pm.1}$	**72.0**$_{\pm.2}$	**2.54**$_{\pm.03}$
GPT-2 L(FT)*	774.03M	68.5	8.78	46.0	69.9	2.45
GPT-2 L(Adpt^{L})*	0.88M	$69.1_{\pm.1}$	$8.68_{\pm.03}$	$46.3_{\pm.0}$	$71.4_{\pm.2}$	**$2.49_{\pm.0}$**
GPT-2 L(Adpt^{L})*	23.00M	$68.9_{\pm.3}$	$8.70_{\pm.04}$	$46.1_{\pm.1}$	$71.3_{\pm.2}$	$2.45_{\pm.02}$
GPT-2 L(PreLayer)*	0.77M	70.3	8.85	46.2	71.7	2.47
GPT-2 L(LoRA)*	0.77M	$70.4_{\pm.1}$	$8.89_{\pm.02}$	$46.8_{\pm.2}$	**$72.0_{\pm.2}$**	$2.47_{\pm.02}$
GPT-2 L(BiLoRA)	0.77M	**70.5**$_{\pm.3}$	**$8.90_{\pm.04}$**	**47.0**$_{\pm.3}$	**72.0**$_{\pm.4}$	**2.49**$_{\pm.03}$

Implementation Details. Our implementation is based on *Huggingface Transformers* (Wolf et al., 2019) and *Betty* (Choe et al., 2022). *Betty* is a software library for solving large-scale multilevel optimization (MLO) problems. Specifically, we load RoBERETa and DeBERTa models with *Huggingface Transformers* and build our bi-level optimization framework with *Betty*.

Experimental Settings. Following LoRA, we used the development set in GLUE as test data since the test set is not publicly available. We divided the training set into two datasets, with an 8:2 split, serving as the lower-level and upper-level datasets respectively in our bi-level formulation. We maintained this fixed ratio for all tasks. Singular values were parameterized as Softmax if not otherwise stated and R_1 was added to the lower level as a regularizer. For RoBERTa base/large, we kept our experimental settings the same as LoRA. For DeBERTa-v3-base, we kept our experimental settings close to AdaLoRA while maintaining a lower parameter budget. We also kept hyperparameters such as sequence length, total batch size, LoRA rank, and LoRA alpha exactly the same as LoRA/AdaLoRA where necessary. These experimental settings allow for a fair comparison with all baseline methods. Please see the Appendix for all the hyperparameter settings.

Main Results. The same as LoRA, we report the overall (matched and mismatched) accuracy for MNLI, Matthew's correlation for CoLA, Pearson correlation for STS-B, and accuracy for the other tasks. Table 1 shows the results of RoBERTa base/large on the GLUE development set. As can be seen, our method outperforms LoRA on all datasets with the same number of trainable parameters. On most datasets, our method achieves better or on par performance compared with baselines. The average score of BiLoRA notably outperforms all the baselines. Table 2 shows the results of DeBERTa-v3-base on the GLUE development set. BiLoRA outperforms all baselines with equal or less trainable parameters. The improvements achieved by our method over baselines are attributed to its bi-level learning mechanism which separates the training of pseudo singular vectors and values on two distinct datasets. As a result, it effectively alleviates the risk of overfitting to one dataset and yields better generalization performance. In contrast, baseline methods train all parameters on the same dataset and thus lead to overfitting to this dataset. This is particularly evidenced by the observation that on smaller datasets such as CoLA, RTE, and MRPC where overfitting is more likely to occur, BiLoRA outperforms baselines by a larger margin.

4.3 Natural Language Generation

For natural language generation (NLG) tasks, we followed the setup of Prefix-Tuning (Li & Liang, 2021) and LoRA (Hu et al., 2021) on GPT-2 for a direct comparison with LoRA and other adaptation methods. We evaluated GPT-2 medium and large on the E2E NLG Challenge. Please see Appendix A for more details on the models and datasets we used.

Implementation Details. Our implementation is based on the fine-tuning code for GPT-2 in Huggingface and Betty (Choe et al., 2022). Specifically, we load GPT-2 models with the code of Huggingface and build our bi-level optimization framework with Betty.

Experimental Settings. In our method, the training set and validation set are used as the lower-level and upper-level datasets respectively, and we report performance on the test set. Singular values were parameterized as Softmax if not otherwise stated. We kept our experimental settings the same as LoRA. Specifically, we kept hyperparameters such as sequence length, batch size, LoRA rank, LoRA alpha, and label smoothing exactly the same as LoRA. These experimental settings allow for a fair comparison with LoRA and other adaptation methods.

Main Results. Table 3 shows the results of GPT-2 medium/large on the E2E test set. Our method outperforms LoRA and other methods on all metrics for both GPT-2 M and GPT-2 L. The results demonstrate the effectiveness of our method in Natural Language Generation (NLG) downstream tasks and the generalization capabilities of our method across different models and task types.

4.4 Analysis

Scaling Up to DeBERTa-XXL. We use DeBERTa-v2-xxlarge(1.5B) to evaluate the scaling-up performance of our method. The study was performed on three datasets of the GLUE benchmark due to the constraint of computational resources for keeping the same experimental settings with LoRA. Results in Table 4 show that BiLoRA achieves better or on par performance compared with LoRA and full fine-tuning (FT), indicating that BiLoRA yields better generalization when applied to fine-tuning models with a very large number of parameters.

Table 4: Experiment results for scaling up to DeBERTa-XXL (D_{v2}). In BiLoRA, the values of hyperparameters including LoRA rank, LoRA alpha, and max length are the same as those in LoRA. * indicates numbers published in prior works.

Method	params	MNLI	MRPC	CoLA	Avg.
D_{v2}(FT)*	1500.0M	91.8	92.0	72.0	85.3
D_{v2}(LoRA)*	4.7M	**91.9**$_{\pm.2}$	92.6$_{\pm.6}$	72.4$_{\pm1.1}$	85.6
D_{v2}(BiLoRA)	4.7M	**91.9**$_{\pm.3}$	**92.7**$_{\pm.4}$	**73.0**$_{\pm.4}$	**85.9**

Ablation Studies on Pseudo Singular Values. In Section 3.1, we introduced three ways to parameterize the pseudo singular values: Real Value, Softmax, and Approximately Binary. We conduct experiments separately using these three parameterization methods while keeping other experimental settings the same. We test RoBERTa's performance on the GLUE dataset. Results in Table 5 show that the Softmax parameterization exhibits the best performance, with Approximately Binary coming in a close second. Softmax and Approximately Binary outperform Real Value because they yield positive values which meet the constraint that singular values need to be non-negative while Real Value does not. Approximately Binary performs slightly worse than Softmax since it imposes a stronger constraint that the values need to be close to zero or one. Such a constraint limits the expressivity of the parameterization. Another observation is that under all the three parameterization methods, BiLoRA outperforms LoRA, demonstrating that BiLoRA is robust against different ways of representing the pseudo singular values and thus does not require extensive tuning for selecting the best parameterization.

Table 5: Experiment results on three different parameterizations of pseudo singular values: Real Value, Softmax, and Approximately Binary.

Method	MNLI	SST-2	MRPC	CoLA	QNLI	QQP	RTE	STS-B	Avg.
R_b(LoRA)	87.5	**95.1**	89.7	63.4	**93.3**	90.8	86.6	91.5	87.2
R_b(Real Value)	87.5	94.6	91.7	63.6	93.0	90.8	86.6	91.3	87.4
R_b(Softmax)	**87.9**	**95.1**	**91.7**	**64.8**	**93.3**	**91.4**	**87.2**	**91.7**	**87.9**
R_b(Binary)	87.6	94.8	91.4	64.4	93.0	91.2	86.6	91.5	87.6

Ablation Study on Orthogonality-Promoting Regularization. We investigated how the tradeoff parameter γ_1 associated with the orthogonality-promoting regularizer R_1 in Eq.(1) affects the performance of our method. The study was performed on RoBERTa-base. Results in Table 6 show that our method is robust against different values of γ_1, which implies that using our method does not need to extensively tune this hyperparameter.

Table 6: Experiment results of RoBERTa$_{\text{base}}$ (R$_\text{b}$) on GLUE, under different values of γ_1.

Method	MNLI	SST-2	MRPC	CoLA	QNLI	QQP	RTE	STS-B	Avg.
R$_\text{b}$($\gamma_1 = 0.0$)	87.8	95.0	91.7	**64.8**	93.1	**91.5**	87.2	**91.7**	**87.9**
R$_\text{b}$($\gamma_1 = 0.1$)	**87.9**	**95.1**	91.7	**64.8**	**93.3**	91.4	87.2	**91.7**	**87.9**
R$_\text{b}$($\gamma_1 = 0.2$)	87.8	95.0	**91.9**	64.4	93.1	91.2	86.9	91.5	87.7
R$_\text{b}$($\gamma_1 = 0.3$)	87.2	94.6	91.4	63.6	92.8	90.9	**87.4**	91.2	87.4

Computation Costs. Table 7 shows the training time of LoRA and our method. The total training time of our method on the eight datasets is lower than that of LoRA. This arises from the fact that BiLoRA converges with much fewer training epochs than LoRA. In the Softmax parameterization of pseudo singular values, each value is initialized with a mean equal to $1/r$, larger than that in Real-Value, which increases the overall magnitude of ΔW and allows a larger learning rate for the training process. The bi-level optimization framework effectively accommodates this larger learning rate by iteratively optimizing between the two levels without affecting the training stability. With such a large learning rate, even though bi-level optimization takes longer time for each training step, it takes much fewer training steps for training low-rank adapters compared to LoRA, thus reducing the total training time.

Table 7: Training time (minutes) of LoRA and BiLoRA on RoBERTa$_{\text{base/large}}$ (R$_{\text{b/l}}$) and the GLUE benchmark.

Method	MNLI	SST-2	MRPC	CoLA	QNLI	QQP	RTE	STS-B	Total.
R$_\text{b}$(LoRA)	3190.7	1096.2	**30.2**	**193.0**	709.8	2464.3	**55.5**	**62.4**	7802.1
R$_\text{b}$(BiLoRA)	**1407.1**	**260.1**	240.3	260.3	**375.2**	**1732.6**	97.5	158.3	**4531.4**
R$_\text{l}$(LoRA)	789.7	**133.9**	**14.7**	**34.1**	209.1	1446.7	10.0	**23.1**	2661.3
R$_\text{l}$(BiLoRA)	**707.5**	160.8	19.2	62.5	**200.4**	**1166.7**	**4.4**	43.3	**2363.8**

The results in Table 1 and 4 jointly demonstrate that BiLoRA enhances training performance while reducing the overall training time. These results substantiate the effectiveness of our method.

5 Conclusion and Future Work

We propose BiLoRA, a novel and general bi-level optimization framework for further enhancing the performance of low-rank adapters through addressing the overfitting issue in LoRA and its variants. By utilizing the SVD parameterization form of low-rank incremental matrices, our method separately trains pseudo singular vectors and singular values on different datasets in two different optimization levels. Such a method effectively alleviates overfitting and enhances the performance of low-rank incremental matrices while reducing the total training time. Results of extensive experiments on various NLU and NLG tasks and different large pre-trained models show that our method achieves notable performance improvements over existing adaptation methods.

Our method opens up several potential directions for future research: 1) The parameterization form of pseudo singular values can be further developed to support automated rank selection. 2) Our bi-level optimization framework enhances the generalization capability of fine-tuned models, which encourages further in-depth theoretical analysis in this regard.

REFERENCES

Armen Aghajanyan, Luke Zettlemoyer, and Sonal Gupta. Intrinsic dimensionality explains the effectiveness of language model fine-tuning. *arXiv preprint arXiv:2012.13255*, 2020.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.

Daniel Cer, Mona Diab, Eneko Agirre, Inigo Lopez-Gazpio, and Lucia Specia. Semeval-2017 task 1: Semantic textual similarity-multilingual and cross-lingual focused evaluation. *arXiv preprint arXiv:1708.00055*, 2017.

Sang Keun Choe, Willie Neiswanger, Pengtao Xie, and Eric Xing. Betty: An automatic differentiation library for multilevel optimization. *arXiv preprint arXiv:2207.02849*, 2022.

Hua Cui and Jie Bai. A new hyperparameters optimization method for convolutional neural networks. *Pattern Recognition Letters*, 125:828–834, 2019.

Tim Dettmers, Artidoro Pagnoni, Ari Holtzman, and Luke Zettlemoyer. Qlora: Efficient finetuning of quantized llms. *arXiv preprint arXiv:2305.14314*, 2023.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.

Ning Ding, Yujia Qin, Guang Yang, Fuchao Wei, Zonghan Yang, Yusheng Su, Shengding Hu, Yulin Chen, Chi-Min Chan, Weize Chen, et al. Parameter-efficient fine-tuning of large-scale pre-trained language models. *Nature Machine Intelligence*, 5(3):220–235, 2023.

Bill Dolan and Chris Brockett. Automatically constructing a corpus of sentential paraphrases. In *Third International Workshop on Paraphrasing (IWP2005)*, 2005.

Chelsea Finn, Pieter Abbeel, and Sergey Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In *International conference on machine learning*, pp. 1126–1135. PMLR, 2017.

Luca Franceschi, Michele Donini, Paolo Frasconi, and Massimiliano Pontil. Forward and reverse gradient-based hyperparameter optimization. In *International Conference on Machine Learning*, pp. 1165–1173. PMLR, 2017.

Pengcheng He, Xiaodong Liu, Jianfeng Gao, and Weizhu Chen. Deberta: Decoding-enhanced bert with disentangled attention. *arXiv preprint arXiv:2006.03654*, 2020.

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

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

Chengsong Huang, Qian Liu, Bill Yuchen Lin, Tianyu Pang, Chao Du, and Min Lin. Lorahub: Efficient cross-task generalization via dynamic lora composition. *arXiv preprint arXiv:2307.13269*, 2023.

Rabeeh Karimi Mahabadi, James Henderson, and Sebastian Ruder. Compacter: Efficient low-rank hypercomplex adapter layers. *Advances in Neural Information Processing Systems*, 34:1022–1035, 2021.

Chunyuan Li, Heerad Farkhoor, Rosanne Liu, and Jason Yosinski. Measuring the intrinsic dimension of objective landscapes. *arXiv preprint arXiv:1804.08838*, 2018.

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

Zhaojiang Lin, Andrea Madotto, and Pascale Fung. Exploring versatile generative language model via parameter-efficient transfer learning. *arXiv preprint arXiv:2004.03829*, 2020.

Hanxiao Liu, Karen Simonyan, and Yiming Yang. Darts: Differentiable architecture search. *arXiv preprint arXiv:1806.09055*, 2018.

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

Jonathan Lorraine, Paul Vicol, and David Duvenaud. Optimizing millions of hyperparameters by implicit differentiation. In *International conference on artificial intelligence and statistics*, pp. 1540–1552. PMLR, 2020.

Yuning Mao, Lambert Mathias, Rui Hou, Amjad Almahairi, Hao Ma, Jiawei Han, Wen-tau Yih, and Madian Khabsa. Unipelt: A unified framework for parameter-efficient language model tuning. *arXiv preprint arXiv:2110.07577*, 2021.

Jekaterina Novikova, Ondřej Dušek, and Verena Rieser. The e2e dataset: New challenges for end-to-end generation. *arXiv preprint arXiv:1706.09254*, 2017.

Barak A Pearlmutter and Jeffrey Mark Siskind. Reverse-mode ad in a functional framework: Lambda the ultimate backpropagator. *ACM Transactions on Programming Languages and Systems (TOPLAS)*, 30(2):1–36, 2008.

Jonas Pfeiffer, Aishwarya Kamath, Andreas Rücklé, Kyunghyun Cho, and Iryna Gurevych. Adapterfusion: Non-destructive task composition for transfer learning. *arXiv preprint arXiv:2005.00247*, 2020.

Xipeng Qiu, Tianxiang Sun, Yige Xu, Yunfan Shao, Ning Dai, and Xuanjing Huang. Pre-trained models for natural language processing: A survey. *Science China Technological Sciences*, 63(10): 1872–1897, 2020.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9, 2019.

Aravind Rajeswaran, Chelsea Finn, Sham M Kakade, and Sergey Levine. Meta-learning with implicit gradients. *Advances in neural information processing systems*, 32, 2019.

Aravind Rajeswaran, Igor Mordatch, and Vikash Kumar. A game theoretic framework for model based reinforcement learning. In *International conference on machine learning*, pp. 7953–7963. PMLR, 2020.

Pranav Rajpurkar, Robin Jia, and Percy Liang. Know what you don't know: Unanswerable questions for squad. *arXiv preprint arXiv:1806.03822*, 2018.

Sylvestre-Alvise Rebuffi, Hakan Bilen, and Andrea Vedaldi. Learning multiple visual domains with residual adapters. *Advances in neural information processing systems*, 30, 2017.

Andreas Rücklé, Gregor Geigle, Max Glockner, Tilman Beck, Jonas Pfeiffer, Nils Reimers, and Iryna Gurevych. Adapterdrop: On the efficiency of adapters in transformers. *arXiv preprint arXiv:2010.11918*, 2020.

Ankur Sinha, Pekka Malo, and Kalyanmoy Deb. A review on bilevel optimization: From classical to evolutionary approaches and applications. *IEEE Transactions on Evolutionary Computation*, 22(2):276–295, 2017.

Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Christopher D Manning, Andrew Y Ng, and Christopher Potts. Recursive deep models for semantic compositionality over a sentiment treebank. In *Proceedings of the 2013 conference on empirical methods in natural language processing*, pp. 1631–1642, 2013.

Mojtaba Valipour, Mehdi Rezagholizadeh, Ivan Kobyzev, and Ali Ghodsi. Dylora: Parameter efficient tuning of pre-trained models using dynamic search-free low-rank adaptation. *arXiv preprint arXiv:2210.07558*, 2022.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R Bowman. Glue: A multi-task benchmark and analysis platform for natural language understanding. *arXiv preprint arXiv:1804.07461*, 2018.

Alex Warstadt, Amanpreet Singh, and Samuel R Bowman. Neural network acceptability judgments. *Transactions of the Association for Computational Linguistics*, 7:625–641, 2019.

Adina Williams, Nikita Nangia, and Samuel R Bowman. A broad-coverage challenge corpus for sentence understanding through inference. *arXiv preprint arXiv:1704.05426*, 2017.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, et al. Huggingface's transformers: State-of-the-art natural language processing. *arXiv preprint arXiv:1910.03771*, 2019.

Elad Ben Zaken, Shauli Ravfogel, and Yoav Goldberg. Bitfit: Simple parameter-efficient fine-tuning for transformer-based masked language-models. *arXiv preprint arXiv:2106.10199*, 2021.

Miao Zhang, Steven W Su, Shirui Pan, Xiaojun Chang, Ehsan M Abbasnejad, and Reza Haffari. idarts: Differentiable architecture search with stochastic implicit gradients. In *International Conference on Machine Learning*, pp. 12557–12566. PMLR, 2021.

Qingru Zhang, Minshuo Chen, Alexander Bukharin, Pengcheng He, Yu Cheng, Weizhu Chen, and Tuo Zhao. Adaptive budget allocation for parameter-efficient fine-tuning. *arXiv preprint arXiv:2303.10512*, 2023.

A Datasets and Models

A.1 Natural Language Understanding

GLUE Benchmark comprises a diverse array of natural language understanding tasks widely employed for evaluation. It encompasses two single-sentence classification tasks, three tasks assessing similarity and paraphrasing, and four tasks focusing on natural language inference. Specifically, it includes MNLI (MultiNLI, Williams et al. (2017)), SST-2 (Stanford Sentiment Treebank, Socher et al. (2013)), MRPC (Microsoft Research Paraphrase Corpus, Dolan & Brockett (2005)), CoLA (Corpus of Linguistic Acceptability, Warstadt et al. (2019)), QNLI (Question NLI, Rajpurkar et al. (2018)), QQP (Quora Question Pairs), RTE (Recognizing Textual Entailment), and STS-B (Semantic Textual Similarity Benchmark, Cer et al. (2017)). We summarized the statistical data for all datasets within the GLUE Benchmark in the table below:

Table 8: The statistical data for all datasets within the GLUE Benchmark

Dataset	Metrics	Train	Dev	Test	Label	Task
MNLI	Accuracy	393k	20k	20k	3	NLI
SST-2	Accuracy	67k	872	1.8k	2	Sentiment
MRPC	Accuracy	3.7k	408	1.7k	2	Paraphrase
CoLA	Matthews corr	8.5k	1k	1k	2	Acceptability
QNLI	Accuracy	108k	5.7k	5.7k	2	QA/NLI
QQP	Accuracy	364k	40k	391k	2	Paraphrase
RTE	Accuracy	2.5k	276	3k	2	NLI
STSB	Pearson corr	7.0k	1.5k	1.4k	1	Similarity

A.2 Natural Language Generation

E2E NLG Challenge (Novikova et al., 2017) is now commonly used for data-to-text evaluation. It was first introduced as a dataset for training end-to-end, data-driven natural language generation systems. Multiple references can be associated with each source table used as input. Each sample input (x, y) is composed of a series of slot-value pairs, accompanied by an associated natural language reference text. The E2E dataset consists of approximately 42,000 training examples, 4,600 validation examples, and 4,600 test examples from the restaurant domain.

A.3 Models

RoBERTa (Liu et al., 2019) builds upon the foundational principles and training strategies of BERT (Devlin et al., 2018), offering novel alternatives that enhance downstream task performance. RoBERTa refines and optimizes the pre-training methodology initially proposed in BERT, resulting in notable improvements in task performance while maintaining a comparable number of trainable parameters. We use RoBERTa-base and RoBERTa-large for a convenient and fair comparison with LoRA (Hu et al., 2021).

DeBERTa (He et al., 2020) represents an advanced iteration of BERT, having undergone extensive training at a larger scale. DeBERTa demonstrates strong competitiveness when evaluated on the GLUE benchmark. For our experiments, we use DeBERTa-v2-xxlarge which has 1.5 billions of parameters to evaluate the scaling-up capability of BiLoRA and also for a convenient comparison with LoRA. We use DeBERTa-v3-base which has 183 millions parameters for fair comparison with AdaLoRA (Zhang et al., 2023).

GPT-2 (Radford et al., 2019) developed by OpenAI, was once a state-of-the-art language model renowned for its remarkable text generation capabilities. It is a scaled-up version of its predecessor, GPT-1, and is trained on an extensive corpus of text data. GPT-2 has been widely recognized for its proficiency in generating coherent and contextually relevant text across various natural language understanding and generation tasks, showcasing its versatility and potential in the field of natural language processing.

B EXPERIMENTAL SETTINGS

B.1 ROBERTA

We summarized the experimental settings for the experiments of RoBERTa-base and RoBERTa-large in Table9. In fact, we only introduced an additional level of learning rate compared to LoRA. For hyperparameters such as max seq length, LoRA α, we kept them the same as LoRA. We chose learning rates from the magnitude of 1e-5 for almost all of our experiments. The hyperparameter tuning for our method is quite simple, convenient and straightforward.

Table 9: The hyperparameters we used for RoBERTa on the GLUE benchmark. $*$ indicates model already adapted to MNLI when adapting to MRPC, RTE, and STS-B, while † indicates model started as pre-trained when adapting to all datasets.

Method	Settings	MNLI	SST-2	MRPC	CoLA	QNLI	QQP	RTE	STS-B
	Optimizer	AdamW							
	Warmup Ratio	0.06							
	Scheduler	Linear							
	LoRA rank	$rank_q = rank_v = 8$							
RoBERTa-base*	Total batch size	64							
	Global steps	10k	3k	2k	3k	3k	15k	1.5k	5k
	Lower learning rate	2e-5	3e-5	2e-6	2e-5	3e-5	3e-5	4e-6	4e-6
	Upper learning rate	3e-5	4e-5	8e-6	4e-5	4e-5	4e-5	2e-6	2e-6
	Lower weight decay	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.1
	Upper weight decay	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
	Max Seq Length	512							
RoBERTa-large*	Total batch size	32							
	Global steps	15k	4k	1k	3k	3k	20k	0.12k	2k
	Lower learning rate	1.5e-5	1.5e-5	4e-6	1e-5	1e-5	1e-5	4e-6	1e-5
	Upper learning rate	2e-5	2e-5	6e-6	5e-5	3e-5	2e-5	4e-6	5e-6
	Lower weight decay	0.12	0.12	0.12	0.12	0.12	0.12	0.1	0.1
	Upper weight decay	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
	Max Seq Length	128							
RoBERTa-large†	Total batch size	32							
	Global steps	15k	4k	1k	3k	3k	20k	2k	2k
	Lower learning rate	1.5e-5	1.5e-5	2e-5	1e-5	1e-5	1e-5	1e-5	8e-6
	Upper learning rate	2e-5	2e-5	1e-4	5e-5	3e-5	2e-5	2e-5	4e-6
	Lower weight decay	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.1
	Upper weight decay	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
	Max Seq Length	128							

B.2 DEBERTA

We summarized the experimental settings used in the experiments for DeBERTa-v2-xxlarge and DeBERTa-v3-base in Table10. In fact, we only introduced an additional level of learning rate compared to LoRA. For hyperparameters such as max seq length, LoRA α, we kept them the same as LoRA and AdaLoRA. We chose learning rates from the magnitude of 1e-5 for almost all of our experiments. The hyperparameter tuning for our method is quite simple, convenient and straightforward. Due to our limited computational resources, we were unable to maintain the same experimental settings as LoRA on many datasets, making a fair comparison impossible. Therefore, for DoBERTa-v2-xxlarge, we only conducted experiments on the MNLI, CoLA, and MRPC datasets.

Table 10: The hyperparameters we used for DeBERTa-v2-xxlarge and DeBERTa-v3-base on the GLUE benchmark.

Method	Settings	MNLI	SST-2	MRPC	CoLA	QNLI	QQP	RTE	STS-B
	Optimizer	AdamW							
	Scheduler	Linear							
	LoRA rank	$rank_q = rank_v = 8$							
DeBERTa-v2-XXL	Total batch size	64		32	32				
	Global steps	20k		1k	3k				
	Inner learning rate	0.5e-5		2e-6	1e-5				
	Outer learning rate	1e-5		2e-6	1e-5				
	LoRA α	16		16	16				
	Max Seq Length	128		128	64				
DeBERTa-v3-base	Total batch size	32							
	Global steps	15k	3k	1k	1k	2k	20k	0.5k	1k
	Lower learning rate	1e-5	1.5e-5	2e-6	1e-5	1e-5	1e-5	4e-6	4e-6
	Upper learning rate	2e-5	2.5e-5	4e-6	2e-4	2e-5	2e-5	4e-6	4e-6
	Lower weight decay	0.12	0.12	0.15	0.12	0.12	0.12	0.12	0.12
	Upper weight decay	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
	LoRA α	16							
	Max Seq Length	256	128	320	64	512	320	320	128

B.3 GPT-2

We summarized the experimental settings for the experiments of GPT-2 M and L in Table11. We kept hyperparameters almost the same as LoRA for a fair comparison.

Table 11: The hyperparameters we used for GPT-2 on the E2E NLG benchmark.

Settings	Training
Optimizer	AdamW
Warmup Steps	500
Scheduler	Linear
LoRA rank	$rank_q = rank_v = 4$
LoRA α	32
Label Smooth	0.1
Weight Decay	0.01
Batch Size	8
Settings	**Inference**
Beam Size	10
Length Penalty	0.9
no repeat ngram size	4

C MOTIVATION

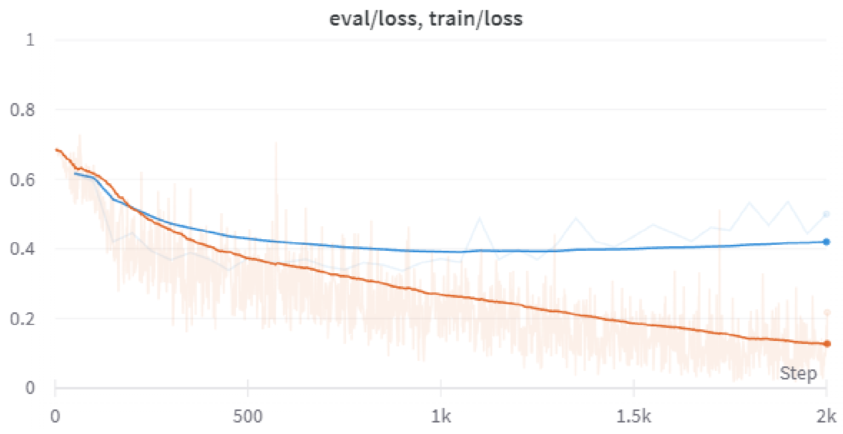
Figure 2.

D PRUNING RATES AND WEIGHT DECAY IN ADALORA

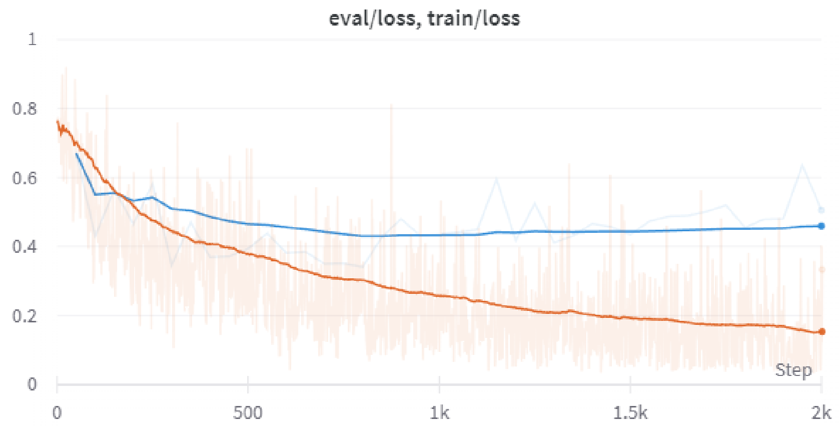
Figure 3 and Figure 4.

E THE DISTRIBUTION OF THE SINGULAR VALUES

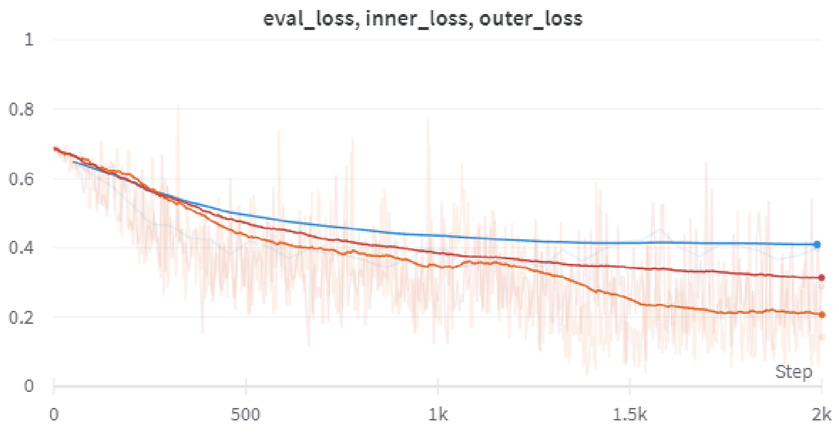
Figure 5.



(a) LoRA

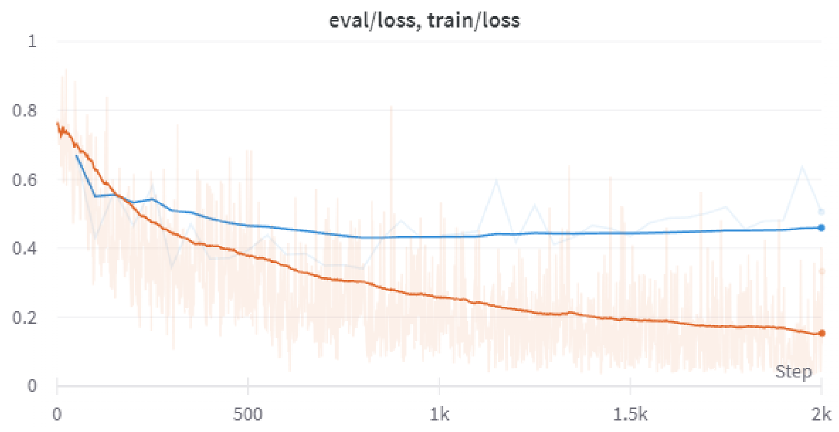


(b) AdaLoRA

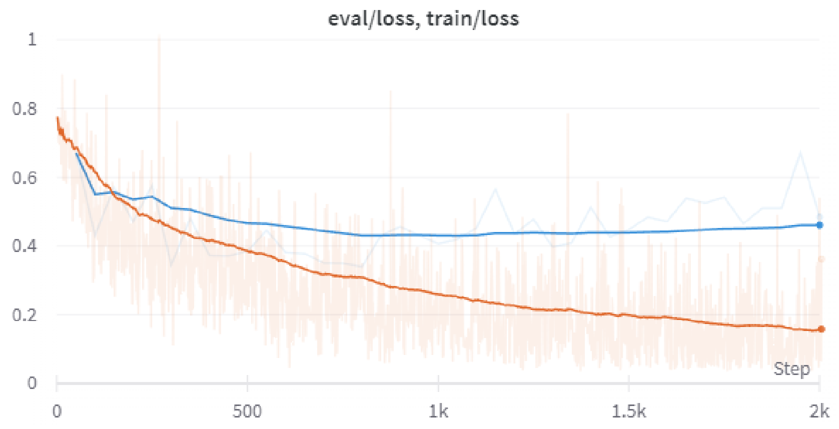


(c) BiLoRA

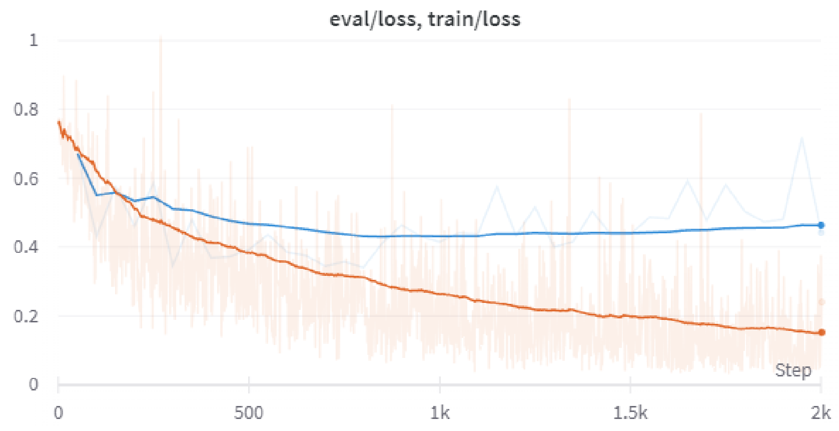
Figure 2: Training/Evaluation Loss Curves for illustrating of the overfitting limitations of existing methods. Blue curves represent evaluation losses. In LoRA and AdaLoRA, yellow curves represent training losses while in BiLoRA yellow/red curves separately represent inner/outer losses.



(a) AdaLoRA 0.00

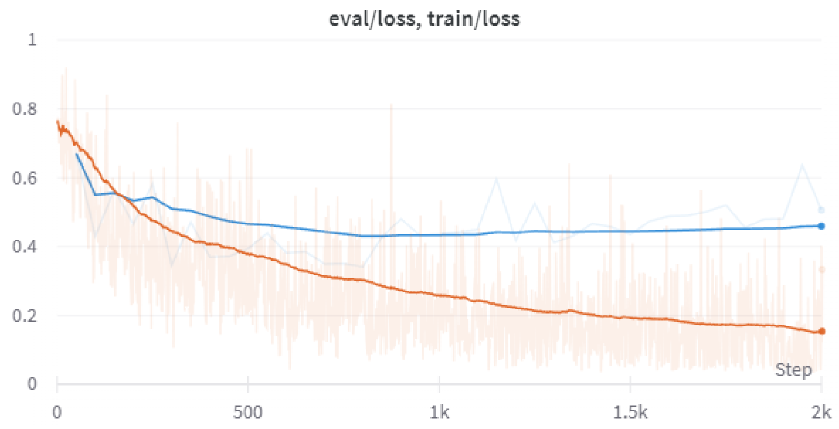


(b) AdaLoRA 0.02

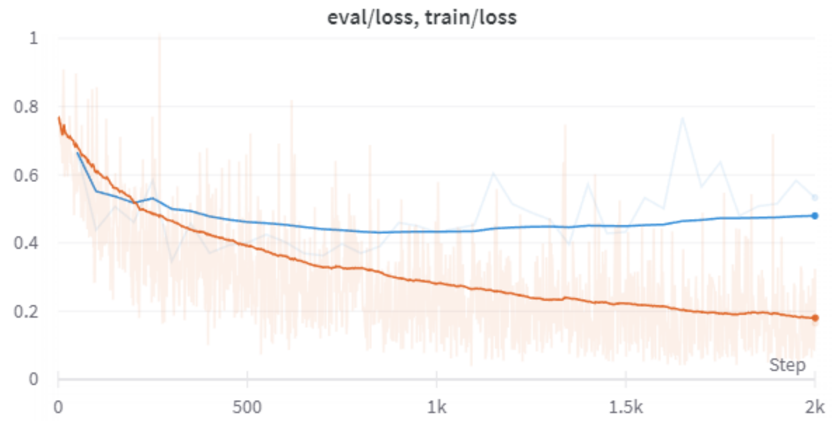


(c) AdaLoRA 0.05

Figure 3: Training/Evaluation Loss Curves for illustrating of the influence of different weight decays in AdaLoRA. Blue curves represent evaluation losses and yellow curves represent training losses.

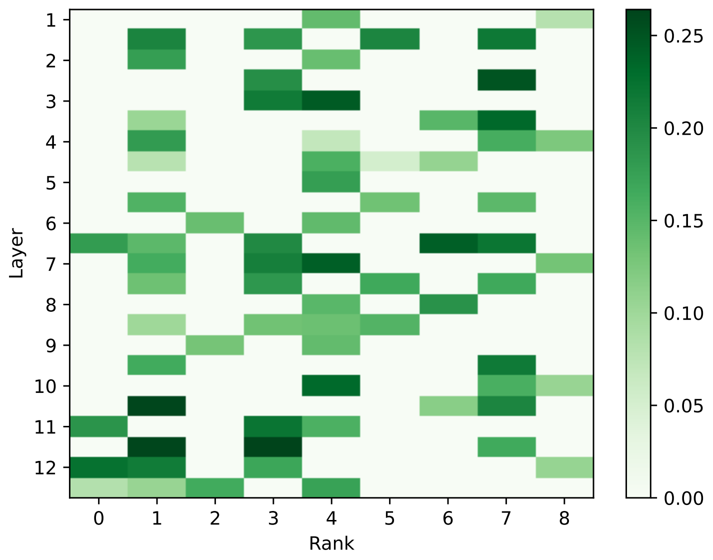


(a) AdaLoRA 6kinds

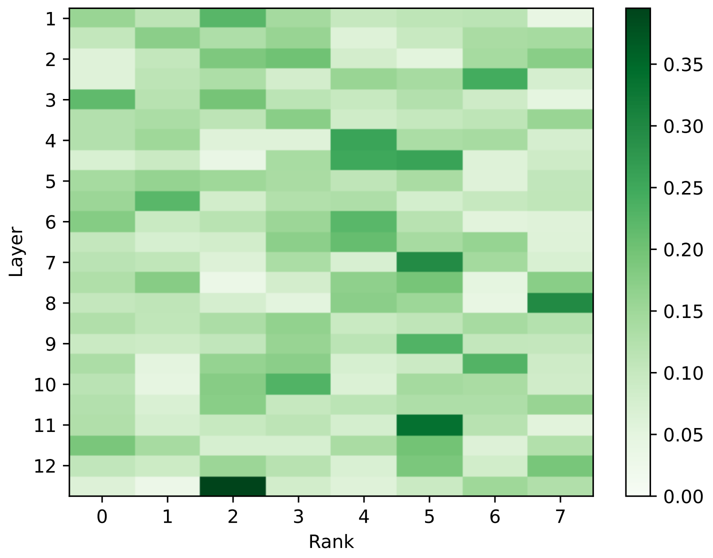


(b) AdaLoRA 4kinds

Figure 4: Training/Evaluation Loss Curves for illustrating of the influence of different pruning rates in AdaLoRA. Blue curves represent evaluation losses and yellow curves represent training losses.



(a) AdaLoRA Singular Value Distribution



(b) BiLoRA Singular Value Distribution

Figure 5: Singular Value Distribution of BiLoRA and AdaLoRA.

F THE ORTHOGONALITY OF OPTIMAL SOLUTIONS

Figure 6 and Figure 7.

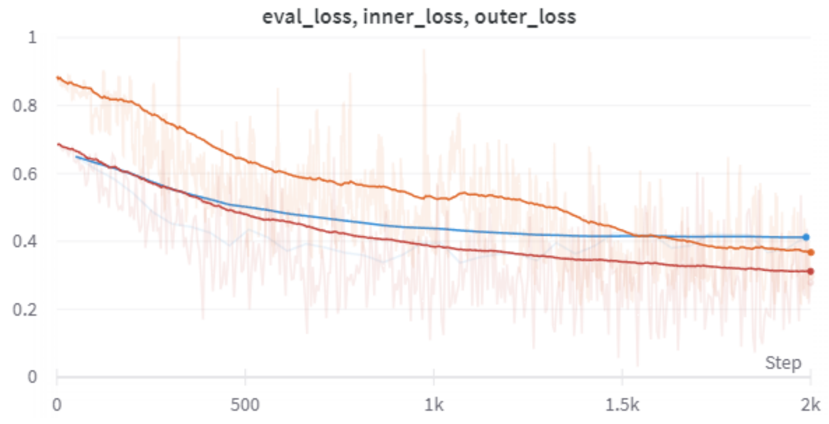
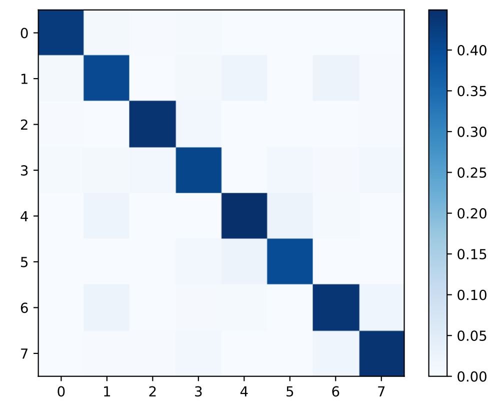
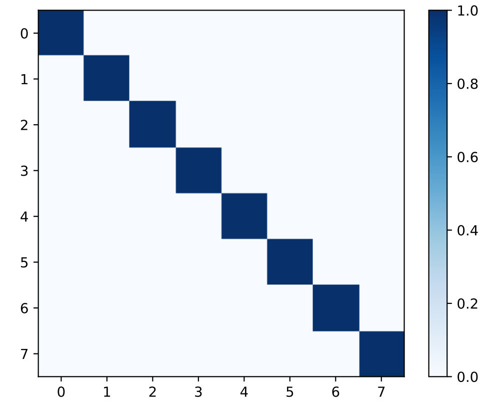


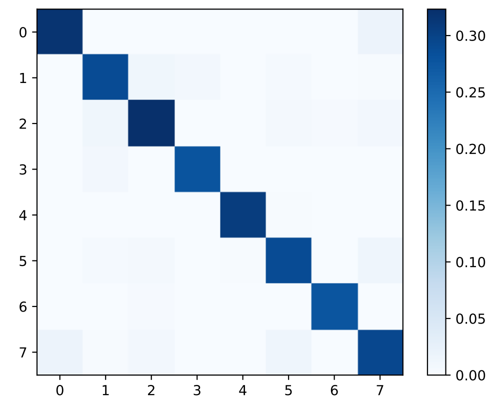
Figure 7: Loss Curve with $\lambda = 0.1$



(a) BiLoRA Without Regularization



(b) BiLoRA With $\lambda = 0.1$



(c) Initialization

Figure 6: The orthogonality of optimal solutions.