AdaMSS: Adaptive Multi-Subspace Approach for Parameter-Efficient Fine-Tuning

Anonymous Author(s)
Affiliation
Address
email

Abstract

In this paper, we propose AdaMSS, an adaptive multi-subspace approach for parameter-efficient fine-tuning of large models. Unlike traditional parameter-efficient fine-tuning methods that operate within a large single subspace of the network weights, AdaMSS leverages subspace segmentation to obtain multiple smaller subspaces and adaptively reduces the number of trainable parameters during training, ultimately updating only those associated with a small subset of subspaces most relevant to the target downstream task. By using the lowest-rank representation, AdaMSS achieves more compact expressiveness and finer tuning of the model parameters. Theoretical analyses demonstrate that AdaMSS has better generalization guarantee than LoRA, PiSSA, and other single-subspace low-rank-based methods. Extensive experiments across image classification, natural language understanding, and natural language generation tasks show that AdaMSS achieves comparable performance to full fine-tuning and outperforms other parameter-efficient fine-tuning methods in most cases, all while requiring fewer trainable parameters. Notably, on the `ViT-Large` model, AdaMSS achieves 4.7% higher average accuracy than LoRA across seven tasks, using just 15.4% of the trainable parameters. On `RoBERTa-Large`, AdaMSS outperforms PiSSA by 7% in average accuracy across six tasks while reducing the number of trainable parameters by approximately 94.4%. These results demonstrate the effectiveness of AdaMSS in parameter-efficient fine-tuning.

1 Introduction

With the successful application of large pre-trained models in natural language processing and computer vision, the parameter-efficient fine-tuning (PEFT) methods have gradually become key strategies for efficiently adapting these models. Among these PEFT methods, LoRA (Low-Rank Adaptation) [1] has gained particular attention, as it adopts learnable low-rank structures to represent weight changes, significantly reducing memory requirements. Following LoRA, numerous low-rank adaptation methods have since been developed [2, 3, 4, 5, 6, 7, 8, 9, 10, 11].

Despite sharing the common goal of PEFT, these methods primarily differ in how they impose low-rank assumptions. For instance, LoRA [1] and AdaLoRA [3] assume that weight changes $\Delta \boldsymbol{W} \in \mathbb{R}^{n\times n}$ are low-rank and represent them using the product of two smaller matrices, $\boldsymbol{A} \in \mathbb{R}^{n\times r}$ and $\boldsymbol{B} \in \mathbb{R}^{r\times n}$, where $r \ll n$. Alternatively, PiSSA [2] assumes that the original weight matrix $\boldsymbol{W}$ is approximately low-rank and achieves efficient fine-tuning by training its principal components. A further line of research is represented by methods such as LoRA-GA [5], which hypothesize that the gradient of the loss function with respect to the weights—*i.e.*, $\nabla \mathcal{L}(\boldsymbol{W})$—exhibits low-rank structure.

These approaches are typical single-subspace methods, as they rely on the assumption that weight changes, weights, or gradients lie in, or approximately lie in, a single low-dimensional subspace.

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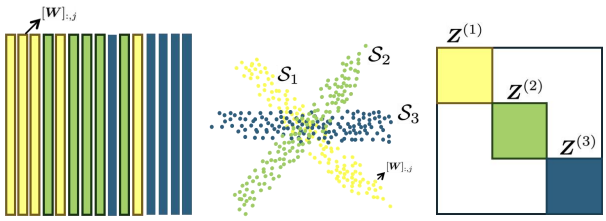


(a) (b) (c)

Figure 1: (a) Weight matrix $\boldsymbol{W}$; (b) Multi-subspaces structure of the columns of $\boldsymbol{W}$ (*i.e.*, $[\boldsymbol{W}]_{:,j}$); (c) The lowest-rank representation of $\boldsymbol{W}$, where each block $\boldsymbol{Z}^{(k)}$ serves as a new representation for the columns lying in the subspace $\mathcal{S}_k$.

However, this assumption inevitably leads to a fundamental trade-off between limited expressiveness and parameter efficiency: approximating the weights with a single low-dimensional subspace with a small r limits the model's capacity for adaptation, while increasing the subspace dimension r improves expressiveness but results in a substantial rise in the number of trainable parameters and memory usage.

To address the dilemma between limited expressiveness and parameter efficiency, we propose an **Ada**ptive **M**ulti-**S**ub**s**pace approach (AdaMSS) that enables finer tuning of model parameters and has stronger expressiveness. As we will illustrate in this work, the columns of the weight matrix are approximately distributed across multiple linear subspaces (Figure 1 (a)-(b) provides a conceptual illustration of multi-subspaces structure of the network weights).

The key features of this work are summarized as follows:

- **Compact Expressiveness**: By leveraging the observation that the network weights are approximately located in multiple subspaces, AdaMSS uses a lowest-rank representation for the network weights, which exhibit an approximate block-diagonal structure (see Figure 1 (c)). This design leads to a more compact representation while preserving both global and local low-rank structure from the original weights (see Property 1), which is essential for ensuring effective adaptation across multiple subspaces.
- **Generalization Guarantee**: We theoretically show that, under the same rank assumption r, the proposed AdaMSS achieves a lower Gaussian complexity bound and is therefore expected to exhibit a stronger generalization capability compared to single-subspace-based methods. Theorem 1 formalizes an upper bound on the expected loss of AdaMSS, providing its generalization guarantee.
- **Multi-Subspace-Based Adaptive Budget Allocation**: Thanks to the multi-subspace structure of the network weights, we can adaptively freeze the parameters associated with subspaces of lower importance, and eventually updates only those associated with a small subset of subspaces relevant to the target downstream task, where the importance of each subspace is evaluated during training.

Experimental results demonstrate the effectiveness of AdaMSS for PEFT across diverse tasks and show that it outperforms existing methods in most cases while significantly reducing the number of trainable parameters. For example, compared with LoRA, AdaMSS achieves 4.7% higher average accuracy on `ViT-Large` [12] and 2.2% higher accuracy on GSM8K [13] with `LLaMA 2-7B` [14], using only 15.35% and 0.28% of the trainable parameters, respectively. On `RoBERTa-Large` [15], AdaMSS achieves comparable performance to LoRA while using just 5.62% of the trainable parameters. These results suggest that multi-subspace-based fine-tuning offers a promising direction for improving the trade-off between expressiveness and parameter efficiency.

2 Preliminaries and Related Works

In this section, we introduce the notations used throughout the paper, and provide preliminaries and a brief review of existing literature relevant to our study. Unless otherwise specified, we use a, $\boldsymbol{a}$, and $\boldsymbol{A}$ to denote scalars, vectors, and matrices, respectively. The transpose of $\boldsymbol{A}$ is denoted by $\boldsymbol{A}^\top$.

We use $[\boldsymbol{A}]_{i,j}$, $[\boldsymbol{A}]_{i,:}$, and $[\boldsymbol{A}]_{:,j}$ to represent the (i,j)-th element, the i-th row vector, and the j-th column vector of $\boldsymbol{A}$, respectively.

2.1 Preliminaries: Low-Rank Representation for Subspace Segmentation

To get the lowest-rank presentation for n given samples [1] $[\boldsymbol{M}]_{:,1}, [\boldsymbol{M}]_{:,2}, \cdots, [\boldsymbol{M}]_{:,n} \in \mathbb{R}^d$, Liu *et al.*proposed the Low-Rank Representation (LRR) model [16] expressed as follows:

$$[\boldsymbol{Z}^\star, \boldsymbol{E}^\star] = \min_{\boldsymbol{Z},\boldsymbol{E}} \operatorname{rank}(\boldsymbol{Z}) + \lambda \|\boldsymbol{E}\|_\diamond \qquad s.t.\ \boldsymbol{M} = \boldsymbol{M}\boldsymbol{Z} + \boldsymbol{E}, \tag{1}$$

where $\boldsymbol{Z}$ is known as the coefficient matrix, $\operatorname{rank}(\boldsymbol{Z})$ denotes the rank of matrix $\boldsymbol{Z} \in \mathbb{R}^{n\times n}$, *i.e.*, the number of singular values of $\boldsymbol{Z}$, $\boldsymbol{M} \in \mathbb{R}^{d\times n}$ represents the matrix composed of the n samples, $\boldsymbol{E}$ represents the residual component (*i.e.*, noise and redundancy in the samples). The norm $\|\cdot\|_\diamond$ is used to quantify the magnitude of the nonzero entries of $\boldsymbol{E}$, and its specific definition depends on the prior knowledge about $\boldsymbol{E}$. The problem (1) can be approximated by a convex formulation and solved iteratively [16], and it is computationally expensive. Fortunately, when $\boldsymbol{E} = \boldsymbol{0}$, problem (1) has a closed-form solution, given by $\boldsymbol{Z}^\star = \boldsymbol{V}\boldsymbol{V}^\top$, where $\boldsymbol{V} \in \mathbb{R}^{n\times \operatorname{rank}(\boldsymbol{M})}$ is obtained through the skinny SVD of $\boldsymbol{M}$, *i.e.*, $\boldsymbol{M} = \boldsymbol{U}\boldsymbol{S}\boldsymbol{V}^\top$.

Assuming the samples $[\boldsymbol{M}]_{:,1}, [\boldsymbol{M}]_{:,2}, \cdots, [\boldsymbol{M}]_{:,n}$ drawn from a union of linear subspaces $\{\mathcal{S}_k\}_{k=1}^K$, where the subspace number K and $\{\mathcal{S}_k\}_{k=1}^K$ are unknown, the goal of subspace segmentation is to simultaneously assign the samples into their respective subspaces. When the subspaces $\{\mathcal{S}_k\}_{k=1}^K$ are independent of each other, samples from different subspaces cannot be expressed as linear combinations of each other. Consequently, $\boldsymbol{Z}^\star$ becomes a block-diagonal matrix. To solve the subspace segmentation problem, Liu *et al.*determine the subspace number K and to obtain the segmentation results based on $\boldsymbol{Z}^\star$ [16]. This LLR-based subspace segmentation method is widely applied in clustering tasks[16, 17, 18, 19].

2.2 Related Works

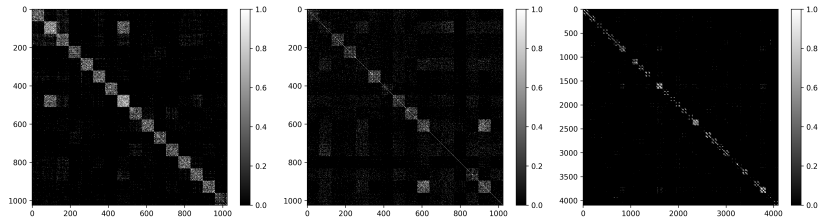
2.2.1 Parameter-Efficient Fine-Tuning (PEFT)

In recent years, a variety of PEFT methods have been proposed to adapt large pre-trained models to downstream tasks while minimizing the number of trainable parameters. Broadly, current PEFT methods include prefix-tuning [20, 21], adapter-based methods [22], sparse fine-tuning [23, 24], orthogonal fine-tuning [25, 26], and low-rank-based adaptation [1, 2, 3, 4, 5, 6, 7, 8, 9]. Specifically, prefix-tuning methods introduce a small task-specific trainable vectors, known as prefixes, while keeping the original model parameters frozen [20, 21]. In contrast, adapter-based methods [22] insert small trainable modules within each layer of the model, allowing efficient task adaptation by updating only these modules. Meanwhile, sparse fine-tuning, such as BitFit [23] and FourierFT [24], update only a small subset of parameters in bias terms or transformed weights. On another front, orthogonal fine-tuning introduces a learnable orthogonal transformation applied to the pre-trained weights, with the goal of preserving the model's original capabilities during adaptation [25, 26]. In addition to the above, low-rank-based adaptation methods, for example LoRA [1], PiSSA [2], LoRA-GA [5], Foura [8], and RoSA [7], approximate weight updates using low-rank matrices, significantly reducing the number of trainable parameters while maintaining performance. These techniques provide effective strategies for adapting large models to new tasks with less computational overhead.

2.2.2 Low-Rank-Based Adaptation Methods

Inspired by the success of LoRA [1], a large number of low-rank-based adaptation methods have emerged over the past three years [2, 3, 4, 5, 6, 7, 8, 9, 10, 11]. LoRA assumes a fixed rank for all incremental matrices across different layers, thereby ignoring the diverse importance of different weight parameters. To address this limitation, AdaLoRA [3] was proposed to allocates parameter budgets by adaptively adjusting the rank during training. Following AdaLoRA, research attention has shifted toward improving the initialization strategies of $\boldsymbol{A}$ and $\boldsymbol{B}$ in LoRA, as opposed to relying on random initialization. Representative works include PiSSA [2] and LoRA-GA[5]. In addition, by incorporating both low-rankness and sparsity constraints, RoSA [7] enhances low-rank adaptation

[1] In this work, the *samples* here does not refer to layer input $\boldsymbol{x}$.



(a) (b) (c)

Figure 2: Illustration of multiple subspaces structure in pretrained network weights: an approximate block-diagonal structure of $\boldsymbol{Z}_0^\star$ from the first layer of the pretrained (a) `ViT-Large` (query), (b) `Roberta-Large` (query), and (c) `LLaMA 2-7B` (query).

to enable more efficient parameter utilization. In another line of work, FouRA [8] extends LoRA into the frequency domain, yielding disentangled feature spaces that enable fine-grained control and editing. Motivated by the success of tensor decomposition in data compression [27], LoTR [11] and LoRETTA [10] leverage Tucker decomposition and Tensor-train decomposition, respectively, to achieve more compact representations of the low-rank update matrices.

3 Multi-Subspace-Based Adaptation

Let $\boldsymbol{W}_0 \in \mathbb{R}^{d\times n}$ denote the pretrained weight matrix of a network layer, where d and n represent the input and output dimensions of the layer, respectively. The full fine-tuning (FF) of the network is formalized as

$$\Delta \boldsymbol{W}^\star = \arg\min_{\Delta \boldsymbol{W}\in\mathbb{R}^{d\times n}} \mathcal{L}(\boldsymbol{W}_0 + \Delta \boldsymbol{W}), \tag{2}$$

where $\mathcal{L}$ denotes the loss function, $\Delta \boldsymbol{W} \in \mathbb{R}^{d\times n}$ is the update on $\boldsymbol{W}_0$, and $\boldsymbol{W} = \boldsymbol{W}_0 + \Delta \boldsymbol{W}$ is the corresponding updated weights. In this section, we aim to find a compact representation of $\boldsymbol{W}_0$ via subspace segmentation [16], which has both low-rank and strictly block-diagonal structure. By doing so, instead of directly updating $\boldsymbol{W}_0$ as FF, we perform incremental updates within this compact representation.

3.1 Motivation: Multi-Subspace Structure of the Network Weights

Motivated by PiSSA [2], we focus on updating the principle components of $\boldsymbol{W}_0$ (denoted as $\hat{\boldsymbol{W}}_0$), and decompose the pretrained weight $\boldsymbol{W}_0$ as $\boldsymbol{W}_0 = \hat{\boldsymbol{W}}_0 + \boldsymbol{W}_{res}$, where $\boldsymbol{W}_{res} := \boldsymbol{W}_0 - [\boldsymbol{U}_0]_{:,1:R}[\boldsymbol{S}_0]_{1:R,1:R}[\boldsymbol{V}_0]_{:,1:R}^\top$ for a given R, and $\hat{\boldsymbol{W}}_0 = [\boldsymbol{U}_0]_{:,1:R}[\boldsymbol{S}_0]_{1:R,1:R}[\boldsymbol{V}_0]_{:,1:R}^\top$ is the truncated SVD of $\boldsymbol{W}_0$. We apply the LRR to obtain a lowest-rank representation of $\hat{\boldsymbol{W}}_0$. Considering computational complexity, we adapt the LRR with $\boldsymbol{E} = \boldsymbol{0}$:

$$\boldsymbol{Z}_0^\star = \arg\min_{\boldsymbol{Z}_0\in\mathbb{R}^{n\times n}} \operatorname{rank}(\boldsymbol{Z}_0) \qquad s.t.\ \hat{\boldsymbol{W}}_0 = \hat{\boldsymbol{W}}_0\boldsymbol{Z}_0. \tag{3}$$

This formulation uses the coefficient matrix $\boldsymbol{Z}_0$ to linearly represent the columns of $\hat{\boldsymbol{W}}_0 \in \mathbb{R}^{d\times n}$. By analyzing $\boldsymbol{Z}_0^\star$, we observe that it exhibits an approximate block-diagonal structure (see Figure 2 for $R = 100$), indicating that the columns of $\hat{\boldsymbol{W}}_0 = \hat{\boldsymbol{W}}_0\boldsymbol{Z}_0^\star$ are grouped into different clusters, where columns within the same cluster are approximately linear combinations of each other. In other words, the row space of $\boldsymbol{W}_0$ can be approximated by multiple smaller low-rank subspaces. By leveraging the approximate block-diagonal structure and low-rank properties of $\boldsymbol{Z}_0^\star$, we drive a more compact representation of $\boldsymbol{W}_0$ than $\hat{\boldsymbol{W}}_0$.

3.2 A Compact Representation By Subspace Segmentation

In the previous subsection, we analyzed the multi-subspace structure of $\boldsymbol{W}_0$ and obtained a compact representation $\boldsymbol{Z}_0^\star$, which exhibits an approximate block-diagonal structure. We now derive a well-organized and strictly block-diagonal representation of $\boldsymbol{W}_0$ by subspace segmentation.

Leveraging subspace segmentation and the multi-subspace structure, the row space of $\boldsymbol{W}_0$ can be approximately segmented into K smaller low-dimensional subspaces. We assume that the columns in $\boldsymbol{W}_0 = [\boldsymbol{W}_0^{(1)}, \boldsymbol{W}_0^{(2)}, \cdots, \boldsymbol{W}_0^{(K)}]$ are well-organized and partitioned based on the segmentation results, where each block $\boldsymbol{W}_0^{(k)} \in \mathbb{R}^{d \times n_k}$ contains the columns assigned to the k-th subspace. Accordingly, $\hat{\boldsymbol{W}}_0$, $\boldsymbol{Z}_0^\star$, and $\boldsymbol{W}_{res}$ are also divided into K blocks, leading to the following decomposition

$$\begin{aligned}
&[\boldsymbol{W}_0^{(1)}, \boldsymbol{W}_0^{(2)}, \cdots, \boldsymbol{W}_0^{(K)}] \\
&= [\hat{\boldsymbol{W}}_0^{(1)}, \hat{\boldsymbol{W}}_0^{(2)}, \cdots, \hat{\boldsymbol{W}}_0^{(K)}]\Big(\operatorname{diag}\Big((\boldsymbol{Z}_0^\star)^{(1)}, (\boldsymbol{Z}_0^\star)^{(2)}, \cdots, (\boldsymbol{Z}_0^\star)^{(K)}\Big) + [\boldsymbol{E}_0^{(1)}, \boldsymbol{E}_0^{(2)}, \cdots, \boldsymbol{E}_0^{(K)}]\Big) \\
&\quad + [\boldsymbol{W}_{res}^{(1)}, \boldsymbol{W}_{res}^{(2)}, \cdots, \boldsymbol{W}_{res}^{(K)}],
\end{aligned} \tag{4}$$

where $\boldsymbol{Z}_0^\star = [[\boldsymbol{Z}_0^\star]^{(1)}, [\boldsymbol{Z}_0^\star]^{(2)}, \cdots, [\boldsymbol{Z}_0^\star]^{(K)}]$ is decomposed into a sum of a strictly block-diagonal matrix $\operatorname{diag}\Big((\boldsymbol{Z}_0^\star)^{(1)}, (\boldsymbol{Z}_0^\star)^{(2)}, \cdots, (\boldsymbol{Z}_0^\star)^{(K)}\Big)$ and a noise matrix $[\boldsymbol{E}_0^{(1)}, \boldsymbol{E}_0^{(2)}, \cdots, \boldsymbol{E}_0^{(K)}]$, and each block $(\boldsymbol{Z}_0^\star)^{(k)} \in \mathbb{R}^{n_k \times n_k}$ is the k-th diagonal block of $\boldsymbol{Z}_0^\star$.

Define $\bar{\boldsymbol{W}}_{res}^{(k)} := \hat{\boldsymbol{W}}_0^{(k)} \boldsymbol{E}_0^{(k)} + \boldsymbol{W}_{res}^{(k)}$, we have

$$\boldsymbol{W}_0^{(k)} = \hat{\boldsymbol{W}}_0^{(k)} (\boldsymbol{Z}_0^\star)^{(k)} + \bar{\boldsymbol{W}}_{res}^{(k)} \tag{5}$$

for each k, where $(\boldsymbol{Z}_0^\star)^{(k)} \in \mathbb{R}^{n_k \times n_k}$ is used to approximately represents $\boldsymbol{W}_0^{(k)}$. We thus obtain

$$\begin{aligned}
[\boldsymbol{W}_0^{(1)}, \boldsymbol{W}_0^{(2)}, \cdots, \boldsymbol{W}_0^{(K)}] = [\hat{\boldsymbol{W}}_0^{(1)}, \hat{\boldsymbol{W}}_0^{(2)}, \cdots, \hat{\boldsymbol{W}}_0^{(K)}] \operatorname{diag}\Big((\boldsymbol{Z}_0^\star)^{(1)}, (\boldsymbol{Z}_0^\star)^{(2)}, \cdots, (\boldsymbol{Z}_0^\star)^{(K)}\Big) \\
+ [\bar{\boldsymbol{W}}_{res}^{(1)}, \bar{\boldsymbol{W}}_{res}^{(2)}, \cdots, \bar{\boldsymbol{W}}_{res}^{(K)}],
\end{aligned} \tag{6}$$

and a new representation of $\boldsymbol{W}_0$:

$$\operatorname{diag}\Big((\boldsymbol{Z}_0^\star)^{(1)}, (\boldsymbol{Z}_0^\star)^{(2)}, \cdots, (\boldsymbol{Z}_0^\star)^{(K)}\Big). \tag{7}$$

The following properties hold for this representation.

Property 1. *If the subspaces are independent (*i.e.*,* $\operatorname{rank}(\boldsymbol{Z}_0^\star) = \sum_{k=1}^K \operatorname{rank}([\boldsymbol{Z}_0^\star]^{(k)})$*), then*
(1) (Global structure-preserving) $\sum_{k=1}^K \operatorname{rank}(\hat{\boldsymbol{W}}_0^{(k)}) = \sum_{k=1}^K \operatorname{rank}((\boldsymbol{Z}_0^\star)^{(k)}) = \operatorname{rank}(\hat{\boldsymbol{W}}_0)$*;*
(2) (Local structure-preserving) $\operatorname{rank}((\boldsymbol{Z}_0^\star)^{(k)}) = \operatorname{rank}(\hat{\boldsymbol{W}}_0^{(k)})$ *for* $k = 1, 2, \cdots, K$.

Proof. The corresponding proof is given in the Appendix A. □

Property 1 ensures both global and local low-rank structure preservation by the representation of $\boldsymbol{W}_0$. Specifically, the total rank across all subspaces remains consistent with that of the original weight matrix (Property 1 (1)), while each subspace individually preserves its intrinsic low-rank structure (Property 1 (2)). These properties are critical for maintaining original model abilities and enabling reliable adaptation across multiple subspaces.

3.3 Multi-Subspace-Based Incremental Update

In the previous subsection, we presented a representation of $\boldsymbol{W}_0$ based on subspace segmentation, as shown in (7). In this subsection, we propose a multi-subspace-based adaptation strategy. Rather than updating $\boldsymbol{W}_0$ directly, the proposed adaptation performs incremental updates for each $(\boldsymbol{Z}_0^\star)^{(k)}$.

We introduce an incremental update $\Delta \boldsymbol{Z}^{(k)}$ (with rank r_k) for each $(\boldsymbol{Z}_0^\star)^{(k)}$ in (6), and compute the updated weight block $\boldsymbol{W}^{(k)}$ as

$$\boldsymbol{W}^{(k)} = \hat{\boldsymbol{W}}_0^{(k)}((\boldsymbol{Z}_0^\star)^{(k)} + \Delta \boldsymbol{Z}^{(k)}) + \bar{\boldsymbol{W}}_{res}^{(k)} = \boldsymbol{W}_0^{(k)} + \hat{\boldsymbol{W}}_0^{(k)} \Delta \boldsymbol{Z}^{(k)}, \tag{8}$$

where the second equality follows from (5). Since the computation involves multiplication with the large matrix $\hat{\boldsymbol{W}}_0^{(k)}$, calculating the gradient with respect to $\Delta \boldsymbol{Z}^{(k)}$ can be computationally expensive.

To address this, we decompose $\hat{\boldsymbol{W}}_0^{(k)}$ by the skinny SVD: $\hat{\boldsymbol{W}}_0^{(k)} = \boldsymbol{U}_{\hat{\boldsymbol{W}}_0}^{(k)} \boldsymbol{S}_{\hat{\boldsymbol{W}}_0}^{(k)} (\boldsymbol{V}_{\hat{\boldsymbol{W}}_0}^{(k)})^\top$. Let $R_k := \operatorname{rank}(\hat{\boldsymbol{W}}_0^{(k)})$ and $\boldsymbol{A}^{(k)} := \boldsymbol{U}_{\hat{\boldsymbol{W}}_0}^{(k)} \in \mathbb{R}^{d \times R_k}$. Then, the update becomes:

$$\boldsymbol{W}^{(k)} = \boldsymbol{W}_0^{(k)} + \boldsymbol{A}^{(k)} \boldsymbol{S}_{\hat{\boldsymbol{W}}_0}^{(k)} (\boldsymbol{V}_{\hat{\boldsymbol{W}}_0}^{(k)})^\top \Delta \boldsymbol{Z}^{(k)}. \tag{9}$$

Since $\operatorname{rank}(\boldsymbol{S}_{\hat{\boldsymbol{W}}_0}^{(k)} (\boldsymbol{V}_{\hat{\boldsymbol{W}}_0}^{(k)})^\top \Delta \boldsymbol{Z}^{(k)}) \leq r_k$, we introduce two trainable matrices $\boldsymbol{B}^{(k)} \in \mathbb{R}^{R_k \times r_k}$ and $\boldsymbol{C}^{(k)} \in \mathbb{R}^{r_k \times n_k}$, and reparameterize the k-th updated weight block as:

$$\boldsymbol{W}^{(k)} = \boldsymbol{W}_0^{(k)} + \boldsymbol{A}^{(k)} \boldsymbol{B}^{(k)} \boldsymbol{C}^{(k)}. \tag{10}$$

This formulation yields a low-rank update (*i.e.*, $\boldsymbol{A}^{(k)} \boldsymbol{B}^{(k)} \boldsymbol{C}^{(k)}$) within each subspace.

To ensure that the initial value of $\boldsymbol{W}^{(k)}$ remains consistent with $\boldsymbol{W}_0^{(k)}$, we initialize $\boldsymbol{C}^{(k)}$ in (10) as $\mathbf{0}$. The matrix $\boldsymbol{B}^{(k)} \in \mathbb{R}^{R_k \times r_k}$ can be initialized either as an orthogonal matrix, as described in Steps 7-8 of the Algorithm 1 (see Appendix C), or randomly (following the LoRA initialization strategy). The complete initialization procedure of AdaMSS is presented in Algorithm 1, and the estimation of the subspace number K is detailed in Algorithm 2, both of which are included in Appendix C. The parameter count and computational complexity analysis of the proposed method, along with comparisons to LoRA and PiSSA, are provided in the Appendices D and E, respectively.

4 Multi-Subspace-Based Adaptive Budget Allocation

In this section, we introduce an adaptive multi-subspace-based budget allocation mechanism. By integrating this strategy with the Multi-Subspace-Based Adaptation framework proposed in the previous section, we derive the final method, AdaMSS.

Thanks to the multi-subspace structure of the weights, we can perform adaptive budget allocation during training by calculating the importance score [28] for each $\boldsymbol{H}^{(k)} = [\boldsymbol{B}^{(k)}; (\boldsymbol{C}^{(k)})^\top] \in \mathbb{R}^{(R_k + n_k) \times r_k}$ directly. Following [28], the importance score $s^{(t)}(\cdot)$ is defined as

$$s^{(t)}(\boldsymbol{H}^{(k)}) = \frac{1}{r_k(R + n_k)} \sum_{i,j} \overline{I}^{(t)}([\boldsymbol{H}^{(k)}]_{i,j}) \cdot \overline{U}^{(t)}([\boldsymbol{H}^{(k)}]_{i,j}), \tag{11}$$

where

$$\begin{aligned} \overline{I}^{(t)}([\boldsymbol{H}^{(k)}]_{i,j}) &= \beta_1 \overline{I}^{(t-1)}([\boldsymbol{H}^{(k)}]_{i,j}) + (1 - \beta_1) I^{(t)}([\boldsymbol{H}^{(k)}]_{i,j}), \\ \overline{U}^{(t)}([\boldsymbol{H}^{(k)}]_{i,j}) &= \beta_2 \overline{U}^{(t-1)}([\boldsymbol{H}^{(k)}]_{i,j}) + (1 - \beta_2) \left| I^{(t)}([\boldsymbol{H}^{(k)}]_{i,j}) - \overline{I}^{(t)}([\boldsymbol{H}^{(k)}]_{i,j}) \right|, \\ I([\boldsymbol{H}^{(k)}]_{ij}) &= |[\boldsymbol{H}^{(k)}]_{ij} \nabla_{[\boldsymbol{H}^{(k)}]_{ij}} \mathcal{L}|, \end{aligned} \tag{12}$$

and t denotes the training step. This importance score measures how consistently and significantly each $\boldsymbol{H}^{(k)}$ contributes to loss reduction during training.

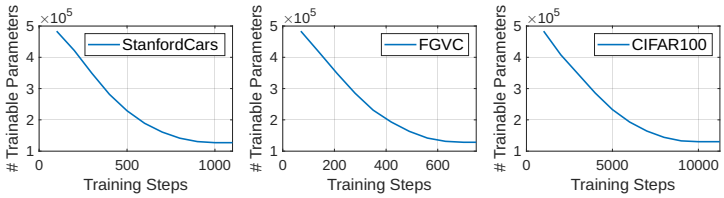
At each update step, we rank all $\boldsymbol{H}^{(k)}$ by their importance scores $s^{(t)}(\boldsymbol{H}^{(k)})$, retain the top-$K_t$ for training, and freeze the rest. The value of K_t is gradually reduced from K to K_{target} following a smooth cubic decay schedule over training steps. The adaptive budget allocation mechanism is stopped when the number of trainable $\boldsymbol{H}^{(k)}$ for $k = 1, 2, \cdots, K$ falls below K_{target}. Figure 3 presents examples on the StanfordCars[2], FGVC[2], and CIFAR100[2] tasks, illustrating the proposed adaptive budget allocation strategy, which gradually reduces the number of trainable parameters during the training process.

5 Analysis of AdaMSS

In the previous section, we introduced AdaMSS that is based on the following reparametrization:

$$\boldsymbol{W} = \boldsymbol{W}_0 + \boldsymbol{A}\boldsymbol{B}\boldsymbol{C}, \tag{13}$$

[2] `https://huggingface.co/datasets/Multimodal-Fatima`



(a) (b) (c)

Figure 3: The adaptive change in the number of trainable parameters of AdaMSS during the training process.

where $\boldsymbol{A} = [\boldsymbol{A}^{(1)}, \boldsymbol{A}^{(2)}, \cdots, \boldsymbol{A}^{(K)}] \in \mathbb{R}^{d\times R}$, $\boldsymbol{B} = \mathrm{diag}(\boldsymbol{B}^{(1)}, \boldsymbol{B}^{(2)}, \cdots, \boldsymbol{B}^{(K)}) \in \mathbb{R}^{R\times\sum_{k=1}^{K} r_k}$, $\boldsymbol{C} = \mathrm{diag}(\boldsymbol{C}^{(1)}, \boldsymbol{C}^{(2)}, \ldots, \boldsymbol{C}^{(K)}) \in \mathbb{R}^{\sum_{k=1}^{K} r_k \times n}$, $(\boldsymbol{A}^{(k)})^\top \boldsymbol{A}^{(k)} = \boldsymbol{I}$ and $\mathrm{rank}(\boldsymbol{C}^{(k)}) \leq r_k$ for $k = 1, 2, \cdots, K$.

We establish the upper bound of expected loss by AdaMSS in Lemma 1 and Theorem 1.

As our discussions given in the Appendix B.2, the upbound of the Gaussian complexity for LoRA and its single subspace variants (such as AdaLoRA, PiSSA and LoRA-GA) is given by $\mathcal{L}(\phi)\hat{R}B\sqrt{\frac{\mathrm{rank}(\Delta\boldsymbol{W})n}{m}}$ for $\|\Delta\boldsymbol{W}\|_2 \leq B$. If $\sum_{k=1}^{K} r_k = \mathrm{rank}(\Delta\boldsymbol{W})$, applying Cauchy–Schwarz inequality and using $\sum_{k=1}^{K} n_k = n$, we have $\sum_{k=1}^{K}\sqrt{r_k n_k} \leq \sqrt{\mathrm{rank}(\Delta\boldsymbol{W})n}$. Therefore, AdaMSS attains a lower Gaussian complexity bound when $B_k \leq B$, and can be expected to have a stronger generalization capability than single subspace-based fine-tuning methods, as indicated by Theorem 1. These results can be further extended to deep Lipschitz neural networks by applying Maurer's Gaussian complexity chain rule [29].

Lemma 1. *[Gaussian complexity of the AdaMSS for a shallow Lipschitz neural network] For the class of spectrally bounded shallow Lipschitz network*

$$\begin{aligned}\mathcal{F}_{\mathrm{AdaMSS}} =& \{f_{\boldsymbol{W}}(\boldsymbol{x}) = \phi(\boldsymbol{x}\boldsymbol{W}) \mid \boldsymbol{W} = \boldsymbol{W}_0 + \boldsymbol{A}\boldsymbol{B}\boldsymbol{C},\\ & (\boldsymbol{A}^{(k)})^\top \boldsymbol{A}^{(k)} = \boldsymbol{I},\ \|\boldsymbol{B}^{(k)}\boldsymbol{C}^{(k)}\|_2 \leq B_k\},\end{aligned} \tag{14}$$

the Gaussian complexity of this function class is upper bounded as follows:

$$\hat{G}_S(\mathcal{F}_{\mathrm{AdaMSS}}) \leq \mathcal{L}(\phi)\sum_{k=1}^{K}\hat{R}B_k\sqrt{\frac{r_k n_k}{m}},$$

where $n = \sum_{k=1}^{K} n_k$, n_k denotes the width of the weight matrix $\boldsymbol{C}^{(k)}$, $\mathcal{L}(\phi)$ is Lipschitz constant for function ϕ, $\boldsymbol{X} = [\boldsymbol{x}_1^\top, \ldots, \boldsymbol{x}_m^\top] \in \mathbb{R}^{d\times m}$ for the samples $\{\boldsymbol{x}_i\}_{i=1}^m$, and $\max_{i=1,2,\cdots,m}\|\boldsymbol{x}_i\| \leq \hat{R}$.

Proof. The corresponding proof is given in the Appendix B.1. □

Theorem 1. *Let $g(\cdot)$ be a $\mathcal{L}(g)$-Lipschitz loss function from $(f_{\mathbf{w}}(\mathbf{x}), \mathbf{y})$ to $[0, 1]$, where $f_{\mathbf{w}} \in \mathcal{F}_{\mathrm{AdaMSS}}$ and $(\boldsymbol{x}, \boldsymbol{y}) \in \mathbb{X} \times \mathbb{Y}$, $\mathbb{X} \subseteq \mathbb{R}^d$ and $\mathbb{Y}$ are feature space and output space, respectively. For any $\delta > 0$, the following holds with probability at least $1 - \delta$ for a randomly chosen i.i.d. samples $\mathbb{S} = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^m$:*

$$\mathbb{E}[g(f_{\mathbf{w}}(\mathbf{x}), \mathbf{y})] \leq \frac{1}{m}\sum_{i=1}^{m} g(f_{\mathbf{w}}(\mathbf{x}_i), \mathbf{y}_i) + \sqrt{\mathcal{L}(g)\pi}\,\hat{G}_S(\mathcal{F}_{\mathrm{AdaMSS}}) + \sqrt{\frac{9\log\frac{2}{\delta}}{2m}}.$$

Proof. Combining Lemma 1 with Vector-valued Gaussian complexity Generalization Bound Theorem [30], we obtain the generalization bound for AdaMSS. □

6 Experiments

In this section, we present comparative experiments to evaluate the effectiveness of AdaMSS across tasks in image classification (IC), natural language understanding (NLU), and natural language

generation (NLG). To better understand the contribution of each component, we define a variant of AdaMSS without the proposed adaptive budget allocation mechanism, referred to as AdaMSS$_{\text{base}}$, for clarity of comparison. The hyperparameter R is set to $R = 100$ for both AdaMSS and AdaMSS$_{\text{base}}$. We report the average number of trainable parameters per epoch in our experimental results, as the number of trainable parameters in AdaMSS is adaptively reduced during the training. Since our focus is on low-rank-based adaptation, we compare AdaMSS not only with baseline methods such as full fine-tuning (FF) and linear probing (LP), which only tune the classification head, but also with several low-rank-based PEFT methods, including LoRA [1], DyLoRA [31], AdaLoRA [3], PiSSA [2], LoRETTA [10], and LoRA-PRO [6]. For each method, we prioritize using hyperparameters (*e.g.*, rank r) recommended by the authors. For a fair comparison, we replicate the experimental setups in [1, 2, 24]. A complete list of all hyperparameters and settings is provided in the Appendix G. All experiments were conducted using an RTX A6000 GPU and Python version 3.12.3. The best results are highlighted in **bold**, and the top three results are underlined. **The code for AdaMSS has been included in the submitted supplementary materials. (Ablation studies are given in Appendix F, and additional experimental results are also available in the submitted supplementary materials.)**

6.1 Image Classification

Table 1: The performance of different fine-tuning methods on various image classification datasets for the `ViT-Base` model and `ViT-Large` model, averaged over 5 random seeds, where the hyperparameter r_k in AdaMSS$_{\text{base}}$ and AdaMSS corresponds to the assumed rank of $\Delta \boldsymbol{Z}^{(k)}$ and is set to the same value for all k.

Model	Method	# Trainable Parameters	Accuracy (%)							
			OxfordPets	StanfordCars	CIFAR10	EuroSAT	FGVC	RESISC45	CIFAR100	Avg.
ViT-Base	LP	-	$90.28_{\pm 0.4}$	$25.76_{\pm 0.3}$	$96.41_{\pm 0.0}$	$88.72_{\pm 0.1}$	$17.44_{\pm 0.4}$	$74.22_{\pm 0.1}$	$84.28_{\pm 0.1}$	68.15
	FF	85.8M	$93.14_{\pm 0.4}$	$79.78_{\pm 1.2}$	$\mathbf{98.92}_{\pm 0.1}$	$\mathbf{99.05}_{\pm 0.1}$	$54.84_{\pm 1.2}$	$\mathbf{96.13}_{\pm 0.1}$	$92.38_{\pm 0.1}$	87.74
	LoRA ($r = 16$)	581K	$93.19_{\pm 0.4}$	$45.38_{\pm 0.4}$	$98.78_{\pm 0.1}$	$98.44_{\pm 0.2}$	$25.16_{\pm 0.2}$	$92.70_{\pm 0.2}$	$92.02_{\pm 0.1}$	77.95
	PiSSA ($r = 8$)	313K	$93.84_{\pm 0.3}$	$78.43_{\pm 0.5}$	$98.74_{\pm 0.0}$	$98.67_{\pm 0.1}$	$51.56_{\pm 1.8}$	$93.81_{\pm 1.8}$	$\mathbf{93.31}_{\pm 0.2}$	86.90
	PiSSA ($r = 1$)	55K	$93.83_{\pm 0.1}$	$60.29_{\pm 0.3}$	$98.7_{\pm 0.0}$	$98.47_{\pm 0.1}$	$29.61_{\pm 0.2}$	$92.87_{\pm 0.2}$	$91.98_{\pm 0.2}$	80.82
	LoRA-PRO	313K	$94.03_{\pm 0.1}$	$72.12_{\pm 0.4}$	$98.77_{\pm 0.1}$	$98.65_{\pm 0.1}$	$43.39_{\pm 0.7}$	$93.66_{\pm 0.2}$	$92.54_{\pm 0.1}$	84.74
	LoRETTA ($r = 5$)	57K	$93.39_{\pm 0.4}$	$74.15_{\pm 0.8}$	$98.73_{\pm 0.1}$	$98.67_{\pm 0.1}$	$48.86_{\pm 0.5}$	$93.36_{\pm 0.1}$	$91.87_{\pm 0.1}$	85.57
	AdaMSS$_{\text{base}}$ ($r_k = 3$)	125K	$94.02_{\pm 0.3}$	$\mathbf{81.55}_{\pm 0.4}$	$98.81_{\pm 0.05}$	$98.7_{\pm 0.06}$	$\mathbf{56.95}_{\pm 0.6}$	$94.18_{\pm 0.1}$	$92.13_{\pm 0.1}$	**88.05**
	AdaMSS ($r_k = 3$)	59K	$\mathbf{94.23}_{\pm 0.1}$	$80.44_{\pm 0.2}$	$98.69_{\pm 0.04}$	$98.59_{\pm 0.09}$	$54.45_{\pm 0.3}$	$94.03_{\pm 0.2}$	$91.91_{\pm 0.1}$	87.47
	AdaMSS$_{\text{base}}$ ($r_k = 1$)	**42K**	$93.91_{\pm 0.2}$	$78.98_{\pm 0.2}$	$98.71_{\pm 0.07}$	$98.64_{\pm 0.07}$	$53.2_{\pm 0.4}$	$93.62_{\pm 0.08}$	$91.90_{\pm 0.1}$	86.99
ViT-Large	LP	-	$91.11_{\pm 0.3}$	$37.91_{\pm 0.3}$	$97.78_{\pm 0.0}$	$92.64_{\pm 0.1}$	$24.62_{\pm 0.2}$	$82.02_{\pm 0.1}$	$84.28_{\pm 0.1}$	72.91
	FF	303.3M	$94.43_{\pm 0.6}$	$\mathbf{88.90}_{\pm 0.3}$	$99.15_{\pm 0.1}$	$\mathbf{99.04}_{\pm 0.1}$	$\mathbf{68.25}_{\pm 1.6}$	$\mathbf{96.43}_{\pm 0.1}$	$93.58_{\pm 0.2}$	**91.40**
	LoRA ($r = 16$)	1.57M	$94.82_{\pm 0.1}$	$73.25_{\pm 0.4}$	$99.13_{\pm 0.0}$	$98.63_{\pm 0.1}$	$42.32_{\pm 1.0}$	$94.71_{\pm 0.3}$	$\mathbf{94.87}_{\pm 0.1}$	85.40
	PiSSA ($r = 8$)	835K	$94.04_{\pm 0.4}$	$84.19_{\pm 0.7}$	$99.13_{\pm 0.0}$	$98.79_{\pm 0.0}$	$59.81_{\pm 0.6}$	$94.99_{\pm 0.2}$	$92.42_{\pm 0.1}$	89.05
	PiSSA ($r = 1$)	147K	$93.98_{\pm 0.3}$	$83.04_{\pm 0.3}$	$99.04_{\pm 0.0}$	$98.71_{\pm 0.0}$	$56.72_{\pm 0.6}$	$94.64_{\pm 0.2}$	$93.25_{\pm 0.1}$	88.48
	LoRA-PRO	835K	$94.67_{\pm 0.1}$	$83.57_{\pm 0.3}$	$\mathbf{99.20}_{\pm 0.1}$	$98.81_{\pm 0.1}$	$57.71_{\pm 0.5}$	$95.12_{\pm 0.1}$	$93.53_{\pm 0.1}$	88.94
	LoRETTA ($r = 5$)	**132K**	$78.28_{\pm 0.3}$	$68.44_{\pm 0.3}$	$88.80_{\pm 0.2}$	$98.68_{\pm 0.1}$	$58.04_{\pm 0.9}$	$94.53_{\pm 0.1}$	$93.28_{\pm 0.1}$	82.86
	AdaMSS$_{\text{base}}$($r_k = 3$)	483K	$94.74_{\pm 0.1}$	$85.40_{\pm 0.3}$	$99.11_{\pm 0.0}$	$98.93_{\pm 0.06}$	$65.30_{\pm 0.6}$	$95.32_{\pm 0.1}$	$93.51_{\pm 0.1}$	90.33
	AdaMSS($r_k = 3$)	241K	$\mathbf{94.87}_{\pm 0.1}$	$85.24_{\pm 0.3}$	$99.12_{\pm 0.0}$	$98.93_{\pm 0.1}$	$64.31_{\pm 0.4}$	$95.2_{\pm 0.2}$	$93.22_{\pm 0.1}$	90.13
	AdaMSS$_{\text{base}}$($r_k = 1$)	178K	$94.58_{\pm 0.1}$	$83.71_{\pm 0.2}$	$99.08_{\pm 0.05}$	$98.85_{\pm 0.1}$	$59.27_{\pm 0.8}$	$94.68_{\pm 0.3}$	$93.43_{\pm 0.2}$	89.09

We evaluate all methods on IC using the widely adopted Vision Transformer (ViT) [12], a prevalent foundation model in computer vision, across seven public datasets: OxfordPets[3], StanfordCars[2], CIFAR10[2], EuroSAT[4], FGVC[2], RESISC45[5], and CIFAR100[2]. The number of training epochs is set as 10. As shown in Table 1, AdaMSS achieves higher average accuracy than other PEFT methods, including LP, LoRA, PiSSA, LoRA-PRO, and LoRETTA, and performs comparable accuracy with FF on the seven image classification datasets while using significantly fewer trainable parameters. More specifically, with the ViT-Base model, AdaMSS (59K) achieves average accuracy comparable to PiSSA ($r = 8$), using only 19.5% of its tranable parameters, and achieves 6.5% higher accuracy than PiSSA ($r = 1$) at a similar parameter budget. This is because that AdaMSS's multi-subspace design allows it to capture richer features with fewer parameters. On the ViT-large model, AdaMSS achieves 4.7% higher average accuracy than LoRA, while requiring only with 15.4% of the trainable parameters, demonstrating AdaMSS's strong parameter efficiency and transfer performance in image classification tasks.

6.2 Natural Language Understanding

We evaluate all methods on the General Language Understanding Evaluation (GLUE) benchmark [32] using the robustly optimized BERT models, *i.e.*, `RoBERTa-Base` and `RoBERTa-Large` [15],

[3]https://huggingface.co/datasets/timm/oxford-iiit-pet

[4]https://huggingface.co/datasets/timm/eurosat-rgb

[5]https://huggingface.co/datasets/timm/resisc45

Table 2: The performance of different fine-tuning methods on six datasets of the GLUE benchmark for the `RoBERTa-Base` model and `RoBERTa-Large` model, averaged over 5 random seeds.

Model	Method	# Trainable Parameters	SST-2 Acc.	MRPC Acc.	CoLA MCC	QNLI Acc.	RTE Acc.	STS-B PCC	Avg.
`RoBERTa-Base`	FF	125M	94.8	**90.2**	63.6	92.8	78.7	91.2	85.2
	LoRA	0.3M	**95.1**$_{\pm 0.2}$	89.7$_{\pm 0.7}$	63.4$_{\pm 1.2}$	**93.3**$_{\pm 0.3}$	78.4$_{\pm 0.8}$	**91.5**$_{\pm 0.2}$	85.2
	AdaLoRA	0.3M	94.5$_{\pm 0.2}$	88.7$_{\pm 0.5}$	62.0$_{\pm 0.6}$	93.1$_{\pm 0.2}$	**81.0**$_{\pm 0.6}$	90.5$_{\pm 0.2}$	85.0
	DyLoRA	0.3M	94.3$_{\pm 0.5}$	89.5$_{\pm 0.5}$	61.1$_{\pm 0.3}$	92.2$_{\pm 0.5}$	78.7$_{\pm 0.7}$	91.1$_{\pm 0.6}$	84.5
	PiSSA ($r = 8$)	0.3M	93.9$_{\pm 0.1}$	89.3$_{\pm 0.8}$	62.1$_{\pm 2.9}$	91.3$_{\pm 0.1}$	77.3$_{\pm 1.4}$	90.5$_{\pm 0.2}$	84.1
	LoRA-PRO	0.3M	94.2$_{\pm 0.3}$	90.1$_{\pm 0.5}$	64.3$_{\pm 0.72}$	92.0$_{\pm 0.2}$	80.2$_{\pm 1.8}$	90.9$_{\pm 0.22}$	**85.3**
	LoRETTA	0.057M	94.6$_{\pm 0.5}$	88.3$_{\pm 0.7}$	61.8$_{\pm 1.3}$	92.7$_{\pm 0.2}$	75.1$_{\pm 5.3}$	90.5$_{\pm 0.1}$	83.8
	AdaMSS$_{\text{base}}$ ($r_k = 1$)	0.042M	94.6$_{\pm 0.2}$	89.2$_{\pm 1.0}$	64.3$_{\pm 0.9}$	92.4$_{\pm 0.1}$	77.2$_{\pm 0.7}$	90.6$_{\pm 0.1}$	84.7
	AdaMSS ($r_k = 1$)	**0.032M**	94.6$_{\pm 0.2}$	88.8$_{\pm 1.4}$	**64.5**$_{\pm 1.1}$	92.4$_{\pm 0.1}$	77.3$_{\pm 0.7}$	90.4$_{\pm 0.1}$	84.7
`RoBERTa-Large`	FF	356M	**96.4**	**90.9**	68	94.7	86.6	**92.4**	**88.2**
	LoRA	0.8M	96.2$_{\pm 0.5}$	90.2$_{\pm 1.0}$	68.2$_{\pm 1.9}$	**94.8**$_{\pm 0.3}$	85.2$_{\pm 1.1}$	92.3$_{\pm 0.5}$	87.8
	PiSSA ($r = 8$)	0.8M	95.5$_{\pm 0.2}$	86.9$_{\pm 2.6}$	61.1$_{\pm 3.4}$	92.1$_{\pm 1.7}$	56.8$_{\pm 8.2}$	91.8$_{\pm 0.4}$	80.7
	LoRA-PRO	0.8M	95.9$_{\pm 0.2}$	**90.9**$_{\pm 0.4}$	66.7$_{\pm 2.0}$	93.0$_{\pm 0.5}$	60.5$_{\pm 13.5}$	92.0$_{\pm 0.1}$	83.2
	LoRETTA	0.132M	96.2$_{\pm 0.2}$	90.5$_{\pm 0.4}$	**69.5**$_{\pm 0.6}$	94.1$_{\pm 0.9}$	53.0$_{\pm 0.5}$	92.0$_{\pm 0.2}$	82.6
	AdaMSS$_{\text{base}}$ ($r_k = 1$)	0.097M	96.3$_{\pm 0.2}$	90.5$_{\pm 0.3}$	68.0$_{\pm 0.9}$	94.6$_{\pm 0.1}$	**87.3**$_{\pm 1.0}$	92.0$_{\pm 0.0}$	88.1
	AdaMSS ($r_k = 1$)	**0.045M**	96.1$_{\pm 0.0}$	90.3$_{\pm 0.5}$	67.2$_{\pm 1.2}$	94.5$_{\pm 0.1}$	87.1$_{\pm 2.1}$	91.9$_{\pm 0.0}$	87.9

for the evaluation. We evaluate the performance of the fine-tuned models using three key metrics: Matthew's correlation coefficient (MCC) for CoLA, Pearson correlation coefficient (PCC) for STS-B, and accuracy (Acc.) for all other tasks. For all methods, the maximum number of training epochs is set to 100 and select the best epoch for each run. Table 2 presents the results of all methods. As shown in the Table 2, on `RoBERTa-Base`, AdaMSS achieves average accuracy comparable to other low-rank-based PEFT methods while using the fewest trainable parameters. For `RoBERTa-Large`, AdaMss outperforms PiSSA, LoRA-PRO, and LoRETTA by around 5% in average accuracy while using fewer parameters, and achieves performance comparable to both LoRA and FF.

6.3 Natural Language Generation

In this subsection, we use `LLaMA 2-7B` [14] and compare AdaMSS with the traditional low-rank-based methods, including PiSSA, LoRA, LoRETTA, LoRA-PRO, and FF on natural language generation (NLG) tasks. As shown in Table 3, AdaMSS achieves competitive or even superior performance on NLG tasks while requiring significantly fewer trainable parameters. For instance, on both the GSM8K and MATH datasets, AdaMSS outperforms LoRA, PiSSA, and LoRETTA, despite using only 0.9M trainable parameters.

Table 3: Comparing different methods on NLG tasks

Model	Method	Trainable Parameters	GSM8K [13]	MATH [33]
`LLaMA 2-7B`	Full FT	6738M	**49.05**	**7.22**
	LoRA	320M	42.30	5.50
	PiSSA	19M	44.11	5.84
	LoRA-PRO	19M	46.61	6.4
	LoRETTA	**0.3M**	37.86	4.6
	AdaMSS$_{\text{base}}$ ($r_k = 3$)	0.9M	44.50	6.04

7 Conclusions and Future Works

In this work, inspired by our observation of the multi-subspace structure in network weights, we proposed AdaMSS, a novel PEFT approach, to address the limitations of single-subspace methods that often struggle with the dilemma between limited expressiveness and parameter efficiency. Compared to low-rank-based fine-tuning methods, AdaMSS enables more expressive and adaptive parameter updates by leveraging subspace segmentation, thereby achieving both parameter efficiency and strong generalization capability. Comprehensive theoretical analysis and extensive empirical evaluations demonstrate the advantages of AdaMSS. In future work, we aim to extend the multi-subspace perspective beyond fine-tuning to broader areas such as network compression and pruning. We believe that subspace segmentation offers a promising direction for learning compact, disentangled, and efficient representations for network weights, which could benefit model compression and pruning in deep neural networks.

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A The Proof of Property 1

Proof. From $\boldsymbol{Z}_0^\star = [\boldsymbol{V}_0]_{:,1:R}[\boldsymbol{V}_0]_{:,1:R}^\top$, we know $\operatorname{rank}(\boldsymbol{Z}_0^\star) = \operatorname{rank}(\hat{\boldsymbol{W}}_0)$.

Since $\hat{\boldsymbol{W}}_0^{(k)} = \hat{\boldsymbol{W}}_0^{(k)}(\boldsymbol{Z}_0^\star)^{(k)}$, it follows that $\operatorname{rank}(\hat{\boldsymbol{W}}_0^{(k)}) \le \operatorname{rank}((\boldsymbol{Z}_0^\star)^{(k)})$. Thus, we have

$$\sum_{k=1}^K \operatorname{rank}(\hat{\boldsymbol{W}}_0^{(k)}) \le \sum_{k=1}^K \operatorname{rank}((\boldsymbol{Z}_0^\star)^{(k)}) \le \sum_{k=1}^K \operatorname{rank}([\boldsymbol{Z}_0^\star]^{(k)}) = \operatorname{rank}(\boldsymbol{Z}_0^\star) = \operatorname{rank}(\hat{\boldsymbol{W}}_0).$$

On the other hand, we know that $\operatorname{rank}(\hat{\boldsymbol{W}}_0) \le \sum_{k=1}^K \operatorname{rank}(\hat{\boldsymbol{W}}_0^{(k)})$. Therefore, we can conclude

$$\sum_{k=1}^K \operatorname{rank}(\hat{\boldsymbol{W}}_0^{(k)}) = \sum_{k=1}^K \operatorname{rank}((\boldsymbol{Z}_0^\star)^{(k)}) = \operatorname{rank}(\hat{\boldsymbol{W}}_0).$$

Since $\operatorname{rank}(\hat{\boldsymbol{W}}_0^{(k)}) \le \operatorname{rank}((\boldsymbol{Z}_0^\star)^{(k)})$ for all k and $\sum_{k=1}^K \operatorname{rank}(\hat{\boldsymbol{W}}_0^{(k)}) = \sum_{k=1}^K \operatorname{rank}((\boldsymbol{Z}_0^\star)^{(k)})$, it must hold that

$$\operatorname{rank}(\hat{\boldsymbol{W}}_0^{(k)}) = \operatorname{rank}((\boldsymbol{Z}_0^\star)^{(k)}).$$

□

B The Proofs of the Results in Section 5

B.1 The Proof of Lemma 1

Proof. By Talagrand's contraction lemma [34], we have

$$\hat{G}_S(\mathcal{F}_{\mathrm{AdaMSS}}) \le \mathcal{L}(\phi)\frac{1}{m}\,\mathbb{E}_\gamma \sup_{\boldsymbol{W}} \langle \boldsymbol{W},\, \boldsymbol{X}\boldsymbol{\Gamma}\rangle, \tag{15}$$

where each entry in $\boldsymbol{\Gamma} \in \mathbb{R}^{m\times n}$, *i.e.*, $[\boldsymbol{\Gamma}]_{ij}$, follows standard Gaussian distribution.

Since

$$\begin{aligned}\mathbb{E}_\gamma[\sup_{\boldsymbol{W}} \langle \boldsymbol{W},\, \boldsymbol{X}\boldsymbol{\Gamma}\rangle] &= \mathbb{E}_\gamma[\langle \boldsymbol{W}_0, \boldsymbol{X}\boldsymbol{\Gamma}\rangle] + \mathbb{E}_\gamma[\sup_{\boldsymbol{B},\boldsymbol{C}} \langle \boldsymbol{A}\boldsymbol{B}\boldsymbol{C},\, \boldsymbol{X}\boldsymbol{\Gamma}\rangle] \\ &= \mathbb{E}_\gamma[\sup_{\boldsymbol{B},\boldsymbol{C}} \langle \boldsymbol{A}\boldsymbol{B}\boldsymbol{C},\, \boldsymbol{X}\boldsymbol{\Gamma}\rangle],\end{aligned} \tag{16}$$

we only need to study the upper bound of $\mathbb{E}_\gamma[\sup_{\boldsymbol{B},\boldsymbol{C}} \langle \boldsymbol{A}\boldsymbol{B}\boldsymbol{C},\, \boldsymbol{X}\boldsymbol{\Gamma}\rangle]$.

We divide $\boldsymbol{\Gamma}$ into K blocks according $\{n_k\}_{k=1}^K$, *i.e.*, $\boldsymbol{\Gamma} = [\boldsymbol{\Gamma}^{(1)}, \boldsymbol{\Gamma}^{(2)}, \cdots, \boldsymbol{\Gamma}^{(K)}]$ for $\boldsymbol{\Gamma}^{(k)} \in \mathbb{R}^{m\times n_k}(k = 1, 2, \cdots, K)$. From the Cauchy-Schwarz inequality, we have

$$\begin{aligned}\sup_{\boldsymbol{B},\boldsymbol{C}} \langle \boldsymbol{A}\boldsymbol{B}\boldsymbol{C}, \boldsymbol{X}\boldsymbol{\Gamma}\rangle = \sum_{k=1}^K \sup_{\boldsymbol{B}^{(k)},\boldsymbol{C}^{(k)}} \langle \boldsymbol{A}^{(k)}\boldsymbol{B}^{(k)}\boldsymbol{C}^{(k)}, \boldsymbol{X}\boldsymbol{\Gamma}^{(k)}\rangle &\le \sum_{k=1}^K \|\boldsymbol{B}^{(k)}\boldsymbol{C}^{(k)}\|_F \|\boldsymbol{X}\boldsymbol{\Gamma}^{(k)}\|_F \\ &\le \sum_{k=1}^K \sqrt{r_k} B_k \,\|\boldsymbol{X}\boldsymbol{\Gamma}^{(k)}\|_F.\end{aligned} \tag{17}$$

Using the fact that $\mathbb{E}[|Y|] \le \sqrt{\mathbb{E}[Y^2]}$ for any random variable Y, we obtain

$$\mathbb{E}_\gamma\big[\|\boldsymbol{X}\boldsymbol{\Gamma}^{(k)}\|_F\big] \le \sqrt{\mathbb{E}_\gamma\big[\|\boldsymbol{X}\boldsymbol{\Gamma}^{(k)}\|_F^2\big]} = \sqrt{\operatorname{Tr}\Big(\boldsymbol{X}\boldsymbol{X}^\top\,\mathbb{E}_\gamma[(\boldsymbol{\Gamma}^{(k)})^\top\boldsymbol{\Gamma}^{(k)}]\Big)} \le \hat{R}\sqrt{n_k m}. \tag{18}$$

Combining (17) and (18), we obtain

$$\mathbb{E}_\gamma[\sup_{\boldsymbol{W}} \langle \boldsymbol{W},\, \boldsymbol{X}\boldsymbol{\Gamma}\rangle] = \mathbb{E}_\gamma \sup_{\boldsymbol{B},\boldsymbol{C}} \langle \boldsymbol{A}\boldsymbol{B}\boldsymbol{C}, \boldsymbol{X}\boldsymbol{\Gamma}\rangle \le \sum_{k=1}^K \sqrt{r_k} B_k\, \mathbb{E}_\gamma[\|\boldsymbol{X}\boldsymbol{\Gamma}^{(k)}\|_F] \le \sum_{k=1}^K \sqrt{r_k} B_k \hat{R}\sqrt{n_k m}. \tag{19}$$

Substituting (19) into (15) leads to

$$\hat{G}_S(\mathcal{F}_{\text{AdaMSS}}) \leq \mathcal{L}(\phi)\frac{1}{m}\,\mathbb{E}_\gamma \sup_{\boldsymbol{W}}\langle \boldsymbol{W},\, \boldsymbol{\Gamma}\boldsymbol{X}\rangle \leq \mathcal{L}(\phi)\sum_{k=1}^{K}\hat{R}B_k\sqrt{\frac{r_k n_k}{m}}.$$

□

B.2 Gaussian Complexity Analysis for LoRA and Its Single Subspace Variants

In this subsection, we analyze the Gaussian complexity of LoRA, as presented in Lemma 2.

Lemma 2. *[Gaussian complexity of the LoRA for a shallow Lipschitz neural network] For the class of spectrally bounded shallow Lipschitz network*

$$\mathcal{F}_{\text{lora}} = \{f_{\boldsymbol{W}}(\boldsymbol{x}) = \phi(\boldsymbol{x}\boldsymbol{W}) \mid \boldsymbol{W} = \boldsymbol{W}_0 + \Delta\boldsymbol{W}, \|\Delta\boldsymbol{W}\|_2 \leq B\} \tag{20}$$

the Gaussian complexity of this function class is upper bounded as follows:

$$\hat{G}_S(\mathcal{F}_{\text{lora}}) \leq \mathcal{L}(\phi)\hat{R}B\sqrt{\frac{rn}{m}}, \tag{21}$$

where $r = \text{rank}(\Delta\boldsymbol{W})$, n denotes the width of the weight matrix $\Delta\boldsymbol{W}$, $\mathcal{L}(\phi)$ is Lipschitz constant for function ϕ, $\boldsymbol{X} = [\boldsymbol{x}_1^\top, \ldots, \boldsymbol{x}_m^\top] \in \mathbb{R}^{d\times m}$ for the samples $\{\boldsymbol{x}_i\}_{i=1}^m$, and $\max_{i=1,2,\cdots,m}\|\boldsymbol{x}_i\| \leq \hat{R}$.

Proof. By Talagrand's contraction lemma [34], we have

$$\hat{G}_S(\mathcal{F}_{\text{lora}}) \leq \mathcal{L}(\phi)\frac{1}{m}\,\mathbb{E}_\gamma \sup_{\Delta\boldsymbol{W}}\langle \boldsymbol{W}_0 + \Delta\boldsymbol{W},\, \boldsymbol{X}\boldsymbol{\Gamma}\rangle = \mathcal{L}(\phi)\frac{1}{m}\,\mathbb{E}_\gamma \sup_{\Delta\boldsymbol{W}}\langle \Delta\boldsymbol{W},\, \boldsymbol{X}\boldsymbol{\Gamma}\rangle, \tag{22}$$

where each entry in $\boldsymbol{\Gamma} \in \mathbb{R}^{m\times n}$ is drawn independently from the standard Gaussian distribution.

Applying the Cauchy-Schwarz inequality and the inequality $\mathbb{E}[|Y|] \leq \sqrt{\mathbb{E}[Y^2]}$, we obtain

$$\begin{aligned}\mathbb{E}_\gamma \sup_{\Delta\boldsymbol{W}}\langle \Delta\boldsymbol{W}, \boldsymbol{X}\boldsymbol{\Gamma}\rangle &\leq \sqrt{r}B\,\mathbb{E}_\gamma[\|\boldsymbol{X}\boldsymbol{\Gamma}\|_F] \leq \sqrt{r}B\sqrt{\mathbb{E}_\gamma\left[\|\boldsymbol{X}\boldsymbol{\Gamma}\|_F^2\right]} \\ &\leq \sqrt{r}B\sqrt{\text{Tr}\Big(\boldsymbol{X}\boldsymbol{X}^\top\,\mathbb{E}_\gamma[(\boldsymbol{\Gamma})^\top\boldsymbol{\Gamma}]\Big)} \leq \sqrt{r}B\hat{R}\sqrt{nm}.\end{aligned} \tag{23}$$

Substituting (23) into (22) yields the desired result: $\hat{G}_S(\mathcal{F}_{\text{lora}}) \leq \mathcal{L}(\phi)\hat{R}B\sqrt{\frac{rn}{m}}$.

□

Using similar proofs, we can obtain the same upper bound in (21) for the Gaussian complexity of PiSSA and other single subspace variants for same samples number.

C Initialization of AdaMSS (Algorithm 1) and Subspace Segmentation (Algorithm 2)

D Parameter Count

Table 4: Comparison of parameter counts among different low-rank-based methods for $d = n$: r represents the rank of the incremental update used in LoRA and PiSSA.

	LoRA	PiSSA	AdaMSS
# Trainable Parameters	$2rn$	$2rn$	$\sum_{k=1}^{K}(r_k n_k + r_k R_k)$

Given $\boldsymbol{W}^{(k)} = \boldsymbol{W}_0^{(k)} + \boldsymbol{A}^{(k)}\boldsymbol{B}^{(k)}\boldsymbol{C}^{(k)}$ for $k = 1, 2, \cdots, K$, where $\boldsymbol{B}^{(k)} \in \mathbb{R}^{R_k\times r_k}$ and $\boldsymbol{C}^{(k)} \in \mathbb{R}^{r_k\times n_k}$ are trainable, the total trainable parameter count in AdaMSS is given by $\sum_{k=1}^{K}(r_k n_k + r_k R_k)$, which is always less than $2(\sum_{k=1}^{K} r_k)\max_{k=1,2,\cdots,K} n_k$ for $d = n$. Compared to the trainable parameter count in LoRA and PiSSA, as shown in Table 4, AdaMSS introduces significantly fewer parameters for $r = \sum_{k=1}^{K} r_k$, owing to the fact that $r_k \leq R_k \leq n_k$ and $n = \sum_{k=1}^{K} n_k$.

Algorithm 1 Initialization of AdaMSS

Input: $\boldsymbol{W}_0$, R, and r_k.

Output: Estimated K, $\{\boldsymbol{A}^{(k)}\}_{k=1}^K$, and the initialized values of $\{\boldsymbol{B}^{(k)}\}_{k=1}^K$ and $\{\boldsymbol{C}^{(k)}\}_{k=1}^K$.

Step 1: Compute the skinny SVD of $\boldsymbol{W}_0$: $\boldsymbol{W}_0 = \boldsymbol{U}_0\boldsymbol{S}_0\boldsymbol{V}_0^\top$;

Step 2: Obtain $\hat{\boldsymbol{W}}_0$ by $\hat{\boldsymbol{W}}_0 = [\boldsymbol{U}_0]_{:,1:R}[\boldsymbol{S}_0]_{1:R,1:R}[\boldsymbol{V}_0]_{:,1:R}^\top$ for given R;

Step 3: Obtain $\boldsymbol{Z}_0^\star$ by $\boldsymbol{Z}_0^\star = [\boldsymbol{V}_0]_{:,1:R}[\boldsymbol{V}_0]_{:,1:R}^\top$; ▷ Steps 1-3 are derived from Section 3.1.

Step 4: Estimate the number of subspaces K and apply clustering to assign the the columns of $\boldsymbol{W}_0$ to K subspaces [16], which are detailed in Algorithm 2;

Step 5: Obtain the matrix blocks $\{\boldsymbol{W}_0^{(k)}\}_{k=1}^K$, $\{\hat{\boldsymbol{W}}_0^{(k)}\}_{k=1}^K$, and $\{(\boldsymbol{Z}_0^\star)^{(k)}\}_{k=1}^K$ by the segmentation results; ▷ Steps 4-5 are derived from Section 3.2.

Step 6: For each k, compute the skinny SVD of $\hat{\boldsymbol{W}}_0^{(k)}$: $\hat{\boldsymbol{W}}_0^{(k)} = \boldsymbol{U}_{\hat{\boldsymbol{W}}_0}^{(k)}\boldsymbol{S}_{\hat{\boldsymbol{W}}_0}^{(k)}(\boldsymbol{V}_{\hat{\boldsymbol{W}}_0}^{(k)})^\top$;

Step 7: Perform the QR decomposition of $\boldsymbol{S}_{\hat{\boldsymbol{W}}_0}^{(k)}(\boldsymbol{V}_{\hat{\boldsymbol{W}}_0}^{(k)})^\top(\boldsymbol{Z}_0^\star)^{(k)}$: $\boldsymbol{S}_{\hat{\boldsymbol{W}}_0}^{(k)}(\boldsymbol{V}_{\hat{\boldsymbol{W}}_0}^{(k)})^\top(\boldsymbol{Z}_0^\star)^{(k)} = \boldsymbol{Q}^{(k)}\boldsymbol{R}^{(k)}$;

Step 8: Set $\boldsymbol{A}^{(k)} = \boldsymbol{U}_{\hat{\boldsymbol{W}}_0}^{(k)}$, initialize $\boldsymbol{B}^{(k)} = \boldsymbol{Q}^{(k)}$ and $\boldsymbol{C}^{(k)} = \boldsymbol{0}$. ▷ Steps 6-8 are derived from Section 3.3.

Algorithm 2 Estimation of K and Subspace Segmentation [16]

Input: $\boldsymbol{V}_0$, R, K_0, and $\tau > 0$.

Step 1: Construct the affinity matrix $[\boldsymbol{F}]_{i,j} = ([\tilde{\boldsymbol{U}}\tilde{\boldsymbol{U}}^T]_{i,j})$, where $\tilde{\boldsymbol{U}}$ is formed by $[\boldsymbol{V}_0]_{:,1:R}$ with normalized rows;

Step 2: Estimate the number of subspaces K by $K = \max(K_0, n - \text{int}\,(\sum_{i=1}^n f_\tau(\sigma_i(\boldsymbol{L}))))$ [16], where $\{\sigma_i(\boldsymbol{L})\}_{i=1}^n$ are the singular values of the Laplacian matrix $\boldsymbol{L} = \mathbf{I} - \boldsymbol{D}^{-\frac{1}{2}}\boldsymbol{F}\boldsymbol{D}^{-\frac{1}{2}}$, where $\boldsymbol{D} = \text{diag}\left(\sum_j[\boldsymbol{F}]_{1j}, \cdots, \sum_j[\boldsymbol{F}]_{nj}\right)$, int$(\cdot)$ is the function of the nearest integer, and

$$f_\tau(\sigma) = \begin{cases} 1, & \text{if } \sigma \geq \tau, \\ \log_2\left(1 + \frac{\sigma^2}{\tau^2}\right), & \text{otherwise.} \end{cases}$$

Step 3: Construct an undirected graph by using the affinity matrix $\boldsymbol{F}$;

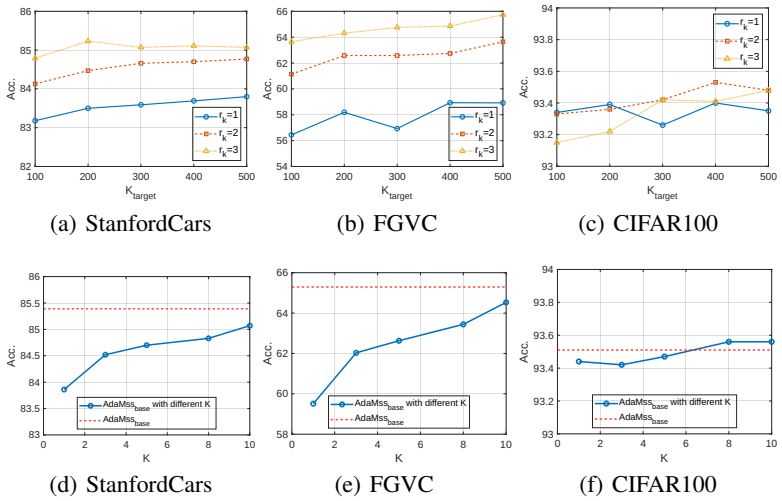
Step 4: Apply the NCut [35] to segment the vertices into K clusters;

E Computation Complexity

By the proposed adaptation, we have $\boldsymbol{Y} = \boldsymbol{X}(\boldsymbol{W}_0 + \boldsymbol{ABC})$, where $\boldsymbol{X} \in \mathbb{R}^{\text{bach size}\times n}$ is the input. In table 5, we compare the computational complexity of gradient computation for LoRA, PiSSA, and AdaMSS. The table shows that AdaMSS's computational complexity is on the same order as LoRA and PiSSA when $\sum_{i=1}^K r_k = r$.

Table 5: Comparison of LoRA, PiSSA and AdaMSS for $d = n$, where underline denotes the trainable parameters, and $\boldsymbol{A} \in \mathbb{R}^{n\times r}$ and $\boldsymbol{B} \in \mathbb{R}^{r\times n}$ for LoRA and PiSSA.

	LoRA	PiSSA	AdaMSS
Forward	$\boldsymbol{Y} = \boldsymbol{X}\boldsymbol{W}_0 + \boldsymbol{X}\underline{\boldsymbol{AB}}$	$\boldsymbol{Y} = \boldsymbol{X}\boldsymbol{W}_{res} + \boldsymbol{X}\underline{\boldsymbol{AB}}$	$\boldsymbol{Y} = \boldsymbol{X}\boldsymbol{W}_0 + \boldsymbol{X}\underline{\boldsymbol{ABC}}$
Gradient	$\frac{\partial\mathcal{L}}{\partial\boldsymbol{A}} = \boldsymbol{X}^\top\left(\frac{\partial\mathcal{L}}{\partial\boldsymbol{Y}}\right)\boldsymbol{B}^\top$	$\frac{\partial\mathcal{L}}{\partial\boldsymbol{A}} = \boldsymbol{X}^\top\left(\frac{\partial\mathcal{L}}{\partial\boldsymbol{Y}}\right)\boldsymbol{B}^\top$	$\frac{\partial\mathcal{L}}{\partial\boldsymbol{B}} = (\boldsymbol{XA})^\top\left(\frac{\partial\mathcal{L}}{\partial\boldsymbol{Y}}\right)\boldsymbol{C}^\top$
	$\frac{\partial\mathcal{L}}{\partial\boldsymbol{B}} = \boldsymbol{A}^\top\boldsymbol{X}^\top\left(\frac{\partial\mathcal{L}}{\partial\boldsymbol{Y}}\right)$	$\frac{\partial\mathcal{L}}{\partial\boldsymbol{B}} = \boldsymbol{A}^\top\boldsymbol{X}^\top\left(\frac{\partial\mathcal{L}}{\partial\boldsymbol{Y}}\right)$	$\frac{\partial\mathcal{L}}{\partial\boldsymbol{C}} = \boldsymbol{B}^\top(\boldsymbol{XA})^\top\left(\frac{\partial\mathcal{L}}{\partial\boldsymbol{Y}}\right)$
Cost	$\mathcal{O}(rn^2 + \text{bach size}\times n^2)$	$\mathcal{O}(rn^2 + \text{bach size}\times n^2)$	$\mathcal{O}(\sum_{i=1}^K r_k n^2 + \text{bach size}\times n^2)$



(a) StanfordCars (b) FGVC (c) CIFAR100

(d) StanfordCars (e) FGVC (f) CIFAR100

Figure 4: The performance of AdaMSS with different values of r_k, K, and K_{target}.

F Ablation Study

In the AdaMSS$_{\text{base}}$ and AdaMSS, the key hyperparameters include r_k, K, and K_{target}, where K represents the number of subspaces for each layer, and K_{target} is used for the proposed adaptive budget allocation mechanism. This subsection explores how the performance of the proposed methods (AdaMSS and AdaMSS$_{\text{base}}$) varies with different values of r_k, K and K_{target} using `ViT-Large`. Each configuration is evaluated on the StanfordCars[2], FGVC datasets[2], and CIFAR100[2]. All results are presented in Figures 4 (a)–(f).

Figures 4 (a)–(c) illustrate the impact of varying r_k and K_{target} on the performance of AdaMSS, where $r_k \in \{1, 2, 3\}$, $K_{\text{target}} \in \{100, 200, 300, 400, 500\}$, and K is estimated according to Algorithm 2 (see Appendix C). Figures 4 (d)–(f) investigate the effect of varying K on the performance of AdaMSS$_{\text{base}}$ at $r_k = 3$, comparing estimated K (shown as red dashed lines) with given values of K. As shown in Figures 4, increasing both r_k and K leads to significant improvements in accuracy. Notably, the improvement associated with increasing K highlights the advantage of the multi-subspace approach.

Table 6: Hyper-parameter setup for AdaMSS$_{\text{base}}$ and AdaMSS for IC.

Model	Hyperparameter	OxfordPets	StanfordCars	CIFAR10	EuroSAT	FGVC	RESISC45	CIFAR100
Both	Optimizer	AdamW						
	Batch Size	10						
	Epochs	10						
	Seeds	{7,77,777,7777,77777}						
`ViT-Base`	Learning Rate	0.005	0.01	0.01	0.01	0.01	0.01	0.01
	Learning Rate (Head)	0.005	0.05	0.005	0.0005	0.005	0.005	0.005
	Weight Decay	0.0005	0.0	0.05	0.05	0.0005	0.0005	0.05
`ViT-Large`	Learning Rate	0.001	0.01	0.01	0.01	0.01	0.01	0.01
	Learning Rate (Head)	0.0005	0.005	0.05	0.0005	0.0005	0.0005	0.05
	Weight Decay	0.0005	0.1	0.1	0.01	0.0005	0.1	0.05

Table 7: Hyper-parameter setup for AdaMSS$_{\text{base}}$ and AdaMSS for NLU.

Model	Hyperparameter	SST-2	MRPC	CoLA	QNLI	RTE	STS-B
Both	Optimizer	AdamW					
	Batch Size	32					
	Epochs	100					
	Seeds	{0,11111,22222,33333,444444}					
`RoBERTa-Base`	Learning Rate	0.001	0.01	0.001	0.001	0.0005	0.001
	Learning Rate (Head)	0.005	0.0005	0.005	0.005	0.005	0.005
	Weight Decay	0.0005	0.0	0.005	0.005	0.005	0.005
`RoBERTa-Large`	Learning Rate	0.001	0.001	0.001	0.0005	0.0005	0.001
	Learning Rate (Head)	0.0005	5e-05	0.05	0.05	0.005	0.0005
	Weight Decay	0.0	0.005	0.0005	0.005	0.0	0.0005

Table 8: The experimental setup

Fine-tuned on	**Evaluated Datasets**
MetaMathQA [33]	GSM8K [13], MATH [33]

Table 9: Hyper-parameter setup for AdaMSS$_{\text{base}}$ for NLG.

Model	Hyperparameter	GSM8K MATH
LLaMA 2-7B	Optimizer	AdamW
	Batch Size	4
	Epochs	1
	Learning Rate	2e-3

G Hyper-parameter setup

For a fair comparison, we replicate the experimental setups in [1, 2, 24]:

- IC and NLU: We tune the hyper-parameters for learning rates and weight decay for all methods. A detailed list of all hyper-parameters and settings can be found in the Tables 6-7. The reported results are averaged over five random seeds. All models are fine-tuned by updating only the query and value projection matrices, while the classification head is updated for every method.
- NLG: Following [2], we use the datasets listed in Table 8, and all experiments are conducted on 100K-example subsets and trained for a single epoch. List of all hyper-parameters and settings can be found in the Table 9. The results are averaged over three runs.

If not specified, K_0 in AdaMSS and AdaMSS$_{\text{base}}$ is set to 10.

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