HyperAdaLoRA: Accelerating LoRA Rank Allocation with Hypernetwork in Training

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Abstract

Parameter-Efficient Fine-Tuning (PEFT), especially Low-Rank Adaptation (LoRA), has emerged as a promising approach to fine-tuning large language models(LLMs) while reducing computational and memory overhead. However, LoRA assumes a uniform rank *r* for each incremental matrix, not accounting for the varying significance of weight matrices across different modules and layers. AdaLoRA leverages Singular Value Decomposition (SVD) to parameterize updates and employs pruning of singular values to introduce dynamic rank allocation, thereby enhancing adaptability. However, during the training process, it often encounters issues of slow convergence speed and high computational overhead. To address this issue, we propose HyperAdaLoRA, a novel framework that accelerates the convergence of AdaLoRA by leveraging a hypernetwork. Instead of directly optimizing the components of Singular Value Decomposition (P, Λ, Q), HyperAdaLoRA employs a hypernetwork based on attention mechanisms to dynamically generate these parameters. By pruning the outputs of the hypernetwork that generates the singular values, dynamic rank allocation is achieved. Comprehensive experiments on various datasets and models demonstrate that our method achieves faster convergence while maintaining accuracy.

1 Introduction

Parameter-efficient fine-tuning (PEFT) has emerged as a practical solution for adapting large language models (LLMs) to downstream tasks by updating a small subset of parameters, thereby reducing computational and memory overhead (Li and Liang, 2021; Lester et al., 2021; Zaken et al., 2022; Hu et al., 2022; Houlsby et al., 2019). A prominent PEFT method, Low-Rank Adaptation (LoRA) (Hu et al., 2022), is particularly notable for introducing trainable low-rank matrices into pre-trained weights during fine-tuning, reparameterizing weight updates as:

$$W = W^{(0)} + \Delta W = W^{(0)} + BA \quad (1)$$

where $W^{(0)}, \Delta W \in \mathbb{R}^{d_1 \times d_2}$, $A \in \mathbb{R}^{r \times d_2}$ and $B \in \mathbb{R}^{d_1 \times r}$ with $r \ll \{d_1, d_2\}$. During fine-tuning, only matrices B and A are updated, substantially reducing the number of trainable parameters. However, LoRA assigns a uniform rank across all layers, neglecting the varying functional importance of different components, potentially limiting performance in deep or heterogeneous models (Hu et al., 2023; Zhang et al., 2023a).

Dynamic rank allocation methods have been introduced to tackle this challenge by adaptively assign different ranks r to various modules or layers. There are three main strategies: 1) Singular value decomposition (SVD) methods (Zhang et al., 2023b; Hu et al., 2023; Zhang et al., 2023a) decompose matrices into singular values and vectors, effectively capturing key components. However, the decomposition process is computationally intensive, with a time complexity of $O(n^3)$, and requires additional memory to store the singular values and vectors. 2) Single-rank decomposition (SRD) methods (Mao et al., 2024; Zhang et al., 2024; Liu et al., 2024b) decompose matrices into rank-1 components, enabling more granular rank allocation. Despite this flexibility, identifying and pruning rank-1 components necessitates multi-stage training, increasing algorithmic complexity. The iterative selection process can also introduce instability, particularly when essential components are mistakenly pruned. 3) Rank sampling methods (Valipour et al., 2022) dynamically allocates ranks during training by sampling from a range of ranks, offering post-training flexibility. However, the stochastic nature of this approach introduces gradient noise, potentially destabilizing convergence.

Hypernetworks (Ha et al., 2016) is a meta-model that generates parameters for a target network, de-

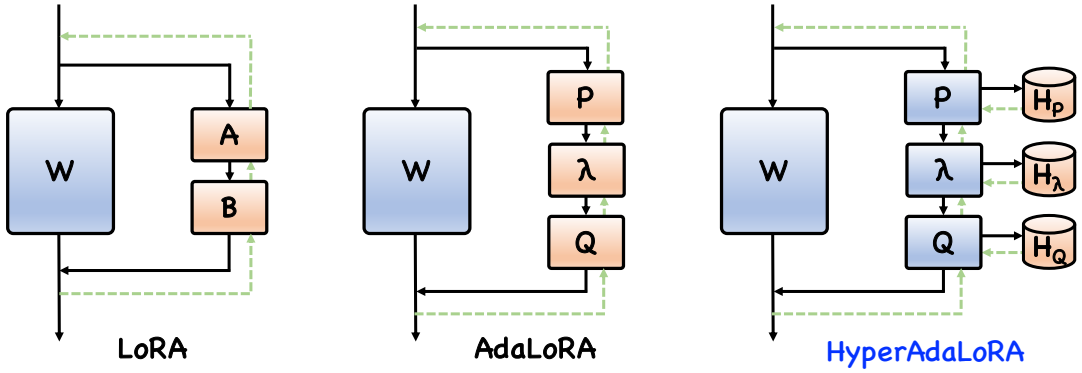


Figure 1: Comparison of LoRA, AdaLoRA, and HyperAdaLoRA frameworks, with black solid lines representing the forward process and green dashed lines indicating backpropagation (gradient flow). LoRA applies fixed-rank low-rank adaptations (A, B). AdaLoRA introduces dynamic rank allocation via Singular Value Decomposition (SVD) and singular value pruning (P, λ, Q). HyperAdaLoRA leverages a hypernetwork to dynamically generate SVD components (H_P, H_λ, H_Q), accelerating convergence and enhancing computational efficiency.

coupling parameter generation from model architecture. By producing task-specific parameters based on contextual inputs, hypernetworks enable dynamic adaptation without explicit iterative optimization, capturing intricate parameter adaptation patterns in real-time. Hypernetworks facilitate adaptive parameter optimization by modulating both the update direction and magnitude in response to the current model state (Lorraine and Duvenaud, 2018). This dynamic modulation fosters efficient navigation through high-dimensional parameter spaces, accelerating convergence while maintaining model expressiveness (Kirsch et al., 2018; Shi et al., 2022).

In this paper, we introduce HyperAdaLoRA, a novel framework that leverages hypernetworks (Ha et al., 2016) to achieve a significant improvement in convergence speed through parameter generation. Unlike traditional methods that directly train the incremental matrices P, Λ, and Q, HyperAdaLoRA employs task-specific hypernetworks to generate these matrices. Architecturally, our hypernetworks are based on a specific attention layer of BERT (Devlin et al., 2019), which enables them to capture the complex dependencies among parameters. Specifically, each hypernetwork takes the current state of P, Λ, or Q as input and outputs their updated versions. Dynamic rank allocation is realized by pruning the output of the hypernetwork that generates Λ. The training objective of HyperAdaLoRA is to minimize the discrepancy between the parameters generated by the hypernetworks and the ideal parameters. Extensive experiments demonstrate that our method achieves faster convergence while maintaining accuracy.

The main contributions of our paper can be summarized as follows:

- We introduce HyperAdaLoRA, a pioneering framework that utilizes hypernetworks to achieve substantial acceleration in convergence speed through advanced parameter generation.
- We employ attention based hypernetworks to capture the complex dependencies among parameters and accurately perform parameter updates during the training process.
- Extensive experiments demonstrate that our method achieves faster convergence while maintaining accuracy.

2 Related Work

2.1 SVD-based Dynamic Rank Allocation

SVD-Based methods parameterize LoRA's low-rank update matrix ΔW in a singular value decomposition form (e.g. splitting into $P\Lambda Q$) to dynamically adjust effective rank. The mathematical representation is as follows:

$$W = W^{(0)} + \Delta W = W^{(0)} + P\Lambda Q \quad (2)$$

where $P \in \mathbb{R}^{d_1 \times r}$ and $Q \in \mathbb{R}^{r \times d_2}$ represent the left/right singular vectors, and the diagonal matrix $\Lambda \in \mathbb{R}^{r \times r}$ contains the singular values $\{\lambda_i\}_{1 \le i \le r}$ with $r \ll \min(d_1, d_2)$. For example, AdaLoRA (Zhang et al., 2023b) prunes less important singular values based on a sensitivity-derived importance score during training. SaLoRA (Hu et al.,

2023) adaptively adjusts the rank by identifying and suppressing less informative singular components, optimizing parameter efficiency across layers. IncreLoRA (Zhang et al., 2023a) incrementally increases the rank during training, starting with a minimal rank and expanding as needed, balancing early training stability with later-stage expressiveness. These methods effectively capture principal components but incur $O(n^3)$ complexity and substantial memory overhead, impacting scalability and training stability, particularly with dynamic rank adjustment.

2.2 SRD-based Dynamic Rank Allocation

SRD-based methods decompose the LoRA update $\Delta W = \sum_{i=1}^{r} u_i v_i^T$ into a series of rank-1 matrices, where each component $u_i v_i^T$ represents a distinct direction in the parameter space. This decomposition allows the model to assess and adjust each rank-1 update independently. AutoLoRA (Zhang et al., 2024) uses a meta-learning scheme to determine which rank-1 slices to retain or prune, while ALoRA (Liu et al., 2024b) trains a 'supernetwork' and reallocates ranks based on importance. SoRA (Ding et al., 2023) applies sparsity penalties to zero out less impactful components, and DoRA (Liu et al., 2024a) adjusts only the direction component, assigning a learnable scalar for each weight. However, SRD methods face limitations such as increased algorithmic complexity from multi-stage training and additional optimization for rank-1 component selection. Abrupt pruning can destabilize training, while iterative selection adds computational overhead and heightens sensitivity to hyperparameter tuning.

2.3 Rank Sampling-based Dynamic Rank Allocation

Rank-sampling methods treat the LoRA rank as a random variable during training. DyLoRA (Valipour et al., 2022) implements this by sampling a truncation level $b \leq R$ in each iteration, zeroing out the bottom $R - b$ components and enabling the model to operate across multiple ranks without retraining. This approach eliminates the need for exhaustive rank search while also serving as a regularizer, concentrating key features in top components to potentially enhance generalization. However, training across multiple ranks can dilute performance at specific ranks compared to fixed-rank LoRA, and dynamic masking introduces slight computational overhead, potentially requiring additional training epochs to converge.

3 Method

3.1 Preliminary

Hypernetworks (Ha et al., 2016) are a type of neural network architecture used to generate the weights of another neural network (the target network). This can be expressed using the following formula:

$$\Theta = H(C; \Phi) \tag{3}$$

where Θ represents the weights of the target network, H denotes the hypernetwork, C is the context vector input to the hypernetwork and Φ corresponds to the weights of the hypernetwork itself.

The input to the hypernetwork (Ha et al., 2016) can be any information related to the target network, such as the input data of the target network, task requirements, or other contextual information. By conditioning parameter generation on these inputs, the hypernetwork can dynamically generate different parameters to adapt to different tasks or environments. This approach mitigates the need for learning a full set of parameters, thereby reducing model complexity and promoting generalization.

In neural architecture search (NAS), hypernetworks (Ha et al., 2016) can generate parameters for multiple sub-networks, thereby efficiently exploring different network architectures. By simultaneously training the hypernetwork and the subnetworks, the performance of a large number of candidate architectures can be evaluated in a relatively short time. This allows for the rapid screening of network structures with better convergence performance. This efficient architecture exploration method helps to find more optimal model architectures, thereby accelerating the overall training and convergence process.

3.2 Hypernetworks Accelerate Convergence

To accelerate the convergence of AdaLoRA, we propose a novel training strategy: employing a hypernetwork to dynamically generate the $P\Lambda Q$ parameters during training, rather than relying on traditional backpropagation for their updates. Specifically, at the beginning of training, we initialize the $P\Lambda Q$ parameters using a normal distribution. As training progresses, the parameters of the hypernetwork are continuously updated through backpropagation, thereby optimizing the generation process of the $P\Lambda Q$ parameters. In this process, the $P\Lambda Q$ parameters serve merely as intermediate results,

with their ultimate goal being the optimized generation via the hypernetwork to achieve faster convergence. The design of the hypernetwork is crucial to this strategy. It takes the parameters before the update as input and, after a series of complex computations and optimization operations, outputs the updated parameters. To conserve computational resources and memory usage, we employ the same hypernetwork for the same parameters across different parameters. For example, we use a single hypernetwork to generate the updated values for the P parameters of all matrix weights. This design not only improves resource efficiency but also ensures consistency and stability in parameter updates. In the i-th iteration, the update process of $P\Lambda Q$ can be specifically represented as follows:

$$P_{i+1} = \mathcal{H}_P(P_i; \Phi_P) \tag{4}$$

$$\Lambda_{i+1} = \mathcal{H}_\Lambda(\Lambda_i; \Phi_\Lambda) \tag{5}$$

$$Q_{i+1} = \mathcal{H}_Q(Q_i; \Phi_Q) \tag{6}$$

where $\mathcal{H}_P$, $\mathcal{H}_\Lambda$, and $\mathcal{H}_Q$ represent the hypernetworks used to update the parameters P, Λ, and Q, respectively. Φ_P, Φ_Λ, and Φ_Q represent the parameters of these hypernetworks. P_i, Λ_i, and Q_i represent the parameters before the i-th iteration update, while P_{i+1}, Λ_{i+1}, and Q_{i+1} represent the parameters after the update.

The process of a hypernetwork generating updated parameters by taking model parameters as input is essentially a dynamic parameter generation process. From a mathematical perspective, this can be likened to a nonlinear transformation within the parameter space, aimed at more efficiently approximating the optimal parameters. From the standpoint of optimization theory, such personalized updates can more effectively explore the parameter space to identify better solutions. Traditional optimization methods, such as gradient descent, follow fixed rules for parameter updates. In contrast, a hypernetwork can dynamically adjust the direction and magnitude of updates based on the current state of the parameters. This flexibility enables it to better adapt to complex loss landscapes and accelerate convergence. As a result, the hypernetwork can more precisely adjust the model's state in each iteration, thereby reducing the number of iterations required to achieve convergence.

During the initial training phases, the hypernetwork designed for Λ generates a full-rank diagonal matrix. To facilitate adaptive budget allocation, we implement an iterative singular value pruning strategy based on magnitude thresholds. At each interval ΔT, the k smallest singular values within Λ are set to zero, effectively reducing the rank of the incremental update Δ. Subsequently, the hypernetworks adjust the patterns they generate to compensate for the pruned dimensions through a gradient-driven process of plasticity.

The loss function integrates task-specific objectives with orthogonality regularization, formulated as:

$$\mathcal{L} = \mathcal{L}_{\text{task}} + \gamma(\|P^\top P - I\|_F^2 + \|QQ^\top - I\|_F^2) \tag{7}$$

where $\gamma > 0$ denotes the regularization coefficient. This formulation ensures that the generated matrices P and Q approximate orthogonal transformations while maintaining compatibility with downstream tasks.

3.3 Attention Driven Parameter Interaction

We adopt a BERT layer as the architecture of the hypernetwork and leverage the self-attention mechanism to capture the dependencies among parameters. Specifically, the interaction between the query and key in the attention mechanism mimics the associations between elements in the parameter matrix. This enables the hypernetwork to generate context-aware updates that preserve the structural patterns of the parameters. For any parameter p_i, its updated output takes into account all parameters in the matrix, as shown in the following equation:

$$p_{i+1} = \sum_{j=1}^{N} \text{Softmax}\left(\frac{Q_i K_j^T}{\sqrt{d}}\right) V_j \tag{8}$$

where p_{i+1} represents the updated value of parameter p_i, Q_i is the query vector associated with p_i, K_j is the key vector associated with parameter p_j, and V_j is the value vector corresponding to parameter p_j. The total number of parameters in the matrix is denoted by N, and d represents the dimensionality of the query and key vectors. This formulation allows the hypernetwork to dynamically compute the updated value of p_i by aggregating information from all parameters in the matrix, capturing their interdependencies and preserving the structural patterns of the parameters.

4 Experiments

4.1 Experimental Setup

Benchmarks. We conduct a comprehensive evaluation of our method, covering a wide range of tasks

Model	Method	Stanford Alpaca		Magpie	
		BLEU-4	ROUGE-1	BLEU-4	ROUGE-1
LLaMA3.1-8B	AdaLoRA	55.06	58.51	70.69	56.76
	HyperAdaLoRA (ours)	55.10	58.48	70.73	56.78
Qwen2.5-7B	AdaLoRA	6.79	20.17	56.21	49.43
	HyperAdaLoRA (ours)	6.79	20.19	56.18	49.42

Table 1: Performance comparison between HyperAdaLoRA and AdaLoRA on NLG tasks using LLaMA3.1-8B and Qwen2.5-7B as backbones. The reported metrics include BLEU-4 and ROUGE-1.

in both natural language understanding (NLU) and natural language generation (NLG). In the realm of natural language understanding, our method is tested on three challenging tasks from the GLUE benchmark (Wang, 2018): MNLI (Williams et al., 2017), RTE (Wang, 2018), and WNLI (Wang, 2018). These tasks represent large scale entailment classification, small-scale binary entailment classification, and coreference resolution presented in the form of binary entailment classification, respectively. In the natural language generation domain, we assess our method using three widely recognized datasets: Stanford Alpaca (Taori et al., 2023), Magpie-Pro-300K-Filtered (Xu et al., 2024), and OpenPlatypus (Lee et al., 2023). In the following text, we sometimes abbreviate Magpie-Pro-300K-Filtered as Magpie. These datasets focus on diverse instruction-following scenarios, designed to test the model's ability to generate text that meets the specified requirements.

Models. We use two prominent pretrained language models for NLU: RoBERTa-base (Liu, 2019), which is renowned for its strong performance across a wide range of NLU tasks, and DeBERTa-v3-base (He et al., 2021), an enhanced version that incorporates advanced pretraining techniques. For NLG, we employ two models: LLaMA3.1-8B (Grattafiori et al., 2024), a powerful 8 billion parameter model optimized for high-quality text generation, and Qwen2.5-7B (Yang et al., 2024), a model that demonstrates exceptional performance in various NLG tasks.

Baseline. Our primary baseline for comparison is AdaLoRA (Zhang et al., 2023b). AdaLoRA uses $P\Lambda Q$ as trainable parameters that are dynamically updated during training. It allocates parameter budgets by parameterizing updates in an SVD form and prunes singular values based on importance scores during training.

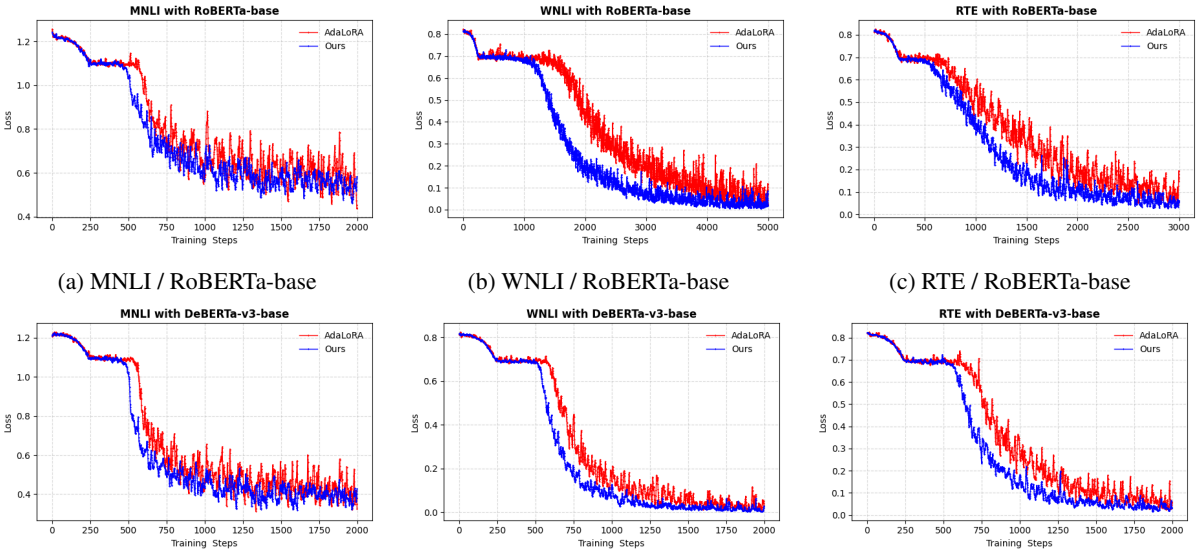
Implementation Details. Our experiments are conducted using the PyTorch framework (Paszke et al., 2019) and the Hugging Face Transformers library (Wolf, 2020), running on a cluster equipped with NVIDIA A100 40GB GPUs. In our experiments, we set the rank r to 3 and the orthogonality regularization coefficient γ to 0.1. We use the Adam optimizer (Kingma and Ba, 2014) with a learning rate of 1×10^{-5} and a batch size of 64 for training. For the comparative experiments, we keep the hyperparameters for the base model fine-tuning consistent across different methods. We use ROUGE-1 and BLEU-4 as the NLG evaluation metrics.

4.2 NLG Task Results

Performance Comparison. We first compare the final generation quality of HyperAdaLoRA and AdaLoRA after fine-tuning the LLaMA3.1-8B and Qwen2.5-7B models on the Stanford Alpaca and Magpie datasets. The results are summarized in Table 1 using BLEU-4 and ROUGE-1 scores.

The results in Table 1 indicate that HyperAdaLoRA does not exhibit any performance degradation compared to AdaLoRA. In most configurations, the scores of the two models are very close, with HyperAdaLoRA occasionally showing a slight edge. For example, on both datasets, HyperAdaLoRA outperforms AdaLoRA in terms of BLEU-4 for the LLaMA3.1-8B model and ROUGE-1 for the Qwen2.5-7B model. This demonstrates that the significant improvements in convergence speed do not negatively affect the final quality of the generated outputs.

Training Efficiency. We further evaluate the effectiveness of HyperAdaLoRA in NLG tasks. We finetune the LLaMA3.1-8B and Qwen2.5-7B models on three instruction-following datasets: Stanford Alpaca, Magpie-Pro-300K-Filtered, and OpenPlatypus. Table 3 presents a comparison of the total training time. In all configurations, HyperAdaLoRA achieves shorter training times than AdaLoRA. This reduction is evident across datasets of varying sizes, from the large Magpie to the smaller Alpaca and OpenPlatypus datasets, consis-



(a) MNLI / RoBERTa-base (b) WNLI / RoBERTa-base (c) RTE / RoBERTa-base

(d) MNLI / DeBERTa-v3-base (e) WNLI / DeBERTa-v3-base (f) RTE / DeBERTa-v3-base

Figure 2: Comparison of training loss convergence between HyperAdaLoRA and AdaLoRA on natural language understanding tasks. The rows correspond to three natural language understanding tasks: MNLI, RTE, and WNLI. The columns represent two pretrained language models: RoBERTa-base and DeBERTa-v3-base.

tent with the accelerated convergence. For instance, when fine-tuning LLaMA3.1-8B on the Stanford Alpaca dataset, HyperAdaLoRA takes 7250 seconds, compared to 8125 seconds for AdaLoRA. Similarly, when fine-tuning Qwen2.5-7B on the large Magpie-Pro dataset, HyperAdaLoRA has a training time of 14250 seconds, while AdaLoRA requires 15000 seconds. This consistent time advantage highlights the efficiency gains brought by hypernetwork based parameter generation. By more rapidly reaching effective parameter states, HyperAdaLoRA significantly reduces the total training duration needed for adaptation to these NLG tasks.

4.3 NLU Task Results

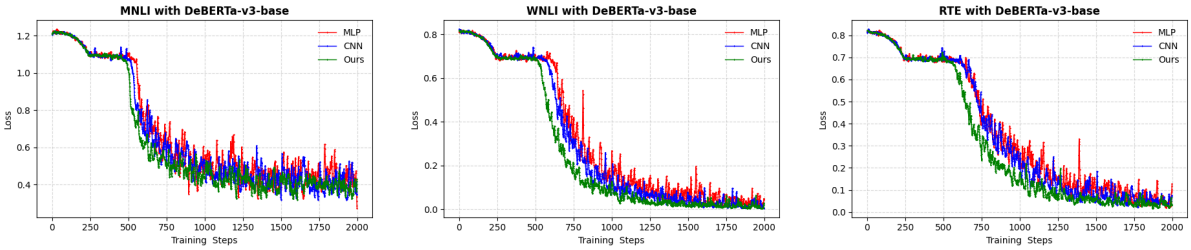
We compare the convergence speed of HyperAdaLoRA (which employs a BERT layered hypernetwork) with that of the baseline AdaLoRA. Figure 2 illustrates the training loss curves of these two methods on the MNLI, RTE, and WNLI datasets, using RoBERTa-base and DeBERTa-v3-base as backbone models. Across all experimental settings, HyperAdaLoRA consistently converges significantly faster than AdaLoRA. The loss curves of HyperAdaLoRA drop more steeply in the early stages of training and reach a lower loss plateau earlier in the training process. For instance, on the RTE task with DeBERTa-v3-base, HyperAdaLoRA achieves a loss level comparable to the final loss of AdaLoRA hundreds of training steps earlier. This accelerated convergence highlights the effectiveness of using a hypernetwork to generate parameter updates, enabling the model to adapt more rapidly to the target task. Moreover, the convergence curves of both methods reach the same convergence point, confirming that our approach does not sacrifice precision performance. This result is robust across different base models and datasets, indicating that the improved convergence speed is a universal characteristic of the HyperAdaLoRA framework.

4.4 Hyperparameter Impact Analysis

We investigate the sensitivity of HyperAdaLoRA's NLG performance to the orthogonality regularization coefficient γ. We finetune LLaMA3.1-8B with γ values set to $\{0.1, 0.15, 0.2\}$. As shown in Table 2, performance remains relatively stable across the tested γ values. Although $\gamma = 0.2$ yields slightly better results in this specific setup, the differences are minimal. This indicates that HyperAdaLoRA is robust to variations in this hyperparameter, thereby simplifying its practical application.

4.5 Ablation Study

To demonstrate the contributions of our hypernetwork design, we compare the performance of HyperAdaLoRA with different hypernetwork architectures (MLP, CNN, and BERT layer) when finetuning DeBERTa-v3-base. Figure 3 shows the training loss curves of these three variants on the MNLI,



(a) MNLI (b) WNLI (c) RTE

Figure 3: Comparison of training loss convergence for different HyperAdaLoRA hypernetwork architectures (MLP, CNN, BERT layer) on the DeBERTa-v3-base model for NLU tasks. The analysis is conducted across three natural language understanding tasks: MNLI, WNLI and RTE.

γ	Stanford Alpaca		Magpie	
	BLEU-4	ROUGE-1	BLEU-4	ROUGE-1
0.10	55.10	58.48	70.73	56.76
0.15	55.06	58.42	70.70	56.68
0.20	55.12	58.30	70.72	56.78

Table 2: Performance of HyperAdaLoRA with different values of γ. We conduct experiments using the LLaMA3.1-8B model on the Stanford Alpaca and Magpie-Pro-300K-Filtered datasets, with evaluation metrics including BLEU-4 and ROUGE-1.

RTE, and WNLI datasets. The results show that the choice of hypernetwork architecture affects the convergence speed. The BERT layer hypernetwork achieves the fastest convergence across all three datasets. This indicates that the attention mechanism is particularly effective at capturing the complex interdependencies among the elements of the P, Λ, and Q matrices, thereby generating more efficient and targeted updates. In contrast, the MLP and CNN-based hypernetworks lag behind the BERT layer variant. The MLP, being the simplest architecture, shows the least acceleration, while the CNN provides intermediate results. This performance hierarchy is consistent with the representation capabilities of these architectures, further demonstrating the benefits of using complex mechanisms like attention to generate parameters in this context.

4.6 Efficiency Analysis

We analyze the computational load of our method compared to AdaLoRA. Table 4 presents the GPU memory usage and per step training latency for both methods under different batch sizes. As shown in Table 4, HyperAdaLoRA exhibits a slight reduction in memory usage compared to AdaLoRA. Additionally, HyperAdaLoRA consistently demonstrates lower training latency per step. Although the per step reduction may appear modest, the faster convergence rate demonstrated earlier leads to a significantly shorter total training time to reach the target performance level. Therefore, HyperAdaLoRA achieves a notable improvement in training efficiency.

4.7 Case Study

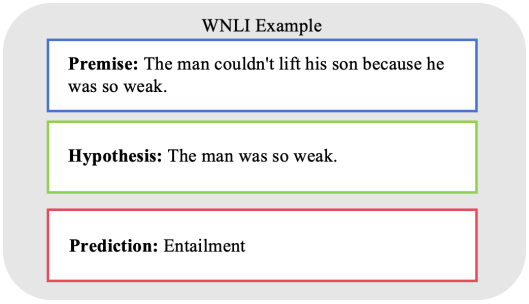


Figure 4: Examples generated by RoBERTa-base and DeBERTa-v3-base for the WNLI dataset.

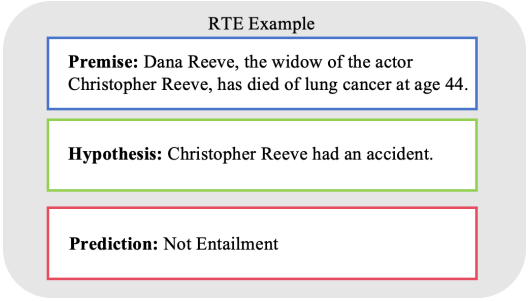


Figure 5: Examples generated by RoBERTa-base and DeBERTa-v3-base for the RTE dataset.

In Figure 4 and 5, we can see examples of two different natural language understanding tasks: WNLI and RTE. These examples demonstrate the models' capabilities in understanding and reasoning with textual information. In the first example,

Model	Method	Stanford Alpaca	Magpie-Pro-300K-Filtered	OpenPlatypus
LLaMA3.1-8B	AdaLoRA	8125	19600	11900
	HyperAdaLoRA (ours)	6650	15720	9750
Qwen2.5-7B	AdaLoRA	4240	15000	6750
	HyperAdaLoRA (ours)	3500	11000	5500

Table 3: Comparison of total training time (in seconds) for AdaLoRA and HyperAdaLoRA across natural language generation tasks. Experiments are conducted using the LLaMA3.1-8B and Qwen2.5-7B models on the Stanford Alpaca, Magpie-Pro-300K-Filtered, and OpenPlatypus datasets. HyperAdaLoRA consistently demonstrates lower training times across these settings.

Batch Size	AdaLoRA		HyperAdaLoRA (ours)	
	Memory (MB)	Latency (ms / step)	Memory (MB)	Latency (ms / step)
1	2758	123.16	2722	118.10
2	2798	132.60	2764	118.82
4	3232	149.38	3196	134.54
8	4115	189.39	4078	178.51
16	5906	284.33	5870	272.72
32	9600	486.16	9564	465.77
64	16566	882.55	16530	872.80

Table 4: Comparison of memory usage and training latency per step between AdaLoRA and HyperAdaLoRA across various batch sizes. The experimental settings are consistent with the implementation details described above.

the premise from the WNLI dataset is "The man couldn't lift his son because he was so weak." The hypothesis is "The man was so weak." The label is "Entailment," which means the hypothesis can be inferred from the premise, indicating that the premise supports the hypothesis. In the second example, the premise from the RTE dataset is "Dana Reeve, the widow of the actor Christopher Reeve, has died of lung cancer at age 44." The hypothesis is "Christopher Reeve had an accident." The label is "Not Entailment," meaning the hypothesis cannot be inferred from the premise, indicating that the premise does not support the hypothesis. These examples illustrate how models perform on different types of textual reasoning tasks when finetuned with our method. By fine-tuning RoBERTa-base and DeBERTa-v3-base models, we can enhance their performance on these tasks, thereby improving their ability to understand and reason with textual information. This is crucial in the field of natural language processing, as understanding and reasoning capabilities are key to building intelligent systems. With these methods, we can better address complex tasks such as question answering systems, conversational systems, and text summarization.

5 Conclusion

In this paper, we tackle the issue of slow convergence in AdaLoRA, an effective dynamic rank allocation method for PEFT. We propose HyperAdaLoRA, a novel framework that leverages hypernetworks to dynamically generate the SVD-based parameters (P, Λ, Q) that are integral to AdaLoRA. By adopting an attention-based hypernetwork architecture, HyperAdaLoRA is capable of capturing intricate parameter dependencies and producing targeted updates. This enables it to navigate the optimization landscape more efficiently compared to traditional AdaLoRA training methods. Extensive experiments conducted on various datasets and models consistently show that HyperAdaLoRA achieves significantly faster convergence, reaching target loss levels much earlier than standard AdaLoRA. This acceleration is achieved while maintaining comparable end-task accuracy and computational efficiency, with a slight reduction in training latency and a similar memory footprint. Furthermore, ablation studies reveal that the attention-based hypernetwork architecture provides the most substantial convergence benefits compared to simpler MLP or CNN designs. Future work may include extending this hypernetwork-based generation approach to other PEFT techniques, exploring different hypernetwork architectures, and evaluating the framework's scalability on even larger language models and a broader range of downstream tasks.

Limitations

In this paper, we conduct extensive experiments to evaluate the effectiveness of our hypernetwork-based training method in accelerating the training process across various tasks. While the results demonstrate significant speedup in most cases, the acceleration effect is less pronounced in certain tasks, suggesting the need for further refinement. Additionally, the robustness of our method under varying data distributions, particularly in low-resource and domain-specific datasets, remains underexplored. Future work will focus on optimizing the hypernetwork architecture to enhance its applicability across diverse task types.

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