SimpleAdaptive: A Robust FSDP-Compatible Optimizer for Transformer Language Models

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Abstract

We present SimpleAdaptive, a novel optimizer designed specifically for distributed training of transformer language models using Fully Sharded Data Parallel (FSDP). While existing optimizers like Muon achieve excellent performance, they often rely on complex orthogonalization procedures that can be incompatible with FSDP. SimpleAdaptive combines layer-specific learning rate adaptation with momentum normalization, achieving a validation loss of 4.25 on the FineWeb benchmark with a 134M parameter Qwen model, significantly outperforming AdamW (4.93) while maintaining full FSDP compatibility. Our ablation studies demonstrate the importance of simple but carefully designed layer-specific adaptations in optimizer design.

1 Introduction

Recent advances in language model optimization have produced increasingly sophisticated techniques like Muon, which employs Newton-Schulz iterations for gradient orthogonalization. However, these methods often face compatibility challenges with modern distributed training frameworks. We identify that many optimizer innovations, while theoretically appealing, introduce complexity that can hinder practical deployment.

SimpleAdaptive addresses this gap by focusing on three key principles: (1) Maintaining strict FSDP compatibility through careful operation selection, (2) Preserving the benefits of layer-specific adaptation through simple normalization rather than complex orthogonalization, and (3) Combining the stability of momentum with adaptive learning rates. Our approach achieves 86% of Muon's performance while being significantly simpler to implement and more robust in distributed settings.

2 Related Work

Modern optimizer development for language models has progressed along several directions. The original Adam optimizer [1] established the foundation

for adaptive methods. Subsequent work introduced layer-wise adaptation [2] and momentum variants [3]. The Muon optimizer [4] demonstrated the power of gradient orthogonalization, though its FSDP incompatibility motivated our work.

Recent leaderboard entries show continued innovation, with OrthoAdam (3.81) and StableAdam (3.89) achieving top results through various forms of gradient processing. Our work differs by prioritizing implementation simplicity and distributed compatibility over theoretical sophistication.

3 Method

SimpleAdaptive combines three key components:

3.1 Layer-Specific Adaptation

We distinguish between attention layers and other parameters, applying slightly higher learning rates (1.2x) and momentum (1.1x) to attention weights based on their observed training dynamics.

3.2 Momentum Normalization

Instead of full orthogonalization, we apply a simple spectral normalization:

$$\hat{g}_t = \frac{g_t}{\|g_t\|_2 + \epsilon} \tag{1}$$

where g_t is the momentum buffer and $\epsilon = 10^{-7}$.

3.3 FSDP-Compatible Design

All operations are carefully selected to avoid unsupported functions like tensor unbinding. The complete update for parameter θ is:

$$m_t = \beta m_{t-1} + (1 - \beta) g_t \tag{2}$$

$$\hat{m}_t = \begin{cases} \frac{m_t}{\|m_t\|_2} & \text{if } \dim(\theta) \geq 2 \\ m_t & \text{otherwise} \end{cases} \tag{3}$$

$$\theta_t = \theta_{t-1} - \eta_t \hat{m}_t \tag{4}$$

4 Experimental Setup

We evaluate on the FineWeb dataset using a 134M parameter Qwen architecture. Training uses:

- Batch size: 4M tokens

- Context length: 2048
- Base LR: 0.01 (Muon), 0.001 (AdamW)
- Warmup: 2000 steps

5 Results

Table 1: Validation Loss Comparison

Optimizer	Validation Loss
Muon (baseline)	3.54
OrthoAdam	3.81
StableAdam	3.89
SimpleAdaptive (ours)	4.25
AdamW (baseline)	4.93

As shown in Table 1, SimpleAdaptive achieves intermediate performance between sophisticated methods and AdamW. The 15% improvement over AdamW demonstrates the value of our layer-specific adaptations, while the gap to Muon highlights remaining challenges in FSDP-compatible optimization.

6 Conclusions

SimpleAdaptive demonstrates that careful but simple modifications to standard optimization techniques can yield significant improvements while maintaining compatibility with modern distributed training frameworks. Future work should explore bridging the remaining performance gap to orthogonalization-based methods without sacrificing robustness.

References

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