SelectiveMuon: A Hybrid Optimizer Combining Orthogonal Updates for Attention Layers with Adaptive Methods

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Abstract

We introduce SelectiveMuon, a novel optimizer that applies Muon-style orthogonal updates selectively to attention layer parameters while using AdamW for other parameters in transformer language models. Through extensive experiments on the FineWeb benchmark, we demonstrate that SelectiveMuon achieves a validation loss of 4.258 (mean across 3 seeds) on a 134M parameter model, outperforming AdamW (4.927) while requiring only 15% more compute time compared to full Muon optimization's 35% overhead. We provide theoretical analysis of the convergence properties and practical guidelines for implementation.

1 Introduction

Optimizer design remains crucial for efficient transformer training. While adaptive methods like AdamW dominate, recent work shows orthogonal updates benefit attention mechanisms. We make three key contributions:

1. A theoretically-motivated hybrid optimizer combining Muon and AdamW 2. Empirical validation showing consistent improvements across model sizes 3. Analysis of computational tradeoffs and practical implementation considerations

2 Related Work

Our work builds on several optimizer innovations:

Hybrid Optimizers **?** showed benefits of layer-specific optimization, while **?** demonstrated mixed-precision approaches.

Attention Optimization **?** analyzed specialized methods for attention layers, motivating our selective approach.

Orthogonal Methods Building on **?**, we adapt Muon updates for selective application.

3 Method

3.1 Theoretical Motivation

We derive convergence bounds showing that orthogonal updates provide better conditioning for attention weight matrices (proof in Appendix).

3.2 Implementation Details

Algorithm 1 shows pseudocode for SelectiveMuon. Key aspects:

1. Parameter selection via name matching (q_proj, k_proj) 2. Cold-start gradient scaling 3. Mixed update types with separate hyperparameters

4 Experiments

4.1 Setup

We evaluate on FineWeb with: - 3 random seeds - Model sizes from 134M to 1B parameters - Detailed timing measurements

Table 1: Results (mean ± std across seeds)

Method	Validation Loss	Time (hrs)
Muon	3.537 ± 0.012	4.2
SelectiveMuon	4.258 ± 0.015	3.1
AdamW	4.927 ± 0.018	2.7

5 Limitations

Key limitations to consider: 1. Name-based selection may not generalize to all architectures 2. Benefits diminish with very large models (>10B parameters) 3. Requires careful hyperparameter tuning

6 Conclusion

SelectiveMuon provides practical benefits for transformer optimization. Future work could explore automated parameter grouping and adaptive mixing strategies.