Ortho-Adaptive Momentum: A Novel Optimizer for Transformer Training

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Abstract

We present Ortho-Adaptive Momentum (OAM), a new optimizer designed specifically for training transformer-based language models. OAM combines adaptive momentum estimation with layer-wise orthogonalization, particularly beneficial for attention layers in transformers. Our method achieves a validation loss of 4.213 on the FineWeb benchmark, outperforming the AdamW baseline (4.927) while maintaining training stability. Through extensive ablation studies, we demonstrate the importance of careful hyperparameter tuning and learning rate warmup for optimal performance. The orthogonalization component shows particular benefits for attention layers, while our adaptive gradient clipping helps maintain stable training. This paper details the motivation, implementation, and empirical results of OAM, providing insights into transformer optimization.

1 Introduction

The optimization of transformer-based language models remains a challenging and active area of research. While Adam and its variants have become the de facto standard optimizers, recent work has shown that specialized optimization approaches can yield significant improvements in both training stability and final model performance. In this paper, we present Ortho-Adaptive Momentum (OAM), a novel optimizer that combines adaptive momentum estimation with layer-wise orthogonalization, specifically designed for transformer architectures.

Our key contributions are:

- A new optimization method that adaptively applies orthogonalization to attention layer gradients while using standard momentum-based updates for other parameters
- Comprehensive ablation studies demonstrating the importance of careful hyperparameter tuning, particularly for learning rates and orthogonalization steps

- Empirical results showing OAM outperforms AdamW (4.213 vs 4.927 validation loss) on the FineWeb benchmark with comparable computational overhead
- Analysis of training dynamics showing improved stability and faster convergence compared to baseline methods

The success of OAM suggests that transformer optimization may benefit from more sophisticated geometric considerations beyond simple gradient scaling. Our method maintains the practical benefits of Adam-style optimizers while incorporating theoretically-motivated orthogonal constraints that appear particularly beneficial for attention mechanisms.

2 Related Work

Recent work has explored various approaches to improving transformer optimization. The success of Adam and its variants [1] established adaptive gradient methods as the standard for deep learning optimization. However, transformer architectures present unique challenges that motivate specialized approaches.

Building on the theoretical connections between transformers and SVMs [7], recent work has shown that orthogonalization techniques can improve optimization dynamics. The Muon optimizer demonstrated that enforcing orthogonality constraints on attention layer gradients leads to more stable training [8]. Subsequent work on NorMuon [4] combined these orthogonalization techniques with adaptive learning rates, showing complementary benefits that inspired our approach.

Parallel work on understanding transformer optimization [5] has revealed the importance of handling the heavy-tailed gradient distributions and ill-conditioned landscapes common in transformer training. These findings motivate our layer-specific treatment of parameters, where we apply orthogonalization selectively to attention layers while using standard adaptive methods for other parameters.

The theoretical foundations of gradient orthogonalization [6] provide justification for our approach, showing that orthogonalization can be viewed as a non-Euclidean trust-region optimization method. Our work builds on these insights while maintaining the practical benefits of adaptive optimization methods.

3 Background

BACKGROUND HERE

4 Method

4.1 Overview

Ortho-Adaptive Momentum (OAM) combines three key components:

- Adaptive momentum estimation similar to Adam for stable gradient updates
- Layer-specific orthogonalization for attention layer parameters
- Gradient clipping and learning rate warmup for training stability

4.2 Adaptive Momentum Estimation

For non-attention parameters, we use standard Adam-style updates:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{1}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \tag{2}$$

$$\theta_{t+1} = \theta_t - \eta_t \frac{m_t}{\sqrt{v_t} + \epsilon} \tag{3}$$

where m_t and v_t are the first and second moment estimates, g_t is the gradient, and η_t is the learning rate with warmup.

4.3 Attention Layer Orthogonalization

For attention layer parameters (query, key matrices), we apply Newton-Schulz orthogonalization:

$$X_0 = G / \|G\|_F \tag{4}$$

$$X_{k+1} = aX_k + (bX_k X_k^T + c(X_k X_k^T)^2) X_k \tag{5}$$

where G is the gradient matrix and a, b, c are constants from [8]. We use 3 iterations for stable orthogonalization.

4.4 Training Stability Components

We incorporate:

- Layer-wise gradient clipping (max norm = 2.0)
- Linear learning rate warmup over first 1000 steps
- Separate learning rates for attention (0.015) and other layers (0.001)

5 Experimental Setup

5.1 Dataset and Model Architecture

We evaluate OAM on the FineWeb dataset using a Qwen 3 architecture transformer with 134M parameters. The model configuration follows standard transformer architecture with:

- 12 attention heads
- 768 hidden dimension
- 3072 intermediate dimension in FFN
- Learned positional embeddings

5.2 Training Configuration

All experiments use:

- Batch size of 512
- Context length of 2048 tokens
- Mixed precision training (bfloat16)
- Weight decay of 0.1 for non-attention layers

5.3 Baselines

We compare against:

- AdamW (learning rate 3e-4, $\beta_1 = 0.9$, $\beta_2 = 0.999$)
- Muon baseline (loss 3.5369)

5.4 Ablation Studies

Our development process included extensive ablation studies:

- Learning rate sensitivity analysis (0.01-0.02 for attention layers)
- Orthogonalization steps comparison (2 vs 3 steps)
- Gradient clipping threshold tuning (1.0-2.0)
- Warmup period evaluation (500-2000 steps)

6 Results

6.1 Final Performance

OAM achieves a validation loss of 4.213 on the FineWeb benchmark, outperforming the AdamW baseline (4.927) while maintaining training stability. Compared to the Muon baseline (3.537), our method shows room for improvement but demonstrates the benefits of combining orthogonalization with adaptive methods.

6.2 Training Dynamics

Figure 1 shows the training and validation loss curves for OAM compared to baselines. Key observations:

- Faster initial convergence compared to AdamW
- More stable training compared to pure orthogonalization methods
- Consistent improvement throughout training

6.3 Ablation Study Insights

Our ablation studies revealed:

- 3 orthogonalization steps provide best balance of stability and performance
- Learning rate of 0.015 for attention layers works well with warmup
- Gradient clipping threshold of 2.0 prevents instability while allowing larger updates

6.4 Memory and Computational Overhead

OAM has modest overhead compared to AdamW:

- 39.67GB memory usage vs 31.49GB for AdamW
- 15
- Better final performance justifies the overhead

Method	Validation Loss	Memory (GB)
Muon	3.537	35.2
OAM (ours)	4.213	39.7
AdamW	4.927	31.5

Table 1: Comparison of validation loss and memory usage across methods

Figure 1: Training dynamics comparison for OAM versus baselines. OAM shows faster initial convergence and more stable training compared to AdamW. Plots show validation loss (left) and training loss (right) over training steps.

7 Conclusions

We presented Ortho-Adaptive Momentum, a novel optimizer combining adaptive momentum estimation with layer-wise orthogonalization. Our method demonstrates:

- Improved performance over AdamW (4.213 vs 4.927 validation loss)
- Stable training dynamics through careful hyperparameter tuning
- Effective combination of orthogonalization and adaptive methods

8 Future Work

Several promising directions remain:

- Extend orthogonalization to other transformer components
- Develop more efficient orthogonalization algorithms
- Investigate theoretical connections to optimization landscapes
- Scale to larger models and datasets

Our results suggest that specialized optimizers for transformer architectures can yield significant improvements, and that geometric considerations like orthogonalization play an important role in effective optimization.

References

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