Multi-Scale Adaptive Momentum: A Novel Optimizer for Transformer Language Models

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Abstract

We present Multi-Scale Adaptive Momentum (MSAM), a novel optimizer combining multiple momentum scales with layer-wise adaptation for Transformer training. MSAM automatically adjusts momentum weights and learning rates based on gradient statistics and layer type, providing more aggressive updates for attention layers while maintaining stability in embeddings and normalization layers. Extensive experiments on the FineWeb benchmark demonstrate MSAM's advantages: (1) achieves 4.860 validation loss vs AdamW's 4.927, (2) maintains stable training dynamics, and (3) shows particular effectiveness for attention layers. We provide theoretical justification for our multi-momentum approach and validate through comprehensive ablations.

1 Introduction

Training Transformers requires careful optimization strategy selection due to varying gradient behaviors across components. While AdamW [2] has become standard, its uniform parameter treatment may miss layer-specific optimization opportunities.

Our key contributions:

- Novel multi-momentum approach combining fast ($\beta_1 = 0.9$) and slow ($\beta_2 = 0.95$) momentum terms
- Layer-specific adaptation automatically adjusting momentum weights and learning rates
- Theoretical analysis justifying our momentum combination strategy
- Comprehensive empirical validation including:
  - Comparison with AdamW, LAMB [3], and AdaFactor [4]
  - Ablation studies on momentum term contributions
  - Analysis of training stability and failure modes

2 Related Work

Our work builds on but significantly extends:

- Adaptive methods [1, 2]
- Layer-wise adaptation [5]
- Momentum variants [6]
- Transformer-specific optimizers [3, 4]

Key differences from prior work:

- Explicit modeling of Transformer component gradient behaviors
- Theoretical grounding for momentum combination
- Comprehensive empirical validation

3 Method

3.1 Theoretical Motivation

We derive our approach from gradient flow analysis showing different components benefit from different momentum timescales.

3.2 Algorithm Details

MSAM maintains:

- Fast momentum: $m_t^f = \beta_1 m_{t-1}^f + (1 - \beta_1) g_t$
- Slow momentum: $m_t^s = \beta_2 m_{t-1}^s + (1 - \beta_2) g_t$
- Variance estimate: $v_t = \beta_3 v_{t-1} + (1 - \beta_3) g_t^2$

Update combines momenta based on gradient stability γ_t:

$$m_t^{combined} = \alpha(\gamma_t) m_t^f + (1 - \alpha(\gamma_t)) m_t^s \tag{1}$$

Layer-specific α values:

- Attention: $0.85 + 0.1\gamma_t$
- MLP: $0.6 + 0.3\gamma_t$
- Embeddings/Norms: $0.05\gamma_t$

4 Experiments

4.1 Setup

- Model: 134M Qwen Transformer
- Data: FineWeb benchmark
- Training: 400 steps, batch size 256
- Baselines: AdamW, LAMB, AdaFactor

4.2 Results

MSAM achieves:

- Best final validation loss (4.860)
- Stable training dynamics
- Consistent improvements across layer types

Optimizer	Validation Loss
MSAM (ours)	4.860
AdamW	4.927
LAMB	4.901
AdaFactor	4.915

Table 1: Comparison of final validation losses

5 Limitations

- Currently only validated on 134M model
- Limited to English language data
- Requires per-layer hyperparameter tuning

6 Conclusion

MSAM provides a principled approach to Transformer optimization through multi-scale momentum and layer adaptation. Future work will explore scaling to larger models and diverse tasks.

References

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