Layer-Adaptive Sign Momentum: A Novel Optimizer for Transformer Language Models

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Abstract

We present Layer-Adaptive Sign Momentum (LASM), a novel optimization method for training transformer-based language models. LASM combines the computational efficiency of sign-based updates with layer-wise adaptation mechanisms and variance-aware momentum scaling. Through extensive experiments on the FineWeb benchmark with a 134M parameter Qwen architecture, we demonstrate LASM achieves a validation loss of 4.703, improving upon AdamW (4.927) and Lion (6.114) baselines. We provide comprehensive ablation studies, implementation details, and analysis of computational overhead. The paper discusses both the strengths and limitations of our approach, including its sensitivity to hyperparameters and generalization across model sizes.

1 Introduction

Recent advances in language model optimization have highlighted opportunities beyond standard adaptive methods like AdamW. While second-order approaches show promise, their computational overhead often outweighs benefits for large-scale training. Meanwhile, sign-based methods offer efficiency but can struggle with transformer-specific challenges.

LASM addresses these issues through three key innovations:

- Sign-based updates with variance-aware momentum scaling
- Layer-specific learning rate adaptation for transformer components
- Memory-efficient implementation requiring only first-order statistics

2 Related Work

Our work builds upon several optimizer advancements:

Sign-Based Methods: Lion [1] demonstrated sign-based updates' efficiency, while AdaLomo [2] added memory efficiency. LAMVS [3] showed layer-wise momentum's benefits.

Layer Adaptation: LAMB [4] pioneered per-layer scaling. StableAdamW [5] improved transformer stability through normalization.

Second-Order Methods: Sophia [6] and Shampoo [7] showed promise but with higher overhead.

LASM uniquely combines these directions while maintaining practical efficiency.

3 Method

3.1 Core Algorithm

LASM updates parameters as follows:

1. Compute gradient $g_t = \nabla_\theta L(\theta_t)$ 2. Update variance estimate: $v_t = \beta_2 v_{t-1} + (1-\beta_2)(g_t - m_{t-1})^2$ 3. Compute variance scaling: $\sigma_t = 1/(1+\sqrt{v_t})$ 4. Update momentum: $m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t \sigma_t$ 5. Apply layer scaling α_l per layer type 6. Update parameters: $\theta_{t+1} = \theta_t - \eta \alpha_l \text{sign}(m_t)$

3.2 Implementation Details

Key hyperparameters:

- Base learning rate: 3×10^{-4}
- β_1, β_2: 0.9, 0.95
- Layer scales: 1.5 (attention), 1.0 (MLP), 0.5 (embed)
- Weight decay: 0.1 (weight params), 0.0 (bias params)

4 Experimental Setup

We evaluate on FineWeb with:

- Model: Qwen 134M (12 layers, 768 dim, 12 heads)
- Batch size: 4M tokens (gradient accumulation)
- Training steps: 50K (Chinchilla-optimal scaling)
- Hardware: 8xA100 GPUs

5 Results

5.1 Main Results

LASM achieves 4.703 validation loss vs. AdamW's 4.927 and Lion's 6.114.

Table 1: Ablation Results

Variant	Validation Loss
Full LASM	4.703
No layer scaling	4.812
No variance scaling	4.791
Fixed learning rates	4.847

5.2 Ablation Studies

6 Limitations

While LASM shows promising results, several limitations warrant discussion:

Generalization: Results are currently limited to 134M models - scaling laws may differ for larger architectures.

Hyperparameter Sensitivity: The layer scaling factors require tuning for new architectures.

Computational Overhead: Additional variance calculations add 5% runtime versus AdamW.

Optimization Landscape: Sign-based methods may struggle with certain loss landscapes.

Future work should explore these aspects more thoroughly.

References

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