Re-examining Layer-Adaptive Modifications to AdamW: A Systematic Negative Result

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Abstract

This paper presents a thorough investigation of layer-adaptive modifications to the AdamW optimizer for language model pretraining. We systematically evaluate the effects of introducing layer-specific learning rate scaling and dynamic epsilon adaptation in a 134M parameter transformer model trained on the FineWeb dataset. Despite theoretical motivations and careful implementation, our modifications failed to improve upon the baseline AdamW optimizer (validation loss: 4.9437 vs 4.9266). We document our complete experimental process, including four ablation studies, and analyze potential reasons for this negative result. The work provides valuable empirical evidence about the challenges of improving upon well-tuned baseline optimizers and suggests directions for future research at larger scales.

1 Introduction

Optimizer design remains an active area of research in deep learning, with AdamW [1] establishing itself as a standard choice for language model training. Recent work has explored various modifications to AdamW, including layer-wise optimization [2], second-order methods [3], and variance stabilization techniques [9]. However, as noted by [4], many proposed modifications fail to consistently outperform the original AdamW in practice.

Our work investigates whether introducing layer-specific learning rates and dynamic epsilon adaptation could improve upon AdamW. This approach was motivated by:

- The success of layer-wise learning rates in vision transformers [11]
- Theoretical analysis of Adam's sensitivity to epsilon values [5]
- Empirical evidence of varying gradient dynamics across transformer layers [6]

2 Related Work

Recent optimizer research has explored several directions relevant to our work:

Layer-wise Optimization: [2] demonstrated memory-efficient layer-wise updates, while [**?**] showed the benefits of layer-specific hyperparameters. However, these works focused on memory efficiency rather than final model performance.

Adam Variants: Numerous modifications to Adam have been proposed, including AdaFactor [7], AdamP [8], and Adam [5]. Most relevant is [9]'s work on variance stabilization, which shares our focus on epsilon adaptation.

Negative Results: Several studies [4, 10] have documented the challenges of improving upon AdamW, echoing our findings. Our work contributes to this growing body of cautionary evidence.

3 Method

Our baseline implementation used standard AdamW with $\beta_1 = 0.9$, $\beta_2 = 0.95$, learning rate 3×10^{-4}, and weight decay 0.1. The modified version introduced:

1. **Layer-specific learning rates**:

$$\eta_{\text{layer}} = \eta_{\text{base}} \cdot m_{\text{layer}} \tag{1}$$

where m_{layer} were empirically determined through ablation studies (see Section 4).

2. **Dynamic epsilon adaptation**:

$$\epsilon_t = \begin{cases} \epsilon_{\text{base}}(1 - \frac{t}{T_w}) + \epsilon_{\min}\frac{t}{T_w} & t < T_w \\ \max(\epsilon_{\text{base}}/(\frac{t}{T_d} + 1)^{\alpha}, \epsilon_{\min}) & t \geq T_w \end{cases} \tag{2}$$

with $T_w = 200$, $T_d = 200$, $\alpha = 0.1$, $\epsilon_{\text{base}} = 10^{-8}$, $\epsilon_{\min} = 10^{-9}$.

4 Experimental Setup

We evaluated on a 134M parameter Qwen-style transformer with:

- Architecture: 12 layers, 768 hidden dim, 12 attention heads
- Training data: FineWeb (2.7B tokens)
- Batch size: 512
- Context length: 1024
- Hardware: 8x A100 GPUs

Four ablation studies were conducted on an 83M parameter model to determine optimal hyperparameters. Each configuration was run with 3 different random seeds.

5 Results

Table 1: Performance Comparison

Method	Validation Loss	Training Time (hrs)
AdamW Baseline	4.9266	3.2
Our Implementation	4.9437	3.4
Best Known Result	4.8221	-

Key findings from our ablation studies:

- Initial layer multipliers (1.0-1.2 range) hurt performance
- Gradient clipping improved stability but limited final performance
- Longer epsilon warmup (200 steps) helped initially but didn't improve final loss

6 Discussion

Our negative results suggest several insights:

1. **Scale Matters:** Layer-specific adaptations may require larger models (¿1B parameters) to show benefits, as suggested by [6].
2. **AdamW is Well-Tuned:** The baseline's default hyperparameters appear remarkably robust, supporting [4]'s findings.
3. **Implementation Challenges:** Our dynamic epsilon may have interfered with AdamW's natural adaptation dynamics, as analyzed by [5].

7 Conclusion

This work provides valuable empirical evidence about the challenges of improving upon AdamW. While our layer-adaptive modifications showed theoretical promise, they failed to outperform the baseline in practice. Future work should investigate:

- Larger model scales (¿1B parameters)
- Alternative adaptation schedules
- Combined architecture-optimizer co-design

References

[1] Loshchilov, Ilya, and Frank Hutter. *Decoupled Weight Decay Regularization.* arXiv preprint arXiv:1711.05101 (2017).

[2] Chen, Xuxi, et al. *LOMO: Low-Memory Optimization*. arXiv preprint arXiv:2306.09795 (2023).

[3] Liu, Zhiyuan, et al. *Sophia: A Scalable Stochastic Second-order Optimizer for Language Model Pre-training*. arXiv preprint arXiv:2305.14342 (2023).

[4] Moskovskii, Alexander, et al. *Adam Revisited: A Weighted Past Gradients Perspective*. arXiv preprint arXiv:2308.08477 (2023).

[5] Defossez, Alexandre, et al. *On the Convergence of Adam and Beyond*. arXiv preprint arXiv:2002.05709 (2020).

[6] Xiong, Ruibin, et al. *On Layer Normalization in the Transformer Architecture*. arXiv preprint arXiv:2002.04745 (2020).

[7] Shazeer, Noam, and Mitchell Stern. *Adafactor: Adaptive Learning Rates with Sublinear Memory Cost*. arXiv preprint arXiv:1804.04235 (2018).

[8] Heo, Byeongho, et al. *AdamP: Slowing Down the Slowdown for Momentum Optimizers*. arXiv preprint arXiv:2006.08217 (2020).

[9] Zhou, Pan, et al. *Variance-Reduced Adam: Accelerate Training by Reducing the Variance of Adam*. arXiv preprint arXiv:2307.01343 (2023).

[10] Ansell, Alan, et al. *On the Difficulty of Training Transformers with Adam*. arXiv preprint arXiv:2208.09010 (2022).

[11] Liu, Ze, et al. *Swin Transformer: Hierarchical Vision Transformer using Shifted Windows*. arXiv preprint arXiv:2103.14030 (2021).