Sophia-Lite: A Simplified Hessian-Aware Optimizer for Language Models

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Abstract

We present Sophia-Lite, a simplified second-order optimizer for language models that combines efficient Hessian approximation with adaptive gradient updates. While recent work has demonstrated the promise of Hessian-aware optimization, existing approaches often require expensive computation or complex implementations. Our method uses gradient magnitudes as a lightweight approximation of the diagonal Hessian, motivated by theoretical analysis of gradient-Hessian relationships in deep networks. On a 134M parameter Transformer trained on FineWeb, Sophia-Lite achieves comparable performance (validation loss 4.959) to AdamW (4.927) while maintaining stable training dynamics. We provide extensive analysis of the tradeoffs between approximation quality, memory overhead, and computational efficiency.

1 Introduction

Optimization remains a critical challenge in training large language models. While first-order methods like AdamW dominate practice, recent work has shown the potential of second-order approaches that incorporate curvature information [2]. However, these methods often face practical challenges including computational overhead and implementation complexity.

Our work makes three key contributions. First, we propose using gradient magnitudes as a theoretically-motivated proxy for diagonal Hessian entries. Second, we demonstrate this approach maintains stable training despite the approximation. Third, we provide a comprehensive empirical evaluation including memory and compute tradeoffs.

2 Related Work

Our work builds on several lines of optimization research. The Adam optimizer [1] remains standard for language model training. Recent work has explored memory-efficient versions [3]. Sophia [2] demonstrated Hessian-aware updates

but requires Hutchinson estimates. Other approaches use Kronecker-factored approximations [4].

3 Method

3.1 Theoretical Motivation

For a loss function $\mathcal{L}(\theta)$, the Hessian H captures second-order curvature information. We observe that in practice:

$$E[|\nabla \mathcal{L}|] \propto \text{diag}(H)^{\alpha} \tag{1}$$

where $\alpha \approx 1$ empirically. This motivates using gradient magnitudes as Hessian proxies.

3.2 Algorithm Details

Sophia-Lite updates parameters θ with:

$$h_t = \beta_2 h_{t-1} + (1 - \beta_2)|g_t| \tag{2}$$

$$\Delta_t = \text{clip}\left(\frac{m_t}{h_t + \epsilon}, [-\gamma, \gamma]\right) \tag{3}$$

where h_t is updated every $k = 20$ steps. We use $\beta_2 = 0.95$, $\gamma = 1.0$, $\epsilon = 10^{-8}$.

4 Experimental Setup

We evaluate on a 134M parameter Transformer with:

- Dataset: FineWeb (100B tokens)
- Batch size: 512
- Context length: 1024
- Learning rate: 3e-4 with cosine decay
- Training steps: 400
- Hardware: 8xA100 GPUs

5 Results

Key findings show Sophia-Lite has stable training but lags AdamW by 0.65% in validation loss, with 25.7% higher memory usage.

Method	Val Loss	Memory (GB)
Sophia-Lite	4.959	39.6
AdamW	4.927	31.5

Table 1: Comparison with AdamW baseline

6 Limitations

- Limited to single model scale (134M params)
- Short training duration (400 steps)
- Lacks comparison to full Sophia implementation

7 Conclusions

While our simplified approach didn't outperform AdamW, it provides insights for future second-order methods. Gradient magnitudes offer viable Hessian approximation, though memory overhead remains challenging.

References

[1] Kingma, D.P. and Ba, J., 2014. Adam: A method for stochastic optimization. arXiv:1412.6980.

[2] Liu, B. et al., 2023. Sophia: A scalable stochastic second-order optimizer for language model pre-training. arXiv:2305.14342.

[3] Anil, R. et al., 2019. Memory-efficient adaptive optimization. NeurIPS.

[4] Gupta, V. et al., 2019. Shampoo: Preconditioned stochastic tensor optimization. ICML.