Eve: Less Memory, Same Might

Aditya Tomar[1], Siddharth Singh[2] (advisor), Tom Goldstein[2] (advisor), Abhinav Bhatele[2] (advisor)

[1]Department of Electrical Engineering and Computer Sciences, University of California, Berkeley [2]Department of Computer Science, University of Maryland

Abstract

Adaptive optimizers, which adjust the learning rate for individual parameters, have become the standard for training deep neural networks. AdamW [1] is a popular adaptive method that maintains two optimizer state values (momentum and variance) per parameter, doubling the model's memory usage during training. Several memory-efficient optimizers claim to match AdamW's performance but lack its desirable qualities such as robustness to learning rate changes. This quality is especially desirable when pre-training LLMs, where experimenting with different hyperparameters is infeasible. We propose Eve, a Memory **E**fficient Adapti**V**e Moment **E**stimation algorithm that saves memory by reducing the variance term while also preserving AdamW's desirable properties across different training hyperparameter settings.

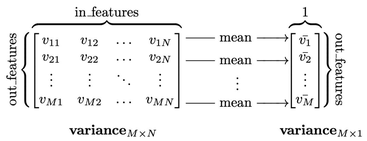
Eve: A Memory Efficient Optimizer

- Linear layers comprise the majority of parameters in modern neural networks
- For every linear layer's weight matrix (MxN), AdamW stores two MxN matrices for the momentum and variance terms
- We compress AdamW's optimizer state by performing a per-row average of the variance matrix, reducing it to an Mx1 vector for each linear layer
- This reduces the optimizer state from storing 2xMxN values to only Mx(N+1) values for a linear layer

Algorithm 1 Eve: Memory Efficient Adaptive Moment Estimation

1: $m_0 \leftarrow 0$ (Initialize MxN momentum matrix)
2: $\hat{v}_0 \leftarrow 0$ (Initialize Mx1 variance vector)
3: $t \leftarrow 0$ (Initialize timestep)
4: **while** θ_t not converged **do**
5: $\quad t \leftarrow t + 1$
6: $\quad g_t \leftarrow \nabla_\theta f(\theta_{t-1})$ (Get gradients w.r.t. objective function at timestep t)
7: $\quad m_t \leftarrow \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot g_t$ (Update momentum matrix)
8: $\quad \hat{v}_t \leftarrow \beta_2 \cdot \hat{v}_{t-1} + (1 - \beta_2) \cdot \mathbf{row\_mean}(g_t^2)$ (Update variance vector)
9: $\quad \theta_t \leftarrow \theta_{t-1} - \alpha \cdot m_t / (\sqrt{\hat{v}_t} + \epsilon)$ (Update parameters)
10: **end while**
11: **return** θ_t (Resulting parameters)

Note: Line 8 is mathematically equivalent to taking the row_mean of the variance matrix. Also, we perform bias correction on the momentum and variance terms in the same fashion as AdamW (not shown here).



Perplexity: Learning Rate Ablation Results

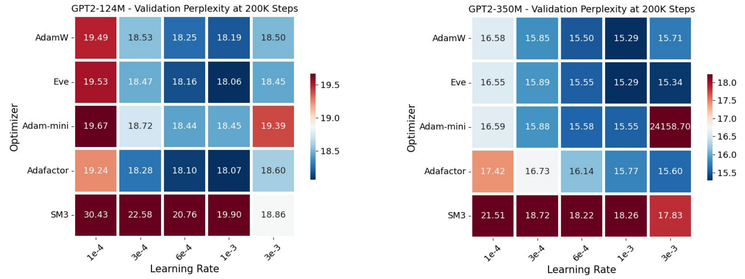


Fig 1: Final validation PPLs across different learning rates and optimizers for two models after 200K steps

- Eve matches AdamW across all learning rates, whereas other optimizers are less performant, especially for GPT2-350M
- Yao et al. [3] empirically showed that a PPL difference > 0.5 is the difference between an X and a 2X parameter model, so the PPL differences above may be non-trivial
- Adam-mini is close to AdamW for smaller learning rates, but AdamW and Eve perform better at higher learning rates

Validation Loss

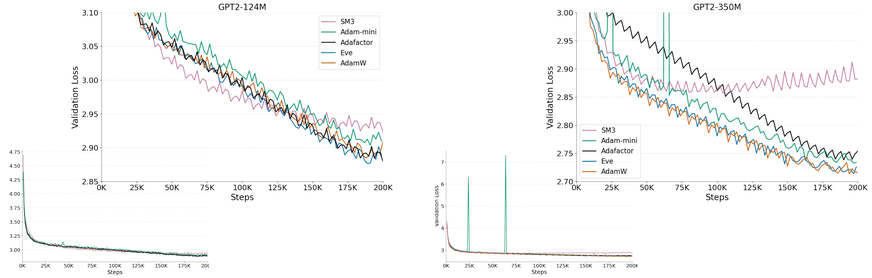


Fig 2: Validation loss curves (zoomed-in and out) using best learning rates for GPT2-124M and GPT2-350M for 200K steps. We find that Eve very closely follows AdamW throughout pre-training with no spikes or instabilities

Memory Savings and Downstream tasks

- We utilize AxoNN [4] to parallelize model training for models ranging from 1.1B to 70B parameters on 64 NVIDIA A100 (40 GB) GPUs using tensor parallelism
- For Llama 2 70B, we save 267 GBs, or 20.27%, more memory than AdamW, the equivalent of ~7 more A100 (40 GB) GPUs!
- This not only helps reduce monetary costs but also saves energy and makes training large models more accessible
- Moreover, as the model size increases, the amount of memory saved also increases

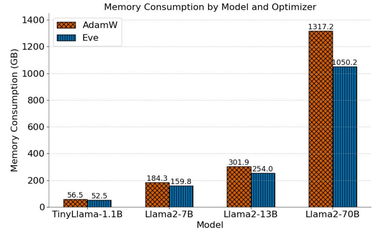


Fig 3: Comparison of total memory utilization across all 64 GPUs between AdamW and Eve for LLMs

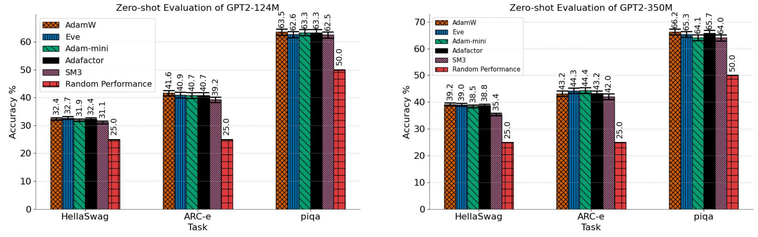


Fig 4: Zero-shot evaluations for final GPT2-124M and GPT2-350M checkpoints with best learning rates

Conclusion

- We introduce Eve, a memory efficient optimizer that matches AdamW's performance across a range of learning rates while using a much smaller memory footprint
- We save memory by maintaining a scalar per row of the variance matrix for all linear layers
- We present an ablation study, where we compare Eve with other established memory-efficient optimizers for different model sizes and learning rates and show better training stability
- We train Llama 2 70B on 64 A100 GPUs, where we use 20% less GPU memory compared to AdamW
- As future work, we plan to pre-train larger models using our optimizer and investigate how and why Eve is able to approximate AdamW so well

Acknowledgements

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References

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