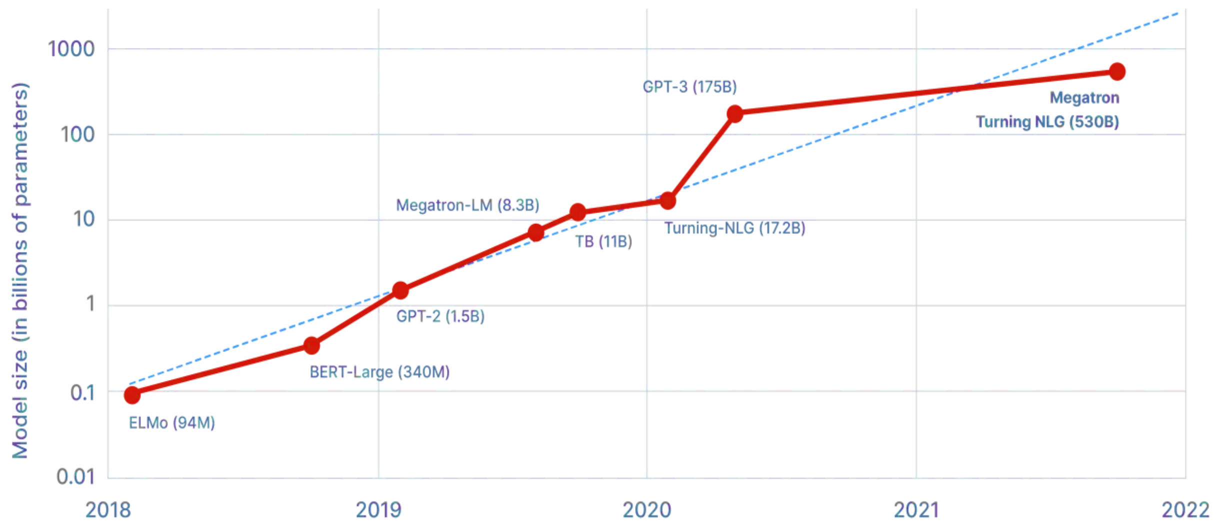
Finding the Right Optimization for Mixture-of-Experts

Zeynep Tandogan
Supervisor: Alexander Hägele – Martin Jaggi

EPFL MLO

LLMs Are Transforming the World

➢ The Need for Scale and Its Growing Costs



Language models are huge and getting bigger — but why?

- *Bigger models understand language better, solve harder tasks.*
- *Emergent abilities (reasoning, coding, multi-step logic) appear with scale*

What about challenges?

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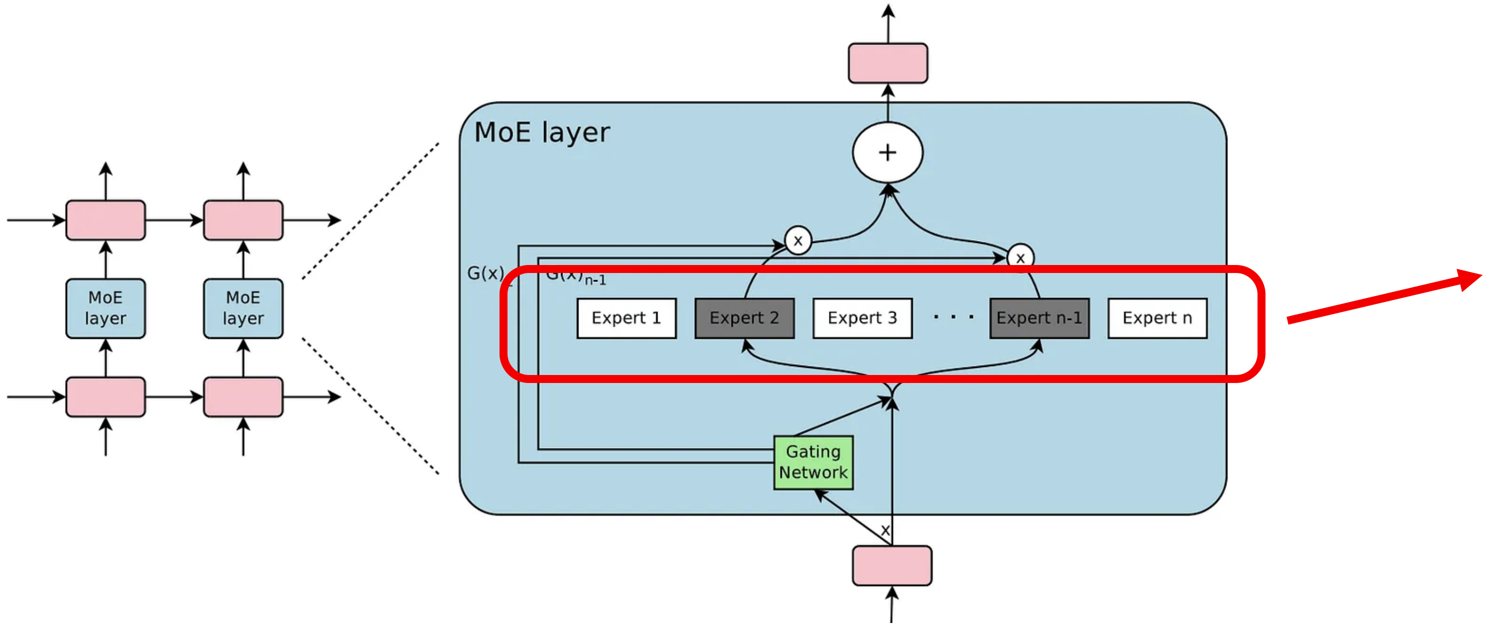
Mixture of Experts: Massive AI with Minimal Compute

➢ Can We Have Bigger Models Without Paying the Full Price?



Two main components:

1) Expert Layers

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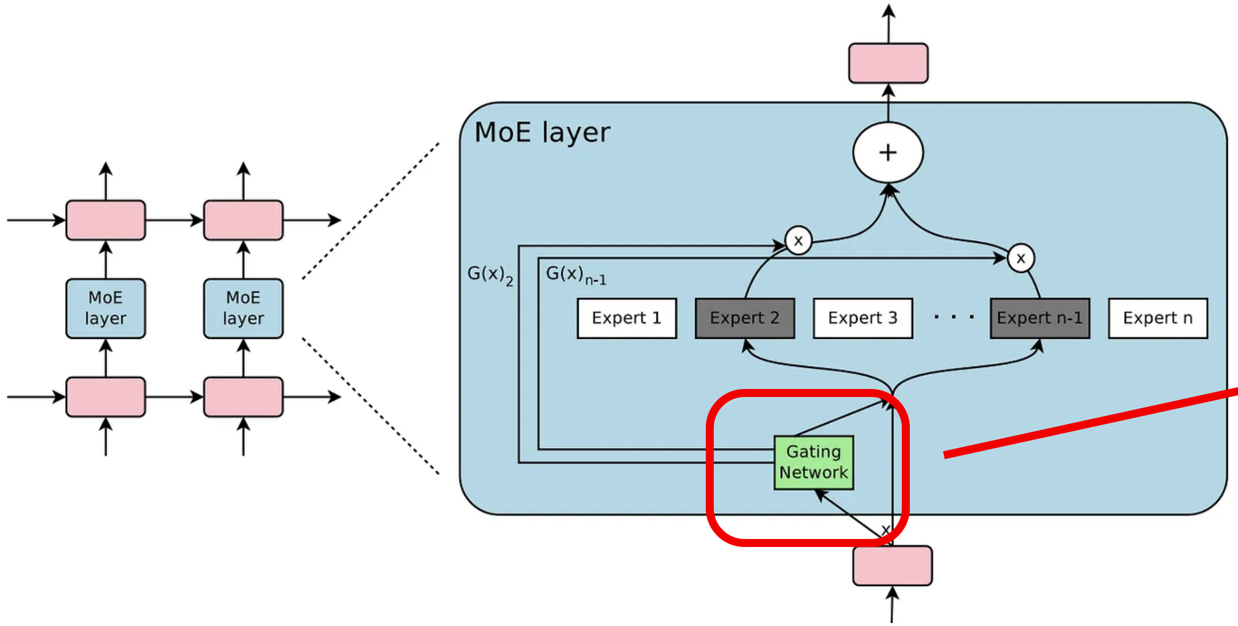

Two main components:

1) Expert Layers

2) Gating Network (Router)

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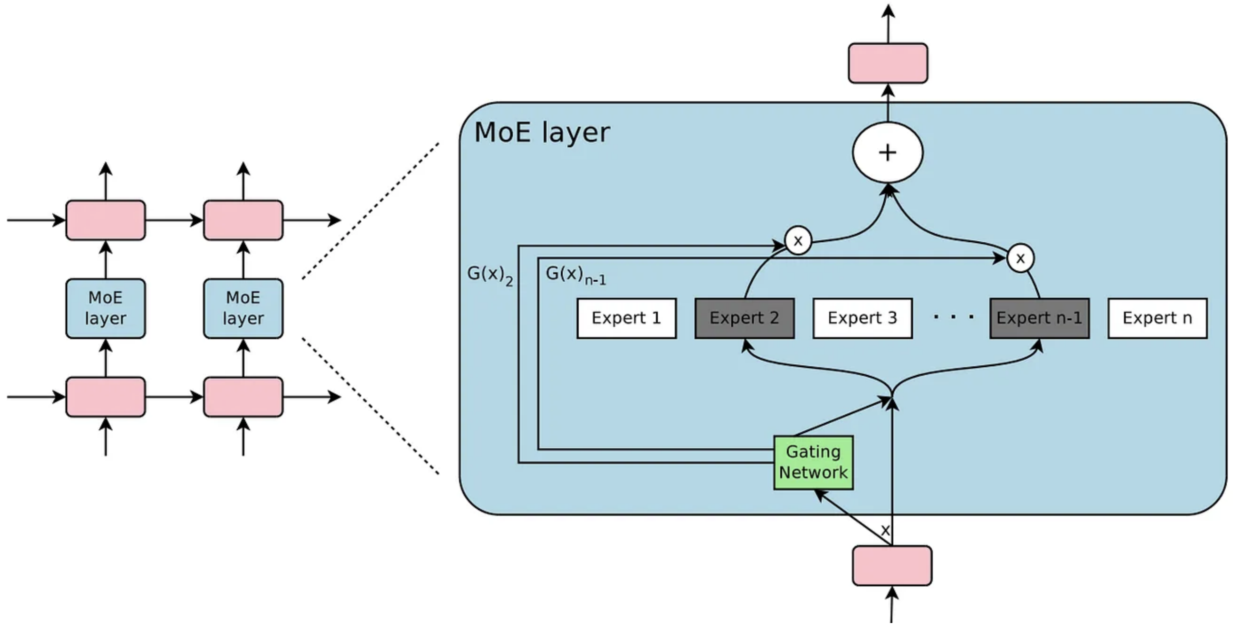

Two main components:

1) Expert Layers

2) Gating Network (Router)

- **Sparse Activation:** Only *k* experts fire per token
- **Efficient Scaling:** Grow to billions or trillions of parameters without a matching rise in compute budget
- **Specialized Expertise:** Experts specialize in niche skills, boosting accuracy on diverse tasks

MoE Trade-Offs: Complexity Under the Hood

➢ What New Bottlenecks Come with Sparse Scaling?

- **Uneven data exposure** per expert - under-/over-utilization
- **Fluctuating expert batches**
- **Loss of expressivity** in seldom-activated experts
- **Trade-off** between **load balancing** and **overall performance**

OUR GOAL:
Ablate and understand optimization dynamics for MoE models to find better recipes for large scale training of MoEs.

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Experimental Setup

Model

- LLaMA-style decoder-only Transformer

Data

- **Fineweb Edu** sample 10Bt
- **Training tokens:** 9.95 B (≈ 9 949 090 040)
- **Validation tokens:** 4.90 M (4 899 304)

Core Hyperparameters

Component	Value
Layers	24 (decoder-only)
Hidden size	768
FFN dim (dense)	2048
Experts per layer	8 (Top-2 routing)
Expert FFN dim	2048
Sequence length	512
Training steps	50,000
Batch size	40 sequences (20 480 tokens/update)
Optimizer	AdamW ($\beta_1 = 0.9$, $\beta_2 = 0.95$)
weight decay	0.1
LR schedule	Cosine decay with 300-step warmup
Gradient clipping	1.0

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Learning Rate Strategies for Experts vs. Non-Experts

➢ **Why experts may need their own LRs?**

$$p = \frac{k}{E} \implies B_{\text{expert}} = p \times B_{\text{global}}$$

- **Experts see a smaller batch.**
  In Top-k routing (E experts, k per token), each expert is active only with probability

Signal-to-Noise Ratio of the Gradient

$$\begin{aligned}
\mathbb{E}[\hat{g}] &= \nabla L, && \text{(true gradient / signal)} \\
\|\mathbb{E}[\hat{g}]\| &= \|\nabla L\|, && \text{(signal magnitude)} \\
\mathrm{Var}(\hat{g}) &= \frac{\sigma^2}{B}, && \text{(variance } 1/B\text{)} \\
\mathrm{Std}(\hat{g}) &= \frac{\sigma}{\sqrt{B}}, && \text{(noise magnitude)} \\
\mathrm{SNR} &= \frac{\|\mathbb{E}[\hat{g}]\|}{\mathrm{Std}(\hat{g})} = \frac{\|\nabla L\|}{\sigma/\sqrt{B}} \propto \sqrt{B}. && \text{(signal-to-noise ratio)}
\end{aligned}$$

- **Each expert's effective batch is smaller**, its SNR is lower—so its gradient updates are **much noisier**.

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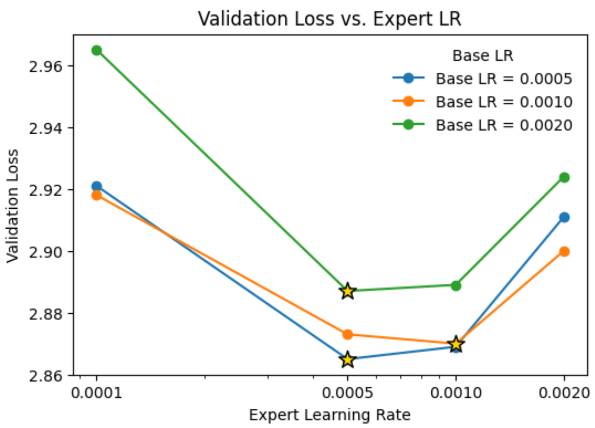
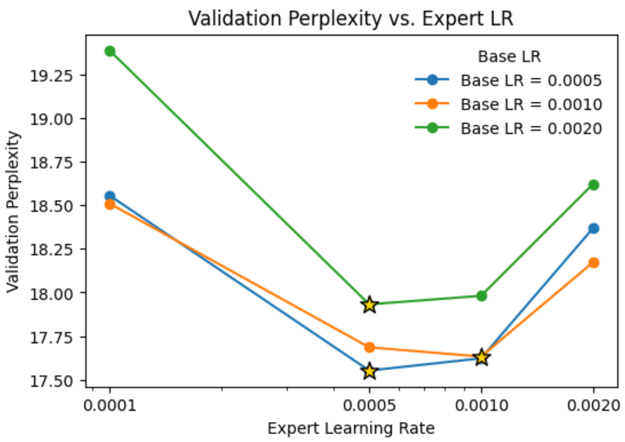
Learning Rate Strategies for Experts vs. Non-Experts

Component	Learning Rates
Non-Experts	0.0005, 0.001, 0.002
Experts	0.0001, 0.0005, 0.001, 0.002





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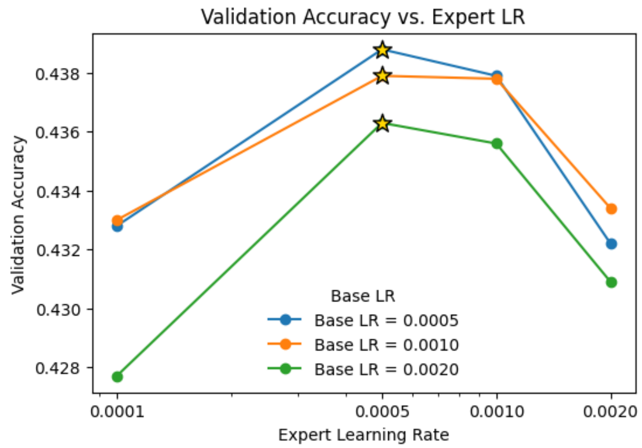
Investigate the impact of using different learning rates for expert (MLP layers) and non-expert parameters in MoE models.



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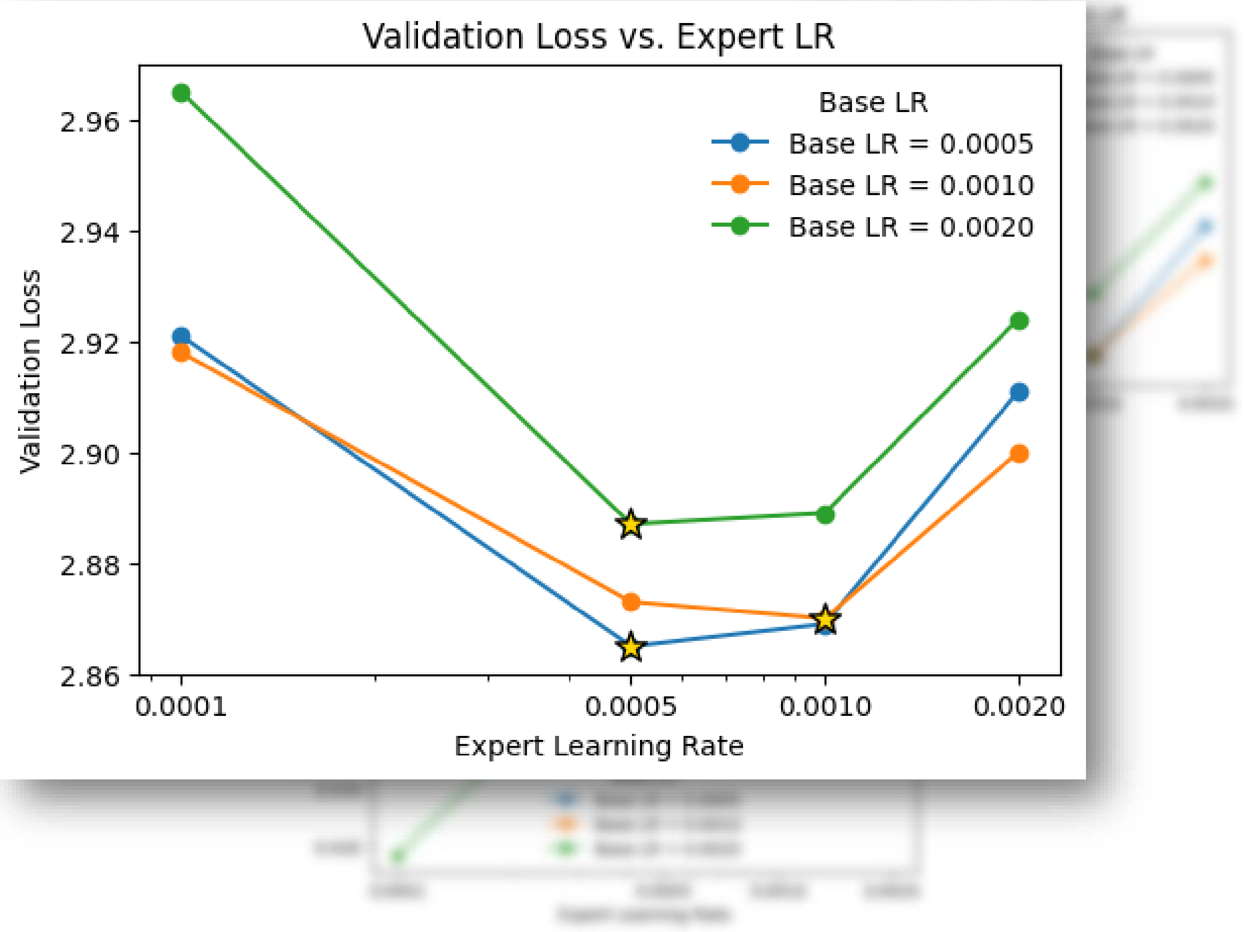

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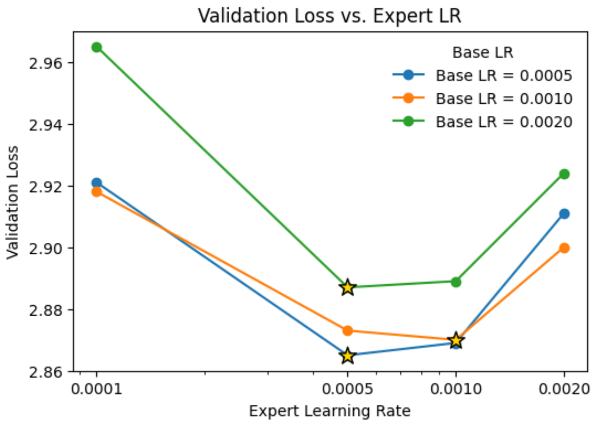

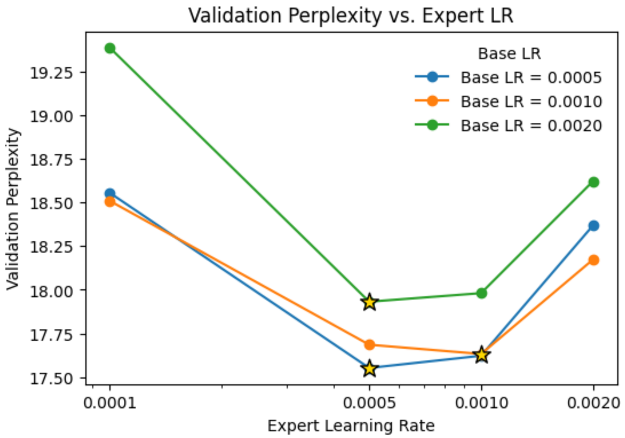

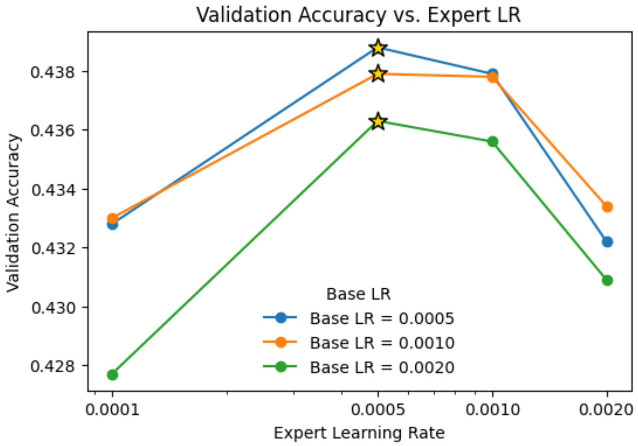

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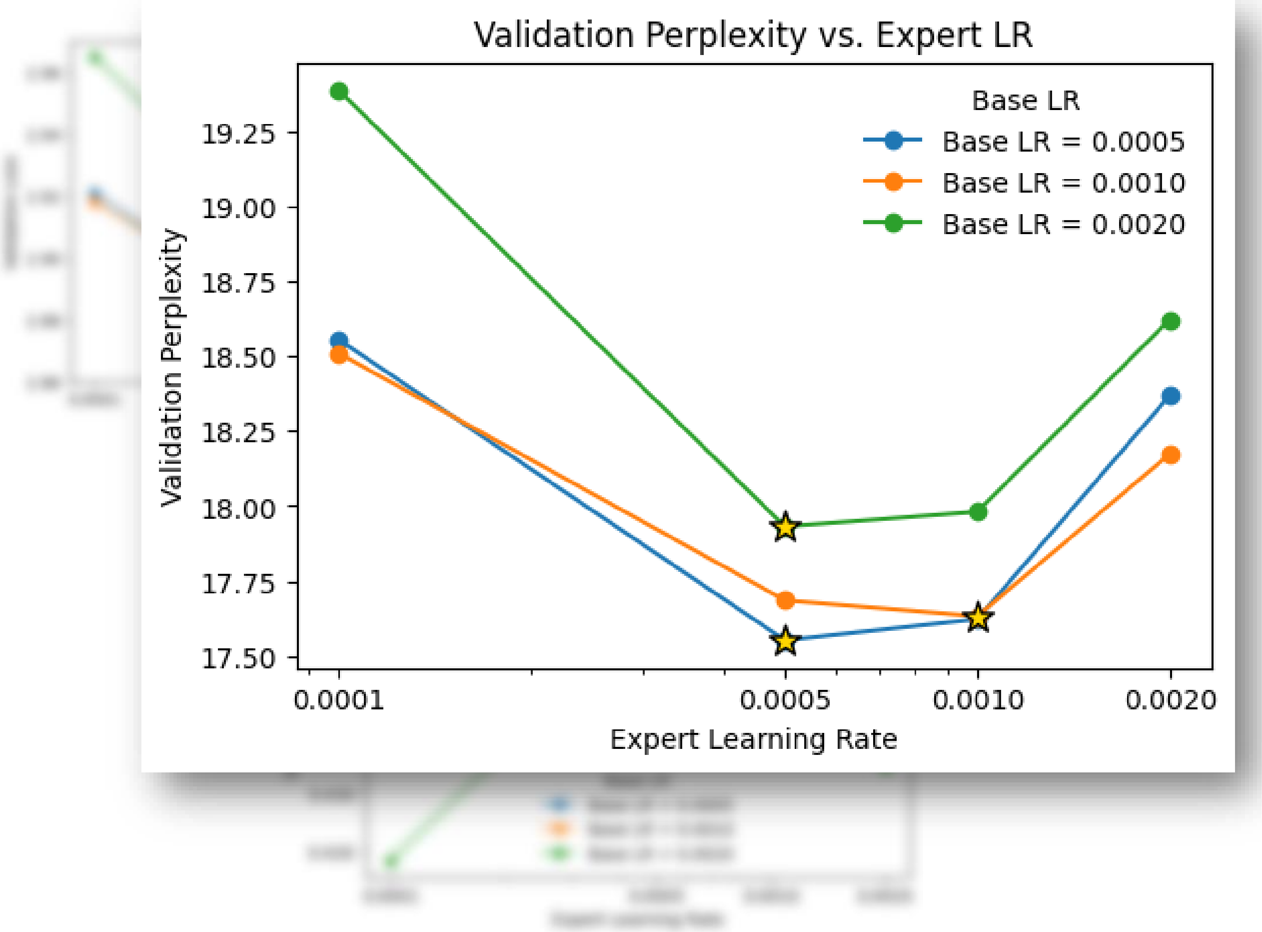

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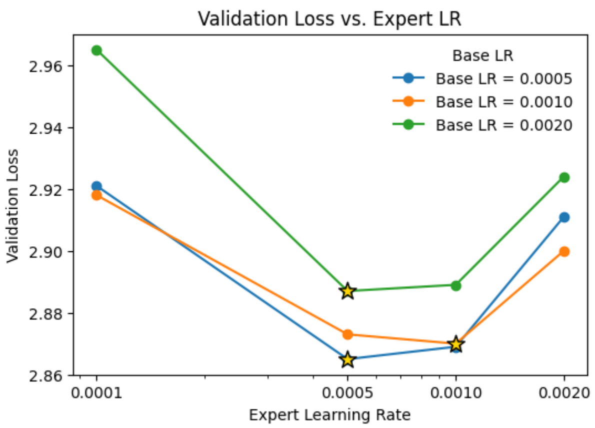

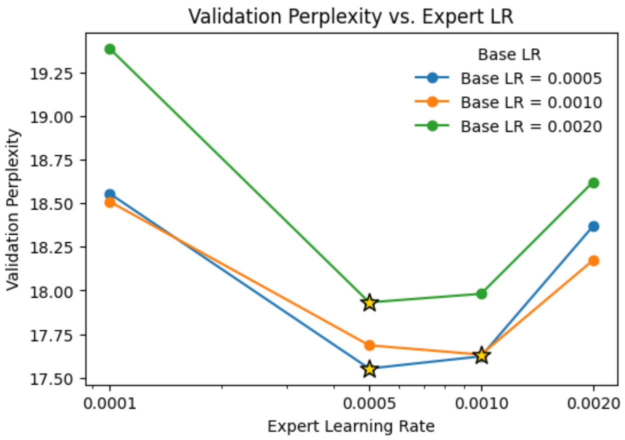

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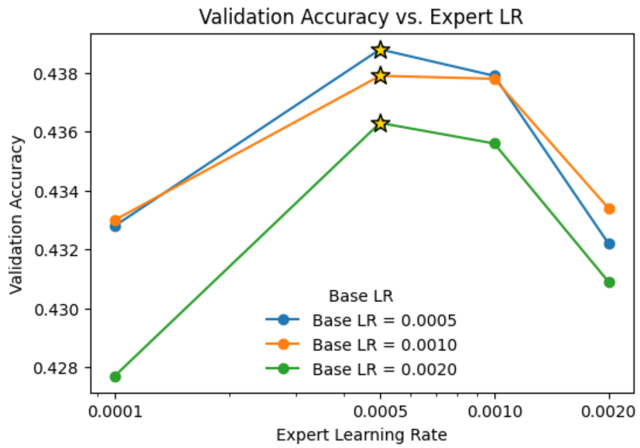

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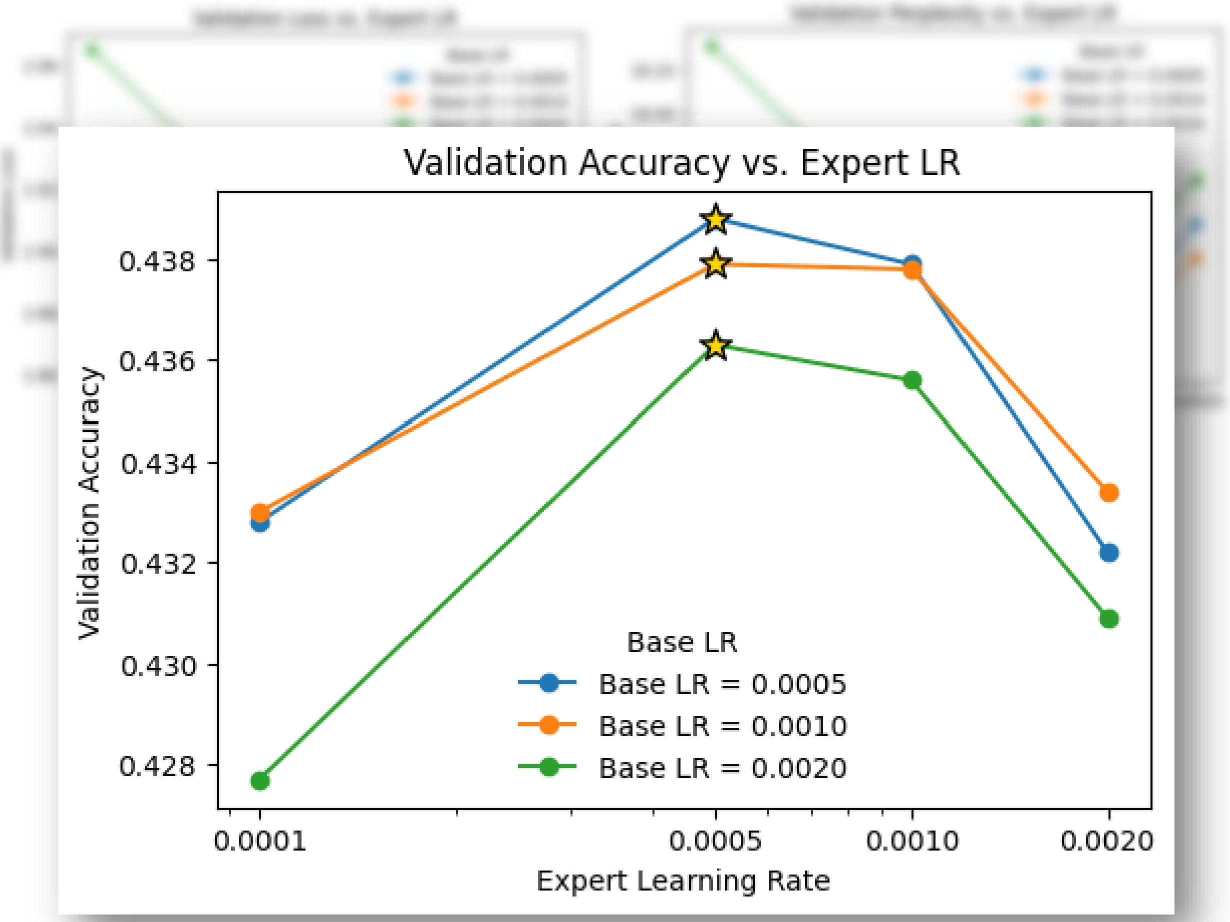


1 Learning Rate Strategies for Experts vs. Non-Experts

➢ What should be different in terms of loss in MoEs?

- **Problem: Expert Imbalance**

  Some experts get most tokens; others are barely used.

- **Solution: Add auxiliary loss**

  Prevent expert collapse: stop the router from sending almost all tokens to a few experts

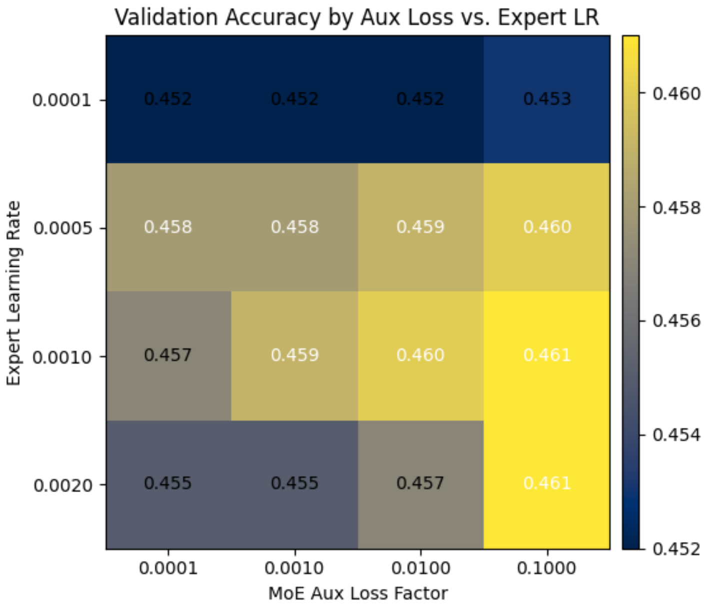
  Improve stability: keep router logits from growing too large

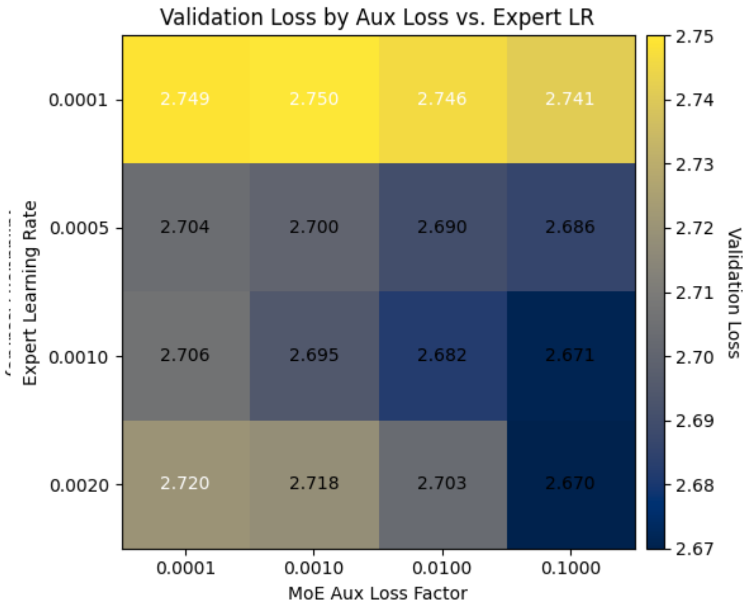
Scalar Weights

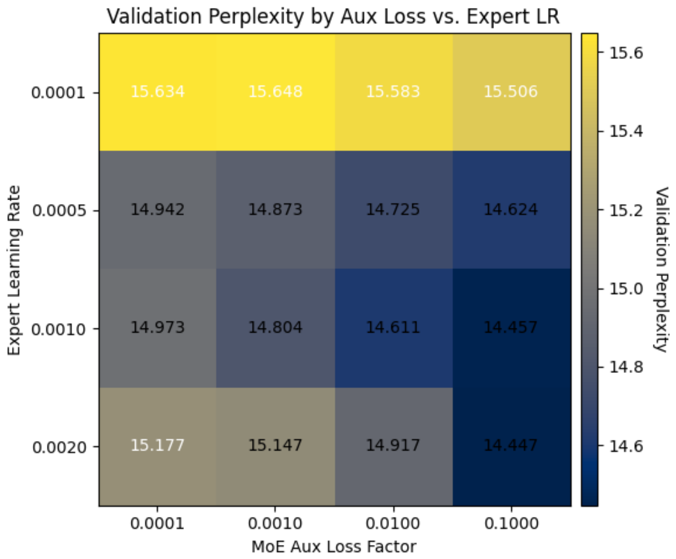
$$L_{tot} = \overbrace{L_{CE}}^{\text{Cross-Entropy Loss}} + c_B \underbrace{L_B}_{\substack{\text{Auxiliary Load}\\ \text{Balance Loss}}} + c_z \overbrace{L_Z}^{\text{Router Z-Loss}}$$

Source: Cameron R. Wolfe, "Conditional Computation: The Birth of Mixture-of-Experts," Substack (Sep 2023), *https://cameronrwolfe.substack.com/p/conditional-computation-the-birth*

Learning Rate Strategies for Experts vs. Non-Experts







- ***Setup:*** Fixed **non-expert LR at 0.001**
- A strong aux-loss weight (**0.1**) consistently **boosts performance**
- With aux weight = 0.1, expert LRs from 5×10^{-4} to 2×10^{-3} all achieve nearly **identical results**
- Lowering expert LR to 1×10^{-4} causes a **clear decline**

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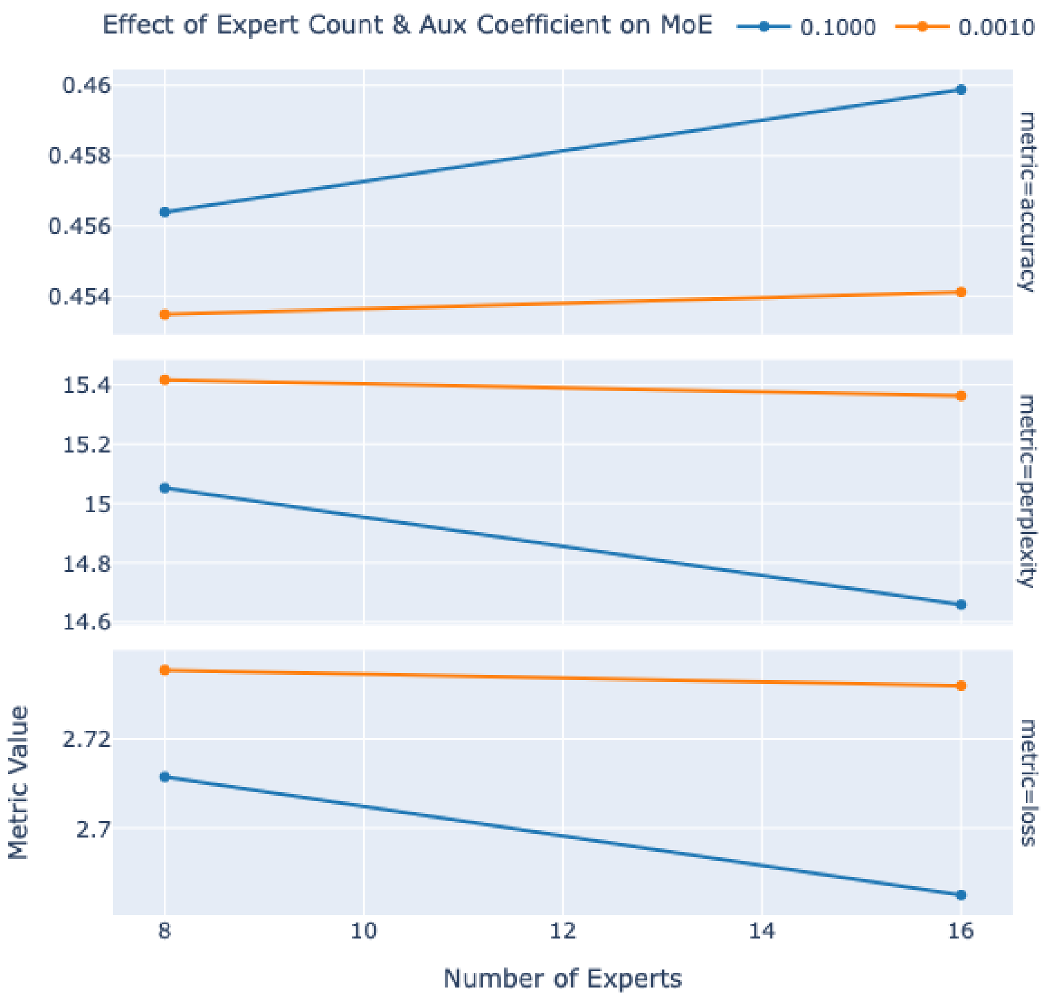
2 Effect of Auxiliary Loss Coefficients and Aux-Free-Loss Reproduction

➢ **How does the aux loss coefficient's impact change as we scale up the number of experts?**

- **Setup:** 8 and 16 experts with LR 0.0005
- Higher aux-loss factor (0.1) gives better baseline performance and **scales effectively** with more experts



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➢ Aux-Free-Loss Reproduction

Problem: Performance Loss

- A large aux "load-balancing" loss injects extra gradients that compete with the main objective, hurting final performance

Solution: Aux-Free Balancing

Algorithm 1: Adjusting the per-expert bias b_i during training

Input: MoE model θ, training batch iterator B, bias update rate u.
1. Initialize $b_i = 0$ for each expert;
for *a batch* $\{(\mathbf{x}_k, \mathbf{y}_k)\}_k$ *in* B **do**
  2. Train MoE model θ on the batch data $\{(\mathbf{x}_k, \mathbf{y}_k)\}_k$, with gating scores calculated according to Eq. (3);
  3. Count the number of assigned tokens c_i for each expert, and the average number $\overline{c_i}$;
  4. Calculate the load violation error $e_i = \overline{c_i} - c_i$;
  4. Update $\mathbf{b}_i$ by $b_i = b_i + u * \mathrm{sign}(e_i)$;
end
Output: trained model θ, corresponding bias $\mathbf{b}_i$

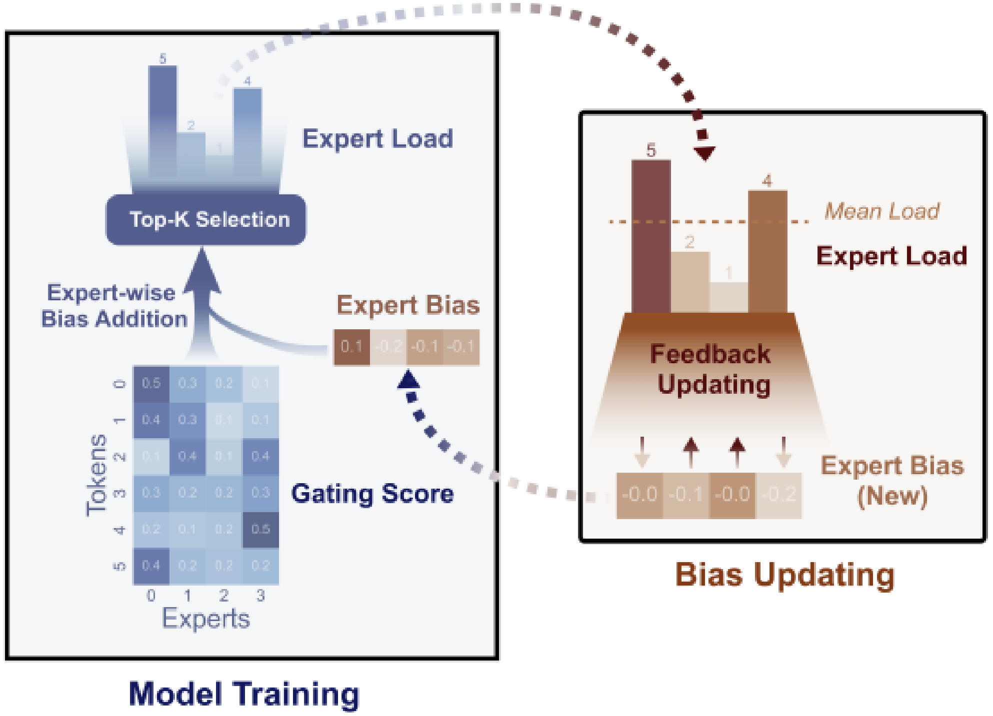
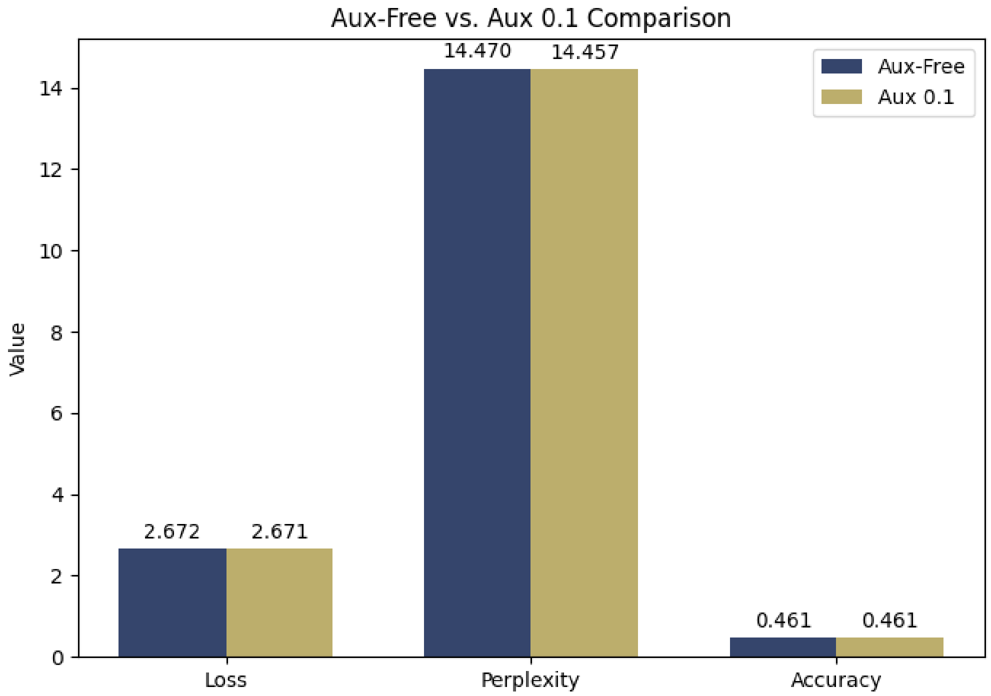


Figure 1: Loss-Free Balancing selects experts according to a "biased gating score" in each training step and updates this expert-wise bias after each training step.

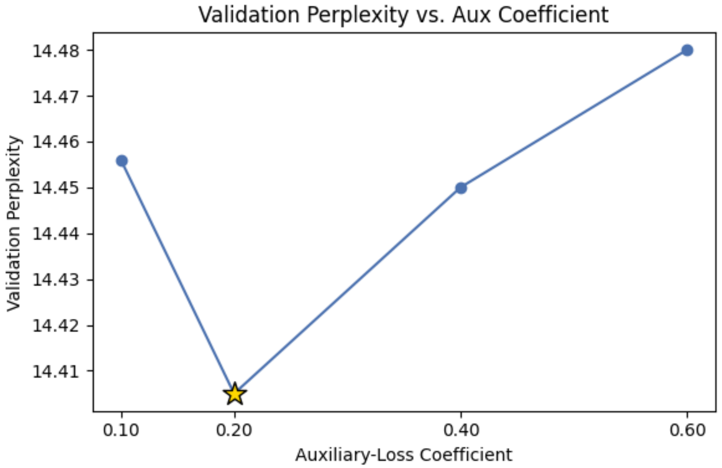
➢ Aux-Free-Loss Reproduction

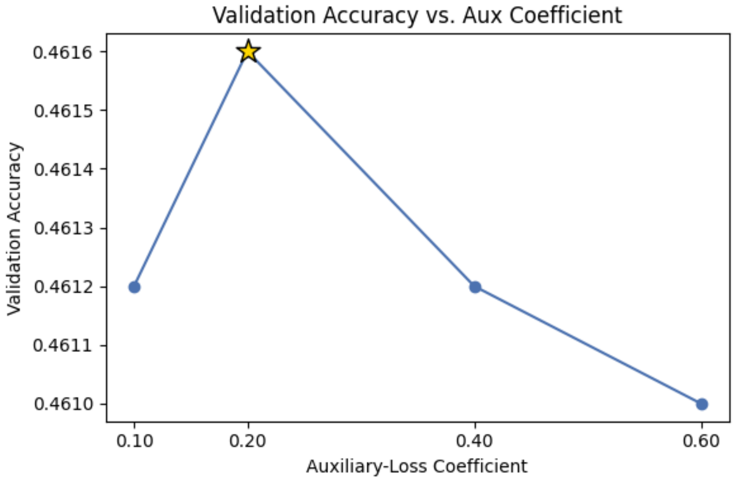


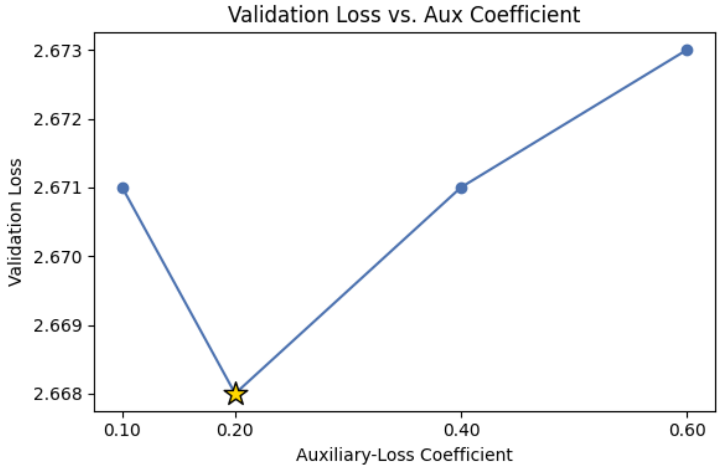
- Loss Free vs Aux 0.1 : **equivalent performance** across all metrics.

2 Effect of Auxiliary Loss Coefficients and Aux-Free-Loss Reproduction

➢ Up to which aux loss coefficient do we still observe performance improvements?







- Swept the aux-loss weight from **0.1 up to 0.6** to identify stability limits.
- **No degradation** in any metric for coefficients up to **0.2**.

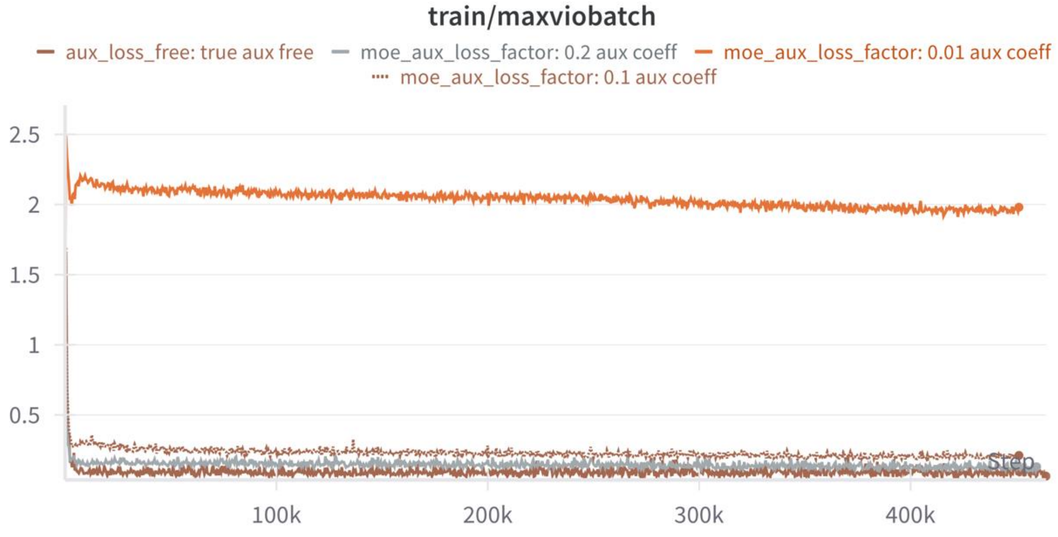
➢ Aux-Free-Loss Reproduction

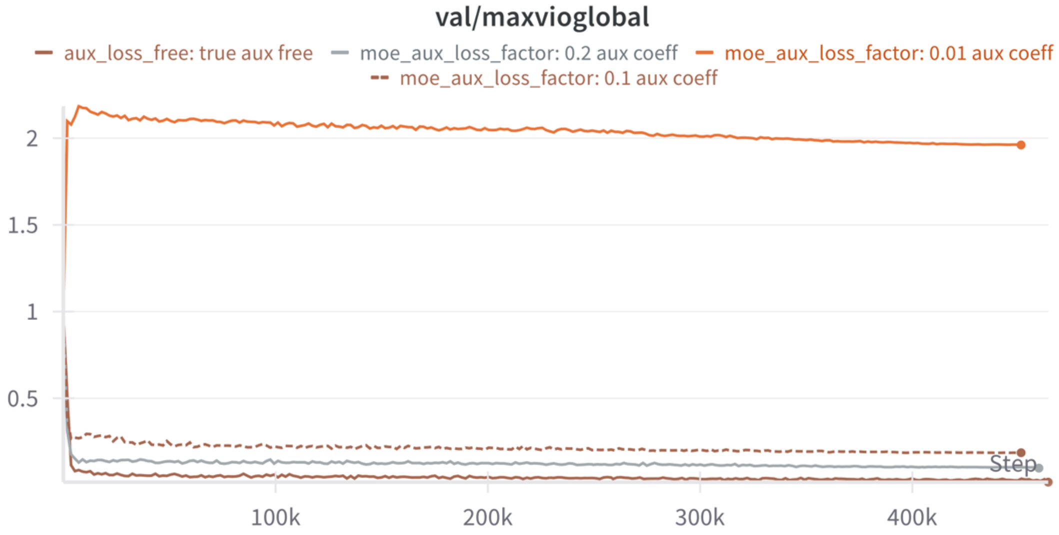
Maximal Violation (MaxVio) Analysis

- 1) MaxVio Global
- 2) MaxVio Batch

$$\text{MaxVio} = \frac{\max_i \text{Load}_i - \overline{\text{Load}_i}}{\overline{\text{Load}_i}}$$

- Loss-Free reduces both Global and Batch MaxVio below those of aux=0.1-0.2, confirming **its superior load balance.**





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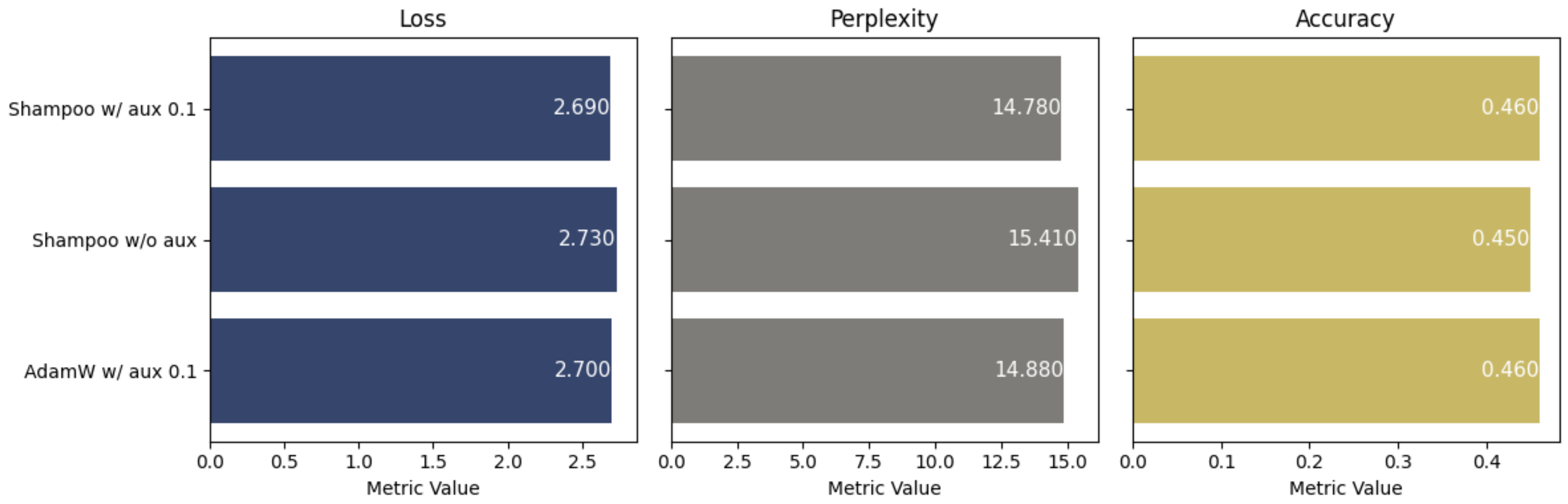
Integration and Evaluation of the Shampoo Optimizer

➢ Can using the Shampoo optimizer naturally lead to more balanced expert selection?



Until now: AdamW

New optimizer: Meta's Distributed Shampoo
- Fall back to AdamW on very large matrices - every step
- Shampoo - in each 100 steps

Hao-Jun Michael Shi, Tsung-Hsien Lee, Shintaro Iwasaki, Jose Gallego-Posada, Zhijing Li, Kaushik Rangadurai, Dheevatsa Mudigere & Michael Rabbat. "A Distributed Data-Parallel PyTorch Implementation of the Distributed Shampoo Optimizer for Training Neural Networks At-Scale." arXiv preprint arXiv:2309.06497, Sep 12 2023

Integration and Evaluation of the Shampoo Optimizer

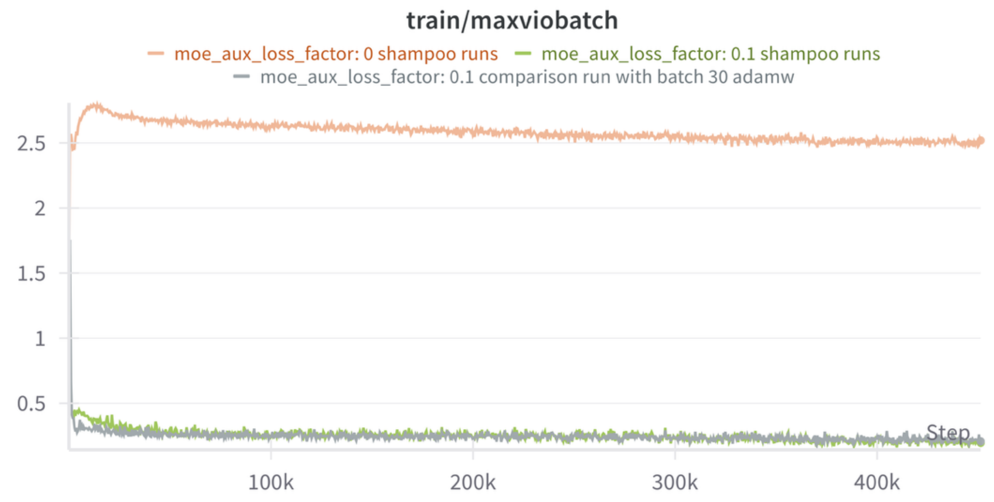
- Shampoo optimizer achieves slightly lower MaxVio in both batch and global settings, indicating **improved load balance**.

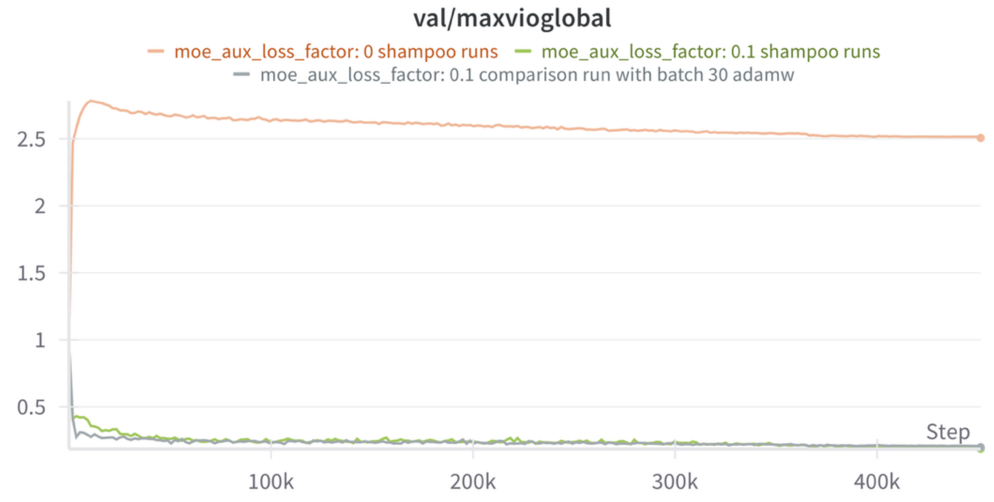
However,

using Shampoo takes longer training times…

Wall-clock time for 50 K steps: AdamW vs. Shampoo.

Optimizer	Wall-clock Time	Relative Cost
AdamW	1 d 16 h (40 h)	1×
Shampoo	2 d 2 h (50 h)	1.25×





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Load Based Learning Rate Updates for Experts

➢ Batch-fraction load ratio

$$r_i = \frac{L_i}{T},$$

$$\sum_i L_i = kT \implies \sum_i r_i = k,$$

$$r_i \in [0, 1].$$

- **Always** scales each expert's learning rate **downward** relative to the base
- **Lightly loaded** experts experience the **largest LR reduction**

➢ Ideal-Normalized load ratio

$$r_i = \frac{L_i}{\bar{L}},$$

$$\bar{L} = \frac{\sum_i L_i}{E} = \frac{kT}{E}.$$

- Bounded below by 0; no fixed upper bound.
- **Overloaded** experts receive an **LR boost**, **underloaded** ones are **dampened**
- Mean scaling remains exactly 1 across all experts

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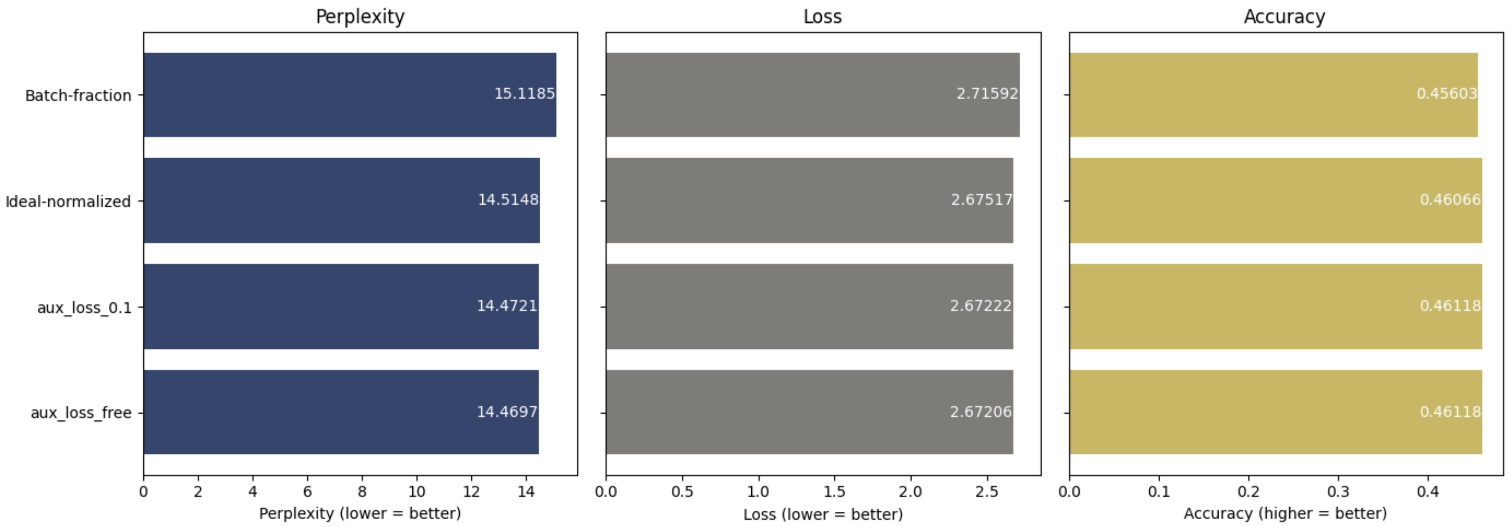
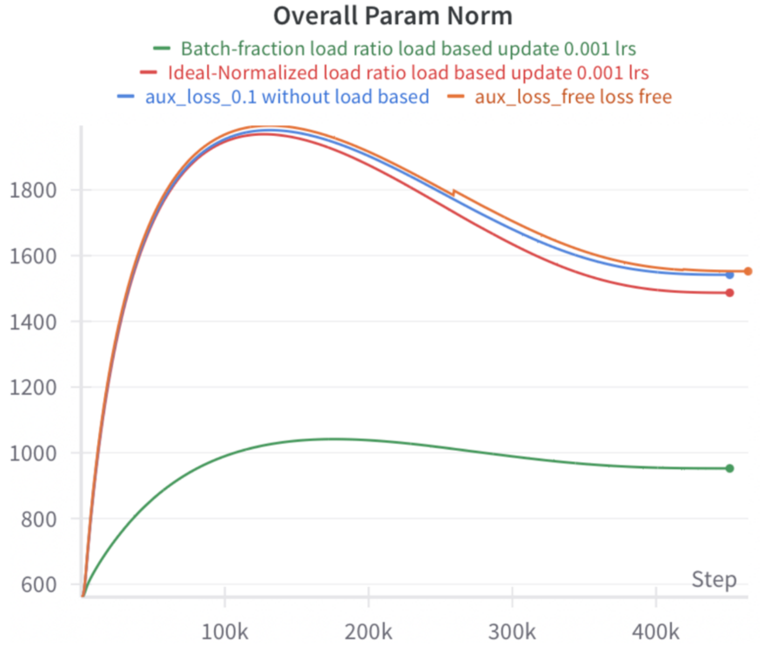
Load Based Learning Rate Updates for Experts

- **Setup:** 8 experts with LR 0.001, top-k 2
- Both batch-fraction and ideal-normalized methods **underperform** relative to the aux-loss 0.1 and aux-free approaches.





Underfitting risk in batch fraction?

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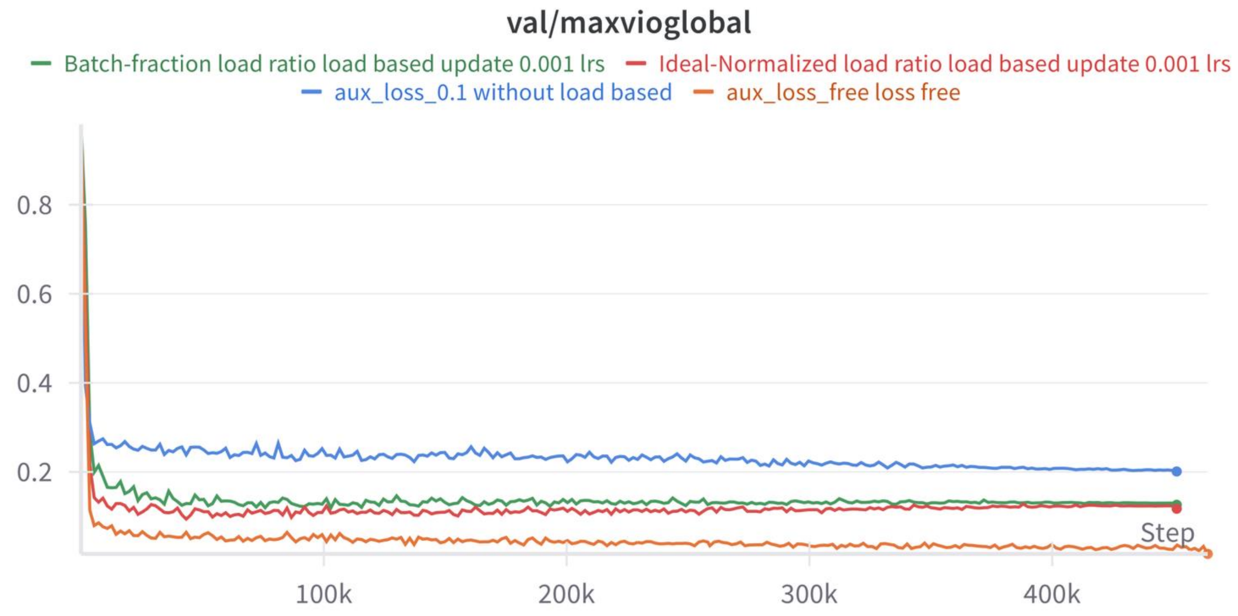
Load Based Learning Rate Updates for Experts

- Ideal-normalized most closely matches the aux-free MaxVio trend, followed by batch-fraction, with aux-loss 0.1 trailing behind.



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Extending Experiments with Megatron LM

Setup: Fixed learning rate at 0.001; compared **sigmoid and softmax** gating with **different bias update rates**.

- With softmax aux-free and a bias update rate of 1×10^{-3}, maxvio stayed around 1.5—significantly higher than the sigmoid variant.
- Increasing the bias update rate to 1×10^{-2} was necessary to bring softmax's maxvio down to acceptable levels.

Configuration	lm loss	maxvio	z_loss
0.001-lr, sigmoid e-3, loss free	**2.871**	0.086	0.003
0.001-lr, sigmoid e-2, loss free	2.893	0.313	0.003
0.001-lr, softmax e-3, loss free	3.068	1.574	0.003
0.001-lr, softmax e-2, loss free	2.890	0.081	0.003
0.001-lr, sigmoid aux 0.1	3.223	0.072	0.010
0.001-lr, softmax aux 0.1	2.896	**0.032**	0.002

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Extending Experiments with Megatron LM

➢ ***How does expert learning rates impact MoE performance as we scale up the number of experts?***

Configuration	lm loss	maxvio	z_loss
0.001 expert lr,	**2.896**	**0.032**	0.002
0.0005 expert lr	2.960	0.041	0.003

Average loss metrics for 8-expert configurations
(non expert LR 0.001 with softmax aux coefficient 0.1)

Configuration	lm loss	maxvio	load_balancing	z_loss
0.0005 expert lr	**3.090**	0.587	0.999	**0.007**
0.001 expert lr	3.109	**0.439**	**0.998**	0.007

Average loss metrics for 128-expert configurations (non expert LR 0.001)

8-Expert Setup: Matched LRs boost both accuracy and balance over a lower expert LR.

128-Expert Setup: Lower expert LR yields minor accuracy gains but worsens load balance.

Note: 128-expert runs use 12 layers & 1024-dim FFNs (down from 24/2048).

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Summary of Our Findings

Hyper-parameter	Recommended Setting	Rationale
Base LR (non-experts)	0.001	Stable across **model & expert counts**.
Expert LR	0.0005–0.001	Clear U-shape (minimum at 5×10^{-4}); avoid 1×10^{-4}; up to 2×10^{-3} safe when aux-loss = 0.1; splitting schedules yields no gain.
Aux-loss weight	0.05–0.1	Boosts accuracy, perplexity & MaxVio by **balancing traffic**; **plateaus beyond 0.2** and reverses if it dominates.
Gating	Sigmoid, top-k = 2	Encourages **balance** with aux-loss 0.1; softmax needs 10× higher **bias update rate** to match.
Load-balance regularizer	Aux-free (or ideal-normalized with clipping)	Yields **lowest MaxVio**; batch-fraction **under-fits**, ideal-normalized can be **unstable** w/o clipping.
Load-based LR scaling	Not recommended	Underperforms both aux-based ,and aux-free: batch-fraction **under-fits**; ideal-normalized risks **instability**.
# Experts	8–16 (128 if FFN dims ↓)	Aux-loss 0.1 scales effectively; impact of aux coef grows with more experts; lower expert LR gives **minor accuracy gains** at 128 but **worsens balance**.
Optimizer	AdamW (Distributed Shampoo optional)	Shampoo lowers **loss/perplexity & MaxVio** but adds **≈25%** training time—use when **balance is critical**.

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Thanks for listening!

Any questions?

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