# SHARPNESS-AWARE PRETRAINING MITIGATES CATASTROPHIC FORGETTING

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## ABSTRACT

Standard optimizer choices for pre-training are designed to minimize pre-training loss. Yet pre-trained models are routinely subjected to further transformations—such as fine-tuning to acquire new capabilities or quantization for efficiency. In this work, we evaluate optimizer choices across model scales, token budgets, and datasets, and find that strategies that explicitly (Sharpness-Aware Minimization) or implicitly (large learning rates and Warmup–Stable–Decay schedules) reduce sharpness yield better downstream performance, even when they achieve comparable or worse pre-training loss. Combining these strategies yields a new pre-training recipe that substantially outperforms standard baselines with minimal compute overhead, delivering a better learning–forgetting frontier during fine-tuning and higher accuracy after quantization.

## 1 INTRODUCTION

Large language models are typically developed via a two-stage pipeline: pre-training followed by post-training adaptation such as fine-tuning, alignment, and quantization. A core assumption is that lower pre-training loss implies better post-training performance. However, recent work challenges this premise, revealing "catastrophic overtraining" that can decouple these metrics. Beyond a certain threshold, adding training data paradoxically degrades post-training performance even as pre-training loss improves (Springer et al., 2025). While optimizer selection plays a decisive role in pre-training, current best practices are driven solely by minimizing pre-training loss. In the overtrained regime where this loss decouples from downstream results, strictly optimizing for the base model's loss becomes insufficient. This motivates us to ask: can we identify optimization choices that yield superior post-training performance compared to standard practice?

Through over 80 pre-training and 3500 fine-tuning runs, we identify two strong candidates. Since adaptation processes inevitably shift model parameters, causing "forgetting" of pre-trained knowledge, we hypothesize that checkpoints where nearby perturbations also maintain low loss will be more robust—pointing toward optimizer choices that minimize not just pre-training loss but also the *sharpness* of the loss landscape. First, we find that Sharpness-Aware Minimization (SAM) (Foret et al., 2021) during pre-training yields a superior learning–forgetting frontier compared to AdamW Loshchilov & Hutter (2019) and reduces degradation under quantization and random perturbations. Second, consistent with the Edge of Stability phenomenon (Cohen et al., 2021), we find that larger learning rates and Warmup-Stable-Decay (WSD) Hu et al. (2024) schedules improve downstream performance over cosine schedules Loshchilov & Hutter (2017), even when pre-training loss is slightly worse.

The two interventions—SAM and learning rate scheduling—are in fact *synergistic*. We synthesize them to propose **Sharpness-Aware Warmup-stable Decay (SAWD)**, which applies SAM only during the decay phase of WSD. Because the decay phase typically occupies only a small fraction of the total token budget ($\approx 10\%$), applying SAM updates during this brief window results in negligible total overhead while achieving consistent downstream improvements.

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## 2 PRELIMINARIES

Canonically, optimizer choices are made to minimize pre-training loss. In this work, we focus on understanding how design choices during pre-training affect downstream properties of the resulting model.

### 2.1 DOWNSTREAM PROPERTIES OF PRE-TRAINED MODELS

Let $\theta_{\mathrm{PT}}$ denote the pre-trained model. We study the following downstream properties.

**Learning–forgetting tradeoff.** Pre-trained models are typically fine-tuned on task-specific data to introduce specific capabilities. However, optimizing for a specific task often leads to forgetting of pre-trained capabilities (Goodfellow et al., 2013; Kirkpatrick et al., 2017; Springer et al., 2025). When a base model $\theta_{\mathrm{PT}}$ is fine-tuned to obtain $\theta_{\mathrm{FT}}$, we measure learning via the fine-tuning loss $\mathcal{L}_{\mathrm{FT}}(\theta_{\mathrm{FT}})$ and forgetting via the pre-training loss evaluated at fine-tuned weights $\mathcal{L}_{\mathrm{PT}}(\theta_{\mathrm{FT}})$. Since this balance is sensitive to optimization choices, we summarize each base model by the Pareto frontier:

$$\left\{ \left( \mathcal{L}_{\mathrm{FT}}(\theta_{\mathrm{FT}}), \mathcal{L}_{\mathrm{PT}}(\theta_{\mathrm{FT}}) \right) \mid \theta_{\mathrm{FT}} \in \Theta_{\mathrm{FT}}(\theta_{\mathrm{PT}}) \right\},$$

where $\Theta_{\mathrm{FT}}(\theta_{\mathrm{PT}})$ represents the set of all models obtained by fine-tuning $\theta_{\mathrm{PT}}$ under varying fine-tuning configurations.

**Post-train quantization.** Beyond fine-tuning, a popular way to reduce inference costs is to quantize model weights to lower precision, yielding $\widetilde{\theta_{\mathrm{PT}}}$. We evaluate degradation via $\mathcal{L}_{\mathrm{PT}}(\widetilde{\theta_{\mathrm{PT}}})$.

### 2.2 SHARPNESS AS AN APPROXIMATION FOR FORGETTING

A local approximation of the pre-train loss around $\theta_{\mathrm{PT}}$ sheds light on what factors might affect downstream performance beyond the pre-train loss. Let $\theta_{\mathrm{PT}} + \Delta$ denote the result of a downstream modification (e.g., fine-tuning), where $\Delta$ is the parameter change. A second-order expansion of the pre-training loss gives

$$\mathcal{L}_{\mathrm{PT}}(\theta_{\mathrm{PT}} + \Delta) \approx \mathcal{L}_{\mathrm{PT}}(\theta_{\mathrm{PT}}) + \nabla \mathcal{L}_{\mathrm{PT}}(\theta_{\mathrm{PT}})^{\top} \Delta + \tfrac{1}{2} \Delta^{\top} H \Delta,$$

where $H \coloneqq \nabla^2 \mathcal{L}_{\mathrm{PT}}(\theta_{\mathrm{PT}})$ is the Hessian of the pre-training loss. After long pre-training the gradient is small, and forgetting is dominated by curvature:

$$\mathcal{L}_{\mathrm{PT}}(\theta_{\mathrm{FT}}) - \mathcal{L}_{\mathrm{PT}}(\theta_{\mathrm{PT}}) \approx \tfrac{1}{2} \Delta^{\top} H \Delta.$$

High curvature (sharpness) leads to significant forgetting, whereas low curvature allows parameter adaptation with minimal impact on original task performance. An optimizer that regularizes $\lambda_{\max}(H)$ could therefore reduce forgetting under downstream changes like fine-tuning or quantization. This is not a formal characterization but rather an approximation to motivate mechanisms for preventing forgetting in practice.

### 2.3 OPTIMIZATION RECIPES TO INDUCE FLATNESS

Motivated by the connection between curvature and forgetting, we consider two mechanisms for inducing flatness: an *explicit* approach via Sharpness-Aware Minimization (SAM) and an *implicit* approach via learning rate dynamics.

**Sharpness-Aware Minimization (SAM).** SAM Foret et al. (2021) explicitly searches for minima that remain low-loss under parameter perturbations. Given the pre-training objective $\mathcal{L}_{\mathrm{PT}}(\theta)$ and a radius $\rho > 0$, SAM solves the robust optimization problem:

$$\min_{\theta} \max_{\|\epsilon\|_2 \leq \rho} \mathcal{L}_{\mathrm{PT}}(\theta + \epsilon). \tag{1}$$

In practice, this is approximated by a first ascent step in the direction of the gradient to find a perturbed weight vector, then updating the original parameters $\theta$ to take a descent step using the gradient evaluated at that perturbed location.

**Learning rates and the Edge of Stability.** The Edge of Stability Cohen et al. (2021) suggests learning rate $\eta$ implicitly caps sharpness, with dynamics hovering at $\lambda_{\max}(H) \approx 2/\eta$. This implies that learning-rate magnitude and annealing duration can strongly affect forgetting, motivating our investigation into pre-training learning-rate schedules.

## 3 Experiments

In this section, we evaluate catastrophic forgetting for two sharpness-aware approaches: explicit minimization with SAM and implicit control through learning-rate schedules.

### 3.1 Experimental Setup

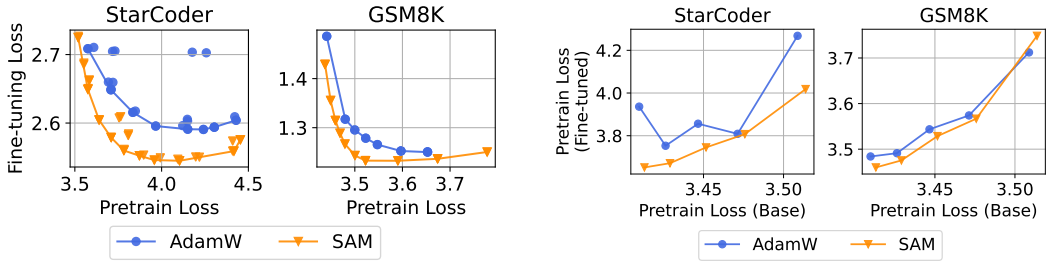
**Pretraining.** We pre-train OLMo models (Groeneveld et al., 2024) at 20M, 60M, and 150M parameters on 4B–192B tokens from DCLM-Baseline (Li et al., 2024), using AdamW or SAM with cosine or WSD schedules. We tune learning rates for AdamW+cosine to minimize pre-training loss, reuse them for all settings, and set $\rho = 0.05$ for SAM. This choice implicitly favors the baseline and ensures our results are not driven by unfair tuning. Details in Appendix C.1.

**Fine-tuning.** We fine-tune on five datasets: StarCoder Li et al. (2023) (code generation), GSM8K Cobbe et al. (2021) and StackMathQA Zhang (2024) (mathematical reasoning), Tülu Lambert et al. (2025) (instruction following), and MusicPile Yuan et al. (2024) (domain-specific). We use AdamW+cosine, sweeping learning rates from $1 \times 10^{-6}$ to $1 \times 10^{-2}$ at batch size 64 for one epoch or 10M tokens (Appendix C.2). Results for only two datasets—StarCoder (code generation) and GSM8K (math reasoning)—are shown in the main paper. For each base model, we evaluate the learning–forgetting frontier by measuring fine-tuning loss and pre-training loss on validation data.

### 3.2 The learning-forgetting frontier of SAM vs AdamW

Our first experiments compare pre-training with SAM and AdamW using the standard *cosine* learning rate schedule for both optimizers.

**Token-matched setting.** We compare SAM and AdamW across model sizes, token budgets, and datasets. SAM consistently yields pre-trained checkpoints that forget less when fine-tuned to the same performance as AdamW counterparts (Figure 1a). For example, in StarCoder, SAM **reduces forgetting by** $80\%$ at matched fine-tuning levels (limiting pre-train loss growth to $+0.1$ vs. $+0.5$ for AdamW). SAM checkpoints also achieve strictly lower fine-tuning loss, showing they can learn more while achieving a better tradeoff. Compute-matched comparisons in Appendix D.2.3.



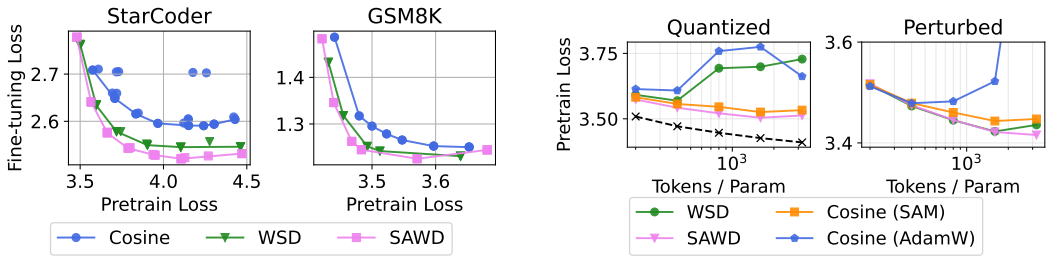

(a) (b)

Figure 1: **SAM yields better learning–forgetting frontiers than AdamW (a) and mitigates catastrophic-overtraining (b).** OLMo-60M models pre-trained on 192B token and then fine-tuned.

**Scaling trends.** We investigate whether benefits persist as we scale data and model size. The performance gap between SAM and AdamW *widens* as tokens increase. While Springer et al. (2025) report that AdamW models become increasingly brittle with prolonged training, SAM mitigates this degradation, demonstrating its strongest advantage in high-token regimes. The gap also remains

consistent and often *widens* at larger model scales, suggesting benefits do not diminish but become more pronounced (Appendix D.2.2 and D.2.4).

**Pre-train loss matched setting.** Traditionally, AdamW is reported to optimize more aggressively than SAM, raising the question of whether SAM's benefits stem simply from 'lagging behind' on the optimization trajectory—effectively acting as a form of early stopping to avoid brittle, over-trained regimes. To rule this out, we compare optimizers at matched pre-train loss. We plot the retained pre-training loss after fine-tuning (subject to a fixed downstream threshold) against the initial loss (Figure 1b) [1]. SAM strictly dominates even in this loss-matched setting: for any given initial loss, SAM checkpoints retain more knowledge than AdamW counterparts. We also recover catastrophic overtraining for AdamW Springer et al. (2025): as the pre-trained model improves, retained pretrain loss eventually rises, indicating "better" base models paradoxically do worse after fine-tuning. In contrast, SAM exhibits a monotonic trend, suggesting the onset of catastrophic overtraining is pushed to significantly lower pretrain loss.




(a) (b)

Figure 2: **WSD mitigates forgetting over Cosine schedule (a). SAM, WSD improve stability to weight perturbations like 4bit-quantization and Gaussian noise (b).** OLMo-60M models pre-trained on: 192B tokens and fine-tuned (a), 4B-192B and quantized/perturbed (b).

### 3.3 Effect of learning rate schedules on the learning–forgetting frontier

As motivated in Section 2, learning-rate dynamics shape sharpness. We systematically evaluate whether different learning rate schedules lead to different downstream behaviors.

**Higher learning rates reduce forgetting.** We find that higher learning rates, despite being slightly suboptimal for pre-training loss, achieve *better* learning-forgetting tradeoffs (Appendix D.3).

**WSD improves the learning–forgetting frontier.** Beyond peak learning rate, the temporal structure of decay impacts model properties. By maintaining high learning rate for most of training, WSD implicitly regularizes the solution, preventing sharpening associated with decaying rates (Figure 2a). We further ablate the annealing fraction and find longer annealing windows lead to worse frontiers (Appendix D.3). This aligns with our intuition that prolonged pre-training at low learning rates drives the model into sharper minima which might have good pre-train loss but suffer when fine-tuned or quantized. To our knowledge, this WSD advantage for downstream adaptation is previously unreported.

### 3.4 Beyond fine-tuning: robustness to weight perturbations

Fine-tuning is the most common setting in which a pre-trained checkpoint is *modified*, but not the only one. Before deployment, practitioners routinely perturb model weights via quantization, pruning, or compression. Unlike fine-tuning, these perturbations perform *no learning*—they are purely weight modifications—so any degradation is entirely *forgetting*, making them a clean test of the sharpness–sensitivity connection. We test robustness under two perturbations—*4-bit quantization*

[1] Formally, we plot the minimum pre-training loss $\mathcal{L}_{\mathrm{PT}}$ achievable subject to $\mathcal{L}_{\mathrm{FT}}(\theta_{\mathrm{FT}}) < \tau$. More details in Appendix C.3.

and *isotropic Gaussian weight noise*—and measure the increase in pre-training validation loss. SAM substantially mitigates quantization-induced forgetting, yielding roughly 2–3× less loss increase than AdamW-trained checkpoints, particularly in the high-token regime (≥800 tokens per parameter). Gaussian perturbations tell a consistent story: AdamW with cosine produces substantially more sensitive checkpoints than SAM or AdamW+WSD, and this gap widens with token budget (Figure 2b). Full details in Appendix D.5 and D.6.

## 4 How to overtrain your language model

Our results suggest that sharpness-aware interventions are especially valuable in the overtraining regime where small models train on large token budgets ($N/D \gg 20$) for inference efficiency.[2] SAM offers robust gains over AdamW, but its two-step update doubles per-iteration cost. Meanwhile, our schedule experiments show that WSD already provides better downstream performance than cosine by maintaining a high learning rate during the stable phase, with only the brief annealing period—where the learning rate drops—responsible for increased brittleness. This suggests we can capture SAM's benefits precisely where they are needed most: during annealing. We therefore propose **Sharpness-Aware Warmup-stable Decay (SAWD)**, which applies SAM updates only during the decay phase of WSD, keeping compute overhead negligible.

Across learning–forgetting, quantization, and perturbation robustness, SAWD consistently outperforms AdamW and AdamW+WSD (Figure 2), yielding strong gains with negligible extra cost. Extended results in Appendix D confirm this advantage holds broadly.

**Sharpness-Aware Warmup-stable Decay (SAWD):** Perform AdamW iterates during the warmup and stable (high learning-rate) phase, and SAM updates (Equation 1) during the decay phase.

- **Efficiency:** Incurs the computational cost of SAM only during the brief annealing phase, minimizing total training overhead.
- **Improved downstream performance:** Dominates AdamW on learning–forgetting Pareto frontier, while also improving robustness to quantization and perturbation perturbations.

## 5 Discussion

We demonstrated that optimizer choices during pre-training—both algorithms and learning rate schedules—profoundly influence downstream model capabilities beyond what pre-training loss captures. We identified landscape sharpness as a critical link between pre-training dynamics and downstream adaptability, showing that both explicit sharpness minimization (SAM) and implicit regularization via learning rate dynamics (WSD, higher learning rates) yield checkpoints that are more amenable to fine-tuning and quantization. We synthesized these findings into SAWD, a simple and efficient pre-training recipe that achieves robust downstream improvements.

There is no formal or complete proof of whether SAM truly optimizes sharpness, or how learning rate affects sharpness in the context of large-scale pre-training. Nevertheless, we find that the implications of these interventions for improved downstream performance hold empirically across model scales, token budgets, and fine-tuning domains.

SAM's two-step update doubles per-iteration compute cost, but we mitigate this by applying SAM only during the decay phase. Additional gains from running SAM throughout the full trajectory may be possible; reducing this overhead via caching or skipping ascent-step gradient computations is promising future work.

Our evaluation focused on fine-tuning and rudimentary post-training quantization. Future work could explore more advanced quantization methods and reinforcement learning for alignment. More broadly, we hope this work encourages a rethinking of pre-training optimization: our results show that evaluating downstream performance rather than pre-training loss can outperform AdamW, the long-standing default—highlighting significant potential for optimizers that target what ultimately matters.

[2] The recent OLMo-2 7B was pre-trained on nearly 4T tokens (OLMo et al., 2024).

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## REFERENCES

Rahaf Aljundi, Francesca Babiloni, Mohamed Elhoseiny, Marcus Rohrbach, and Tinne Tuytelaars. Memory aware synapses: Learning what (not) to forget. In *Proceedings of the European conference on computer vision (ECCV)*, pp. 139–154, 2018.

Jordan T. Ash and Ryan P. Adams. On warm-starting neural network training, 2020. URL https://arxiv.org/abs/1910.08475.

Johan Bjorck, Alon Benhaim, Vishrav Chaudhary, Furu Wei, and Xia Song. Scaling optimal LR across token horizons. In *The Thirteenth International Conference on Learning Representations*, 2025. URL https://openreview.net/forum?id=WYL4eFLcxG.

Arslan Chaudhry, Marc'Aurelio Ranzato, Marcus Rohrbach, and Mohamed Elhoseiny. Efficient lifelong learning with a-gem. *arXiv preprint arXiv:1812.00420*, 2018.

Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, Christopher Hesse, and John Schulman. Training verifiers to solve math word problems, 2021. URL https://arxiv.org/abs/2110.14168.

Jeremy Cohen, Simran Kaur, Yuanzhi Li, J Zico Kolter, and Ameet Talwalkar. Gradient descent on neural networks typically occurs at the edge of stability. In *International Conference on Learning Representations*, 2021. URL https://openreview.net/forum?id=jh-rTtvkGeM.

Laurent Dinh, Razvan Pascanu, Samy Bengio, and Yoshua Bengio. Sharp minima can generalize for deep nets. In *International Conference on Machine Learning*, pp. 1019–1028. PMLR, 2017.

Pierre Foret, Ariel Kleiner, Hossein Mobahi, and Behnam Neyshabur. Sharpness-aware minimization for efficiently improving generalization. In *International Conference on Learning Representations*, 2021. URL https://openreview.net/forum?id=6Tm1mposlrM.

Ian J Goodfellow, Mehdi Mirza, Da Xiao, Aaron Courville, and Yoshua Bengio. An empirical investigation of catastrophic forgetting in gradient-based neural networks. *arXiv preprint arXiv:1312.6211*, 2013.

Dirk Groeneveld, Iz Beltagy, Pete Walsh, Akshita Bhagia, Rodney Kinney, Oyvind Tafjord, Ananya Harsh Jha, Hamish Ivison, Ian Magnusson, Yizhong Wang, Shane Arora, David Atkinson, Russell Authur, Khyathi Raghavi Chandu, Arman Cohan, Jennifer Dumas, Yanai Elazar, Yuling Gu, Jack Hessel, Tushar Khot, William Merrill, Jacob Morrison, Niklas Muennighoff, Aakanksha Naik, Crystal Nam, Matthew E. Peters, Valentina Pyatkin, Abhilasha Ravichander, Dustin Schwenk, Saurabh Shah, Will Smith, Emma Strubell, Nishant Subramani, Mitchell Wortsman, Pradeep Dasigi, Nathan Lambert, Kyle Richardson, Luke Zettlemoyer, Jesse Dodge, Kyle Lo, Luca Soldaini, Noah A. Smith, and Hannaneh Hajishirzi. Olmo: Accelerating the science of language models, 2024. URL https://arxiv.org/abs/2402.00838.

Shengding Hu, Yuge Tu, Xu Han, Ganqu Cui, Chaoqun He, Weilin Zhao, Xiang Long, Zhi Zheng, Yewei Fang, Yuxiang Huang, Xinrong Zhang, Zhen Leng Thai, Chongyi Wang, Yuan Yao,

Chenyang Zhao, Jie Zhou, Jie Cai, Zhongwu Zhai, Ning Ding, Chao Jia, Guoyang Zeng, dahai li, Zhiyuan Liu, and Maosong Sun. MiniCPM: Unveiling the potential of small language models with scalable training strategies. In *First Conference on Language Modeling*, 2024. URL https://openreview.net/forum?id=3X2L2TFr0f.

Nitish Shirish Keskar, Dheevatsa Mudigere, Jorge Nocedal, Mikhail Smelyanskiy, and Ping Tak Peter Tang. On large-batch training for deep learning: Generalization gap and sharp minima. *arXiv preprint arXiv:1609.04836*, 2016.

James Kirkpatrick, Razvan Pascanu, Neil Rabinowitz, Joel Veness, Guillaume Desjardins, Andrei A. Rusu, Kieran Milan, John Quan, Tiago Ramalho, Agnieszka Grabska-Barwinska, Demis Hassabis, Claudia Clopath, Dharshan Kumaran, and Raia Hadsell. Overcoming catastrophic forgetting in neural networks. *Proceedings of the National Academy of Sciences*, 114(13): 3521–3526, March 2017. ISSN 1091-6490. doi: 10.1073/pnas.1611835114. URL http://dx.doi.org/10.1073/pnas.1611835114.

Nathan Lambert, Jacob Morrison, Valentina Pyatkin, Shengyi Huang, Hamish Ivison, Faeze Brahman, Lester James V. Miranda, Alisa Liu, Nouha Dziri, Shane Lyu, Yuling Gu, Saumya Malik, Victoria Graf, Jena D. Hwang, Jiangjiang Yang, Ronan Le Bras, Oyvind Tafjord, Chris Wilhelm, Luca Soldaini, Noah A. Smith, Yizhong Wang, Pradeep Dasigi, and Hannaneh Hajishirzi. Tulu 3: Pushing frontiers in open language model post-training, 2025. URL https://arxiv.org/abs/2411.15124.

Jeffrey Li, Alex Fang, Georgios Smyrnis, Maor Ivgi, Matt Jordan, Samir Yitzhak Gadre, Hritik Bansal, Etash Kumar Guha, Sedrick Keh, Kushal Arora, Saurabh Garg, Rui Xin, Niklas Muennighoff, Reinhard Heckel, Jean Mercat, Mayee F Chen, Suchin Gururangan, Mitchell Wortsman, Alon Albalak, Yonatan Bitton, Marianna Nezhurina, Amro Kamal Mohamed Abbas, Cheng-Yu Hsieh, Dhruba Ghosh, Joshua P Gardner, Maciej Kilian, Hanlin Zhang, Rulin Shao, Sarah M Pratt, Sunny Sanyal, Gabriel Ilharco, Giannis Daras, Kalyani Marathe, Aaron Gokaslan, Jieyu Zhang, Khyathi Chandu, Thao Nguyen, Igor Vasiljevic, Sham M. Kakade, Shuran Song, Sujay Sanghavi, Fartash Faghri, Sewoong Oh, Luke Zettlemoyer, Kyle Lo, Alaaeldin El-Nouby, Hadi Pouransari, Alexander T Toshev, Stephanie Wang, Dirk Groeneveld, Luca Soldaini, Pang Wei Koh, Jenia Jitsev, Thomas Kollar, Alex Dimakis, Yair Carmon, Achal Dave, Ludwig Schmidt, and Vaishaal Shankar. Datacomp-LM: In search of the next generation of training sets for language models. In *The Thirty-eight Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2024. URL https://openreview.net/forum?id=CNWdWn47IE.

Raymond Li, Loubna Ben Allal, Yangtian Zi, Niklas Muennighoff, Denis Kocetkov, Chenghao Mou, Marc Marone, Christopher Akiki, Jia Li, Jenny Chim, Qian Liu, Evgenii Zheltonozhskii, Terry Yue Zhuo, Thomas Wang, Olivier Dehaene, Mishig Davaadorj, Joel Lamy-Poirier, João Monteiro, Oleh Shliazhko, Nicolas Gontier, Nicholas Meade, Armel Zebaze, Ming-Ho Yee, Logesh Kumar Umapathi, Jian Zhu, Benjamin Lipkin, Muhtasham Oblokulov, Zhiruo Wang, Rudra Murthy, Jason Stillerman, Siva Sankalp Patel, Dmitry Abulkhanov, Marco Zocca, Manan Dey, Zhihan Zhang, Nour Fahmy, Urvashi Bhattacharyya, Wenhao Yu, Swayam Singh, Sasha Luccioni, Paulo Villegas, Maxim Kunakov, Fedor Zhdanov, Manuel Romero, Tony Lee, Nadav Timor, Jennifer Ding, Claire Schlesinger, Hailey Schoelkopf, Jan Ebert, Tri Dao, Mayank Mishra, Alex Gu, Jennifer Robinson, Carolyn Jane Anderson, Brendan Dolan-Gavitt, Danish Contractor, Siva Reddy, Daniel Fried, Dzmitry Bahdanau, Yacine Jernite, Carlos Muñoz Ferrandis, Sean Hughes, Thomas Wolf, Arjun Guha, Leandro von Werra, and Harm de Vries. Starcoder: may the source be with you!, 2023. URL https://arxiv.org/abs/2305.06161.

David Lopez-Paz and Marc'Aurelio Ranzato. Gradient episodic memory for continual learning. *Advances in neural information processing systems*, 30, 2017.

Ilya Loshchilov and Frank Hutter. Sgdr: Stochastic gradient descent with warm restarts, 2017. URL https://arxiv.org/abs/1608.03983.

Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. In *International Conference on Learning Representations*, 2019. URL https://openreview.net/forum?id=Bkg6RiCqY7.

Evgenii Nikishin, Max Schwarzer, Pierluca D'Oro, Pierre-Luc Bacon, and Aaron Courville. The primacy bias in deep reinforcement learning, 2022. URL https://arxiv.org/abs/2205.07802.

Team OLMo, Pete Walsh, Luca Soldaini, Dirk Groeneveld, Kyle Lo, Shane Arora, Akshita Bhagia, Yuling Gu, Shengyi Huang, Matt Jordan, Nathan Lambert, Dustin Schwenk, Oyvind Tafjord, Taira Anderson, David Atkinson, Faeze Brahman, Christopher Clark, Pradeep Dasigi, Nouha Dziri, Michal Guerquin, Hamish Ivison, Pang Wei Koh, Jiacheng Liu, Saumya Malik, William Merrill, Lester James V. Miranda, Jacob Morrison, Tyler Murray, Crystal Nam, Valentina Pyatkin, Aman Rangapur, Michael Schmitz, Sam Skjonsberg, David Wadden, Christopher Wilhelm, Michael Wilson, Luke Zettlemoyer, Ali Farhadi, Noah A. Smith, and Hannaneh Hajishirzi. 2 olmo 2 furious, 2024. URL https://arxiv.org/abs/2501.00656.

Andrei A Rusu, Neil C Rabinowitz, Guillaume Desjardins, Hubert Soyer, James Kirkpatrick, Koray Kavukcuoglu, Razvan Pascanu, and Raia Hadsell. Progressive neural networks. *arXiv preprint arXiv:1606.04671*, 2016.

Hanul Shin, Jung Kwon Lee, Jaehong Kim, and Jiwon Kim. Continual learning with deep generative replay, 2017. URL https://arxiv.org/abs/1705.08690.

Jacob Mitchell Springer, Sachin Goyal, Kaiyue Wen, Tanishq Kumar, Xiang Yue, Sadhika Malladi, Graham Neubig, and Aditi Raghunathan. Overtrained language models are harder to fine-tune. In *Forty-second International Conference on Machine Learning*, 2025. URL https://openreview.net/forum?id=YW6edSufht.

Kaiyue Wen, Zhiyuan Li, Jason Wang, David Hall, Percy Liang, and Tengyu Ma. Understanding warmup-stable-decay learning rates: A river valley loss landscape perspective. *arXiv preprint arXiv:2410.05192*, 2024.

Ruibin Yuan, Hanfeng Lin, Yi Wang, Zeyue Tian, Shangda Wu, Tianhao Shen, Ge Zhang, Yuhang Wu, Cong Liu, Ziya Zhou, Ziyang Ma, Liumeng Xue, Ziyu Wang, Qin Liu, Tianyu Zheng, Yizhi Li, Yinghao Ma, Yiming Liang, Xiaowei Chi, Ruibo Liu, Zili Wang, Pengfei Li, Jingcheng Wu, Chenghua Lin, Qifeng Liu, Tao Jiang, Wenhao Huang, Wenhu Chen, Emmanouil Benetos, Jie Fu, Gus Xia, Roger Dannenberg, Wei Xue, Shiyin Kang, and Yike Guo. Chatmusician: Understanding and generating music intrinsically with llm, 2024. URL https://arxiv.org/abs/2402.16153.

Friedemann Zenke, Ben Poole, and Surya Ganguli. Continual learning through synaptic intelligence. In *International conference on machine learning*, pp. 3987–3995. PMLR, 2017.

Yifan Zhang. StackMathQA: A Curated Collection of 2 Million Mathematical Questions and Answers Sourced from Stack Exchange. Technical report, ASI Research, 2024.

## A Related work

**Catastrophic forgetting and continual learning.** The challenge of learning from sequential data without overwriting previously acquired knowledge is classically studied as *catastrophic forgetting* (Goodfellow et al., 2013). Continual learning proposes mitigation strategies including (i) *regularization* to protect important parameters (Kirkpatrick et al., 2017; Zenke et al., 2017; Aljundi et al., 2018); (ii) *replay* of past examples (Shin et al., 2017); (iii) *gradient constraints* (Lopez-Paz & Ranzato, 2017; Chaudhry et al., 2018); or (iv) *architectural* expansion (Rusu et al., 2016). These methods target explicit task sequences; we instead study forgetting *under post-training modifications* as a property of the pretrained checkpoint induced by long-horizon optimization.

**Loss of plasticity and catastrophic overtraining.** A closely related phenomenon is *loss of plasticity*: with continued optimization, networks can become harder to adapt even when training loss continues to improve. This effect has been documented in deep reinforcement learning as *primacy bias* (Nikishin et al., 2022) and in supervised settings where warm-starting can impede later training dynamics (Ash & Adams, 2020). In large language models, catastrophic overtraining formalizes a similar outcome: additional pre-training can make models less amenable to downstream fine-tuning

by increasing update sensitivity (Springer et al., 2025). We build on this line by connecting plasticity loss to sharpness growth under extended pre-training, and by showing that sharpness-aware and schedule-aware pre-training can preserve post-training stability.

**Optimization geometry: sharpness and sharpness-aware training.** A long line of work connects generalization to loss-landscape geometry, including sharpness (Keskar et al., 2016), though interpretation requires care due to parameterization effects (Dinh et al., 2017). Modern training often operates near a critical *edge of stability* where learning rate and Hessian eigenvalues jointly govern dynamics (Cohen et al., 2021). SAM directly targets neighborhood robustness by optimizing for parameters whose perturbations do not significantly increase loss (Foret et al., 2021). We study how extended pre-training changes sharpness and how that controls forgetting under post-training interventions.

**Learning-rate schedules and long-horizon training.** Learning-rate schedules are a primary control for stability and geometry over long training horizons. Cosine schedules with warm restarts are widely used and serve as a standard baseline (Loshchilov & Hutter, 2017). Warmup–Stable–Decay (WSD) schedules have been motivated as practical long-horizon recipes and analyzed through a loss-landscape lens that links schedule structure to stability across training phases (Wen et al., 2024). Our results complement these insights by showing that schedule choices interact with sharpness growth under extended training, and that combining schedule design with sharpness-aware pre-training improves post-training stability.

# B Definitions

## B.1 Optimizers

Optimizers are algorithms used to update a model's parameters during training by minimizing a chosen loss function. Given gradients of the loss with respect to model parameters, optimizers determine the direction and magnitude of parameter updates. Their design plays a critical role in training stability, convergence speed, and generalization performance.

### B.1.1 AdamW

AdamW is an adaptive gradient-based optimizer that combines the benefits of momentum and per-parameter learning rate adaptation, while decoupling weight decay from the gradient update. This decoupling corrects a flaw in standard Adam and leads to improved generalization.

Let $g_t = \nabla_\theta \mathcal{L}(\theta_t)$ denote the gradient at step $t$. AdamW maintains exponential moving averages of the first and second moments:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t, \quad v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2.$$

After bias correction,

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t}, \quad \hat{v}_t = \frac{v_t}{1-\beta_2^t}.$$

The parameter update is given by

$$\theta_{t+1} = \theta_t - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} - \alpha \lambda \theta_t,$$

where $\alpha$ is the learning rate and $\lambda$ is the weight decay coefficient.

### B.1.2 SAM

Sharpness-Aware Minimization (SAM) is an optimization framework designed to improve generalization by explicitly favoring flatter minima. Unlike AdamW, which updates parameters based on gradients at the current point, SAM seeks parameters whose neighborhood exhibits uniformly low loss. This results in solutions that are less sensitive to small perturbations and empirically generalize better.

At each step, SAM first computes a perturbation in the direction of the gradient:

$$\epsilon_t = \rho \frac{\nabla_\theta \mathcal{L}(\theta_t)}{\|\nabla_\theta \mathcal{L}(\theta_t)\|_2},$$

where $\rho$ controls the size of the neighborhood. The parameters are temporarily perturbed to $\tilde{\theta}_t = \theta_t + \epsilon_t$, and the final update is computed using the gradient at this perturbed point:

$$\theta_{t+1} = \theta_t - \alpha \nabla_\theta \mathcal{L}(\tilde{\theta}_t).$$

By optimizing for robustness within a local neighborhood, SAM encourages convergence to flatter minima, which has been shown to yield improved generalization compared to standard optimizers such as AdamW.

### B.2 Learning Rate Schedulers

Learning rate schedules control how the optimizer's step size evolves during training and play a crucial role in convergence stability and generalization. Large learning rates enable rapid progress early in training, while smaller learning rates later help stabilize convergence. Consequently, modern training setups rarely use fixed learning rates, instead opting for dynamic learning rates defined by a schedule.

#### B.2.1 Cosine

The cosine schedule gradually anneals the learning rate following a cosine curve, allowing for large updates early in training and smaller, more stable updates near convergence. It is commonly combined with a warmup phase, during which the learning rate increases linearly from zero to the peak learning rate $\alpha_{\max}$ over $T_{\text{warmup}}$ steps. After warmup, the learning rate follows the cosine decay:

$$\alpha_t = \alpha_{\min} + \frac{1}{2}(\alpha_{\max} - \alpha_{\min}) \left(1 + \cos\left(\frac{\pi(t - T_{\text{warmup}})}{T - T_{\text{warmup}}}\right)\right),$$

where $\alpha_{\min}$ is the minimum learning rate, often set to zero, $T$ is the total number of training steps, and $t > T_{\text{warmup}}$.

#### B.2.2 Warmup–Stable–Decay

This warmup–stable–decay (WSD) schedule consists of three phases: an initial warmup phase where the learning rate increases linearly from zero to a peak value, a stable phase where the learning rate is held constant, and a final decay/anneal phase where the learning rate is gradually reduced. Warmup mitigates optimization instability caused by large gradients at initialization, the stable phase enables effective learning at a fixed scale, and the decay phase promotes convergence.

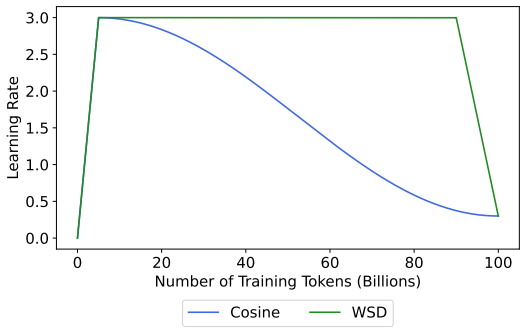


Figure 3: **Learning Rate Schedule for Cosine and WSD**

# C EXPERIMENTAL DETAILS

## C.1 PRETRAINING

We tune the learning rate for each model checkpoint individually to minimize the pre-training validation loss. For SAM, we select $\rho = 0.05$ (defined in Section 2.3), which we determined by tuning preliminary small-scale model checkpoints.

### C.1.1 MODEL CONFIGURATION

We pre-train models from scratch at three parameter scales: 20M, 60M, and 150M using the OLMo architecture Groeneveld et al. (2024) and pre-training recipe. The model configurations can be seen in Table 1. Each model is trained with varying token budgets (Table 2), corresponding to token to parameter ratios of 100 to 3200, on the DCLM web data Li et al. (2024). We evaluate two optimizers, AdamW Loshchilov & Hutter (2019), and Sharpness-Aware Minimization Foret et al. (2021) in combination with two learning rate schedules: cosine Loshchilov & Hutter (2017) and warmup-stable-decay (WSD) Hu et al. (2024).

Table 1: Pre-training hyperparameters used in our controlled experiments.

| **Hyperparameters** | **OLMo-20M** | **OLMo-60M** | **OLMo-150M** |
|---|---|---|---|
| Layers | 8 | 8 | 12 |
| Heads | 8 | 8 | 12 |
| Vocab Size | 100278 | 100278 | 100278 |
| Embedding Size | 100352 | 100352 | 100352 |
| Hidden dimensions | 256 | 528 | 768 |
| Max context length | 1024 | 1024 | 1024 |
| Activation type | SwiGLU | SwiGLU | SwiGLU |
| Attention dropout | 0.0 | 0.0 | 0.0 |
| Residual dropout | 0.0 | 0.0 | 0.0 |
| Embedding dropout | 0.0 | 0.0 | 0.0 |
| Beta1 | 0.9 | 0.9 | 0.9 |
| Beta2 | 0.95 | 0.95 | 0.95 |
| Warmup steps | 1000 | 2000 | 3000 |
| Weight decay | 0.1 | 0.1 | 0.1 |
| Batch size | 256 | 256 | 256 |

Table 2: Pre-training token budgets used in our controlled experiments.

| **Model** | **Token Budgets (B)** |
|---|---|
| OLMo-20M | $4, 8, 16, 32, 64$ |
| OLMo-60M | $12, 24, 48, 96, 192$ |
| OLMo-150M | $15, 30, 60, 120$ |

### C.1.2 LR TUNING

We tune learning rate of the pretrained models with AdamW and Cosine schedule and use the best value found for SAM (which uses AdamW as the base optimizer) and WSD schedule. For each model size, we start with the smallest token budget and sweep over the learning rates $\in [1e-4, 3e-4, 6e-4, 1e-3, 3e-3, 1e-2]$ to find the one which has the lowest pre-training loss on a held out validation set. For the next token budget, we only look at smaller LR's to check it's better based on observation from past work which shows optimal learning rate decreases with increasing token budgets Bjorck et al. (2025). Our final learning rates used for each combination of model size and tokens per parameter can be seen in Table 3 and the corresponding schematic of tuning can be seen in Figure 4.

Table 3: Final pre-training learning rates for different model sizes for varying tokens to parameter ratios. We use the same pre-training learning rate with SAM (which uses AdamW as the base optimizer) and with WSD schedule.

| Tokens / Param | 20M | 60M | 150M |
|---|---|---|---|
| 100 | – | – | 0.001 |
| 200 | 0.003 | 0.001 | 0.001 |
| 400 | 0.003 | 0.001 | 0.0006 |
| 800 | 0.003 | 0.0006 | 0.0003 |
| 1600 | 0.001 | 0.0006 | – |
| 3200 | 0.001 | 0.0003 | – |

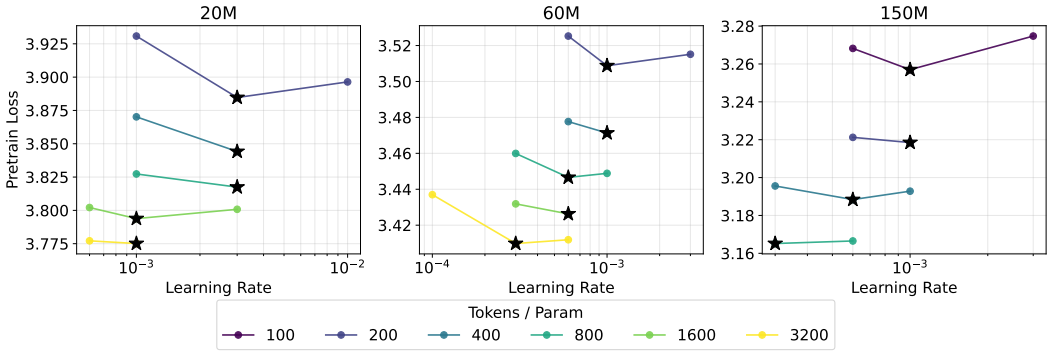


Figure 4: Pretrain learning rate tuning

### C.2 Fine-tuning

We finetune the different pre-trained checkpoints on five publicly available datasets: StarCoder Li et al. (2023) (code generation), GSM8K Cobbe et al. (2021) and StackMathQA Zhang (2024) (mathematical reasoning), Tülu Lambert et al. (2025) (instruction following) and MusicPile Yuan et al. (2024) (domain-specific). We use the AdamW optimizer with a cosine learning rate schedule. To estimate the learning-forgetting tradeoff set, we sweep over learning rates ranging from $1e-6$ to $1e-2$. We tune batch size and weight decay to find 64 and 0 as optimal values respectively. We finetune on each dataset for one epoch or a maximum of 10M tokens. This results in 1 epoch for StackMathQA (1.2M) and 10M for all four other datasets.

Table 4: Fine-tuning hyperparameters used in our controlled experiments.

| Hyperparameters | Values |
|---|---|
| Learning rate | 1e−6, 2e−6, 4e−6, 8e−6, 1e−5, 2e−5, 3e−5, 4e−5, 5e−5, 6e−5, 7e−5, 8e−5, 9e−5, 1e−4, 1.1e−4, 1.2e−4, 1.25e−4, 1.4e−4, 1.5e−4, 1.6e−4, 1.8e−4, 2e−4, 2.4e−4, 2.5e−4, 3e−4, 3.5e−4, 4e−4, 5e−4, 6e−4, 7e−4, 8e−4, 9e−4, 1e−3, 1.25e−3, 1.5e−3, 2e−3, 2.5e−3, 3e−3, 4e−3, 5e−3, 6e−3, 8e−3, 1e−2 |
| Batch size | 32, 64*, 128 |
| Learning rate scheduler | Cosine |
| Optimizer | AdamW |
| Weight decay | 0.0*, 0.1 |
| Warmup steps | 10% of training |
| Tokens | Min(tokens in dataset, 10M) |

### C.3 Evaluation

For a given pre-trained checkpoint $\theta_{\text{PT}}$, we define the learning–forgetting tradeoff set as

$$\mathcal{T}(\theta_{\text{PT}}) = \left\{ \left( \mathcal{L}_{\text{FT}}(\theta_{\text{FT}}), \mathcal{L}_{\text{PT}}(\theta_{\text{FT}}) \right) \;\middle|\; \theta_{\text{FT}} \in \Theta_{\text{FT}}(\theta_{\text{PT}}) \right\}.$$

To enable loss-matched comparison across pre-trained checkpoints, we define a common fine-tuning loss threshold as follows. For each checkpoint $\theta_{\text{PT}}^{(i)}$, we first compute the minimum fine-tuning loss achieved within its tradeoff set:

$$\mathcal{L}_{\min}^{(i)} = \min_{(\mathcal{L}_{\text{FT}}, \mathcal{L}_{\text{PT}}) \in \mathcal{T}(\theta_{\text{PT}}^{(i)})} \mathcal{L}_{\text{FT}}.$$

We then define the global fine-tuning threshold $\tau$ as the maximum over these per-checkpoint minima:

$$\tau = \max_i \; \mathcal{L}_{\min}^{(i)}.$$

For each pre-trained checkpoint, we report the retained pre-training loss $\mathcal{L}_{\text{PT}}$ corresponding to the model on its tradeoff frontier whose fine-tuning loss satisfies $\mathcal{L}_{\text{FT}} \leq \tau$.

## D Additional Results

### D.1 Pretrain Loss

On a token-matched setting, we see that SAM indeed lags behind AdamW on small models (20M, 60M). However, on larger model sizes (≈150M), we see that SAM matches or even slightly outperforms AdamW in just the raw pre-train loss for the same number of tokens (Figure 5). In this work, our focus is on downstream properties of the pre-trained model, but it's interesting future work to evaluate rigorously if SAM can also achieve better pre-train loss to start with.

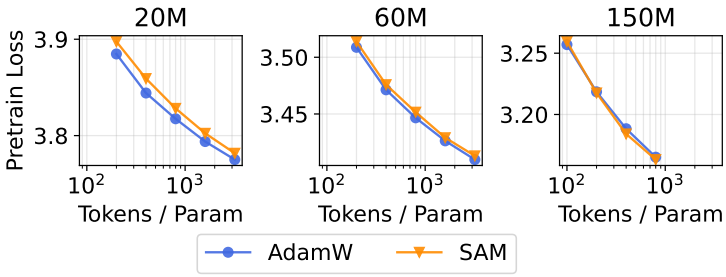


Figure 5: **SAM has worse pre-training loss than AdamW at small scale, but converges as model size increases.** Across model sizes and token budgets, SAM pre-trained models achieve a worse or similar pre-training loss compared to AdamW. However, better pretrain loss alone does not translate into mitigating forgetting.

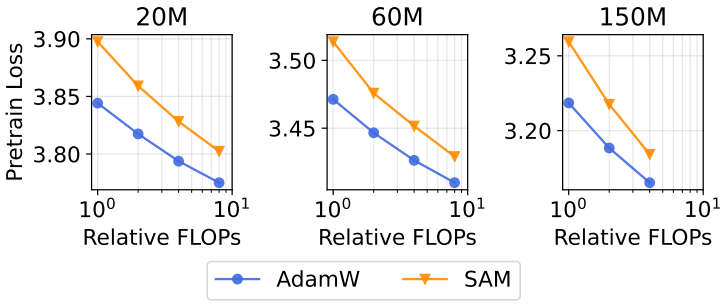


Figure 6: **SAM vs AdamW Pretrain Loss across model sizes in compute matched settings**

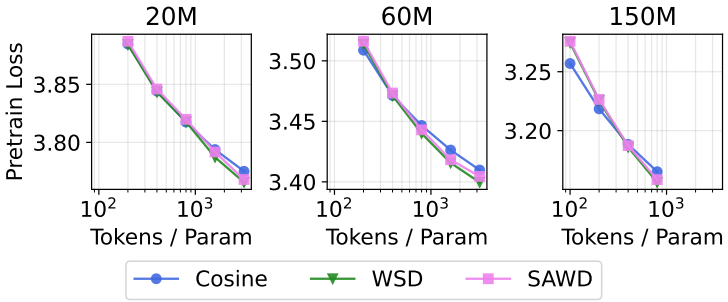


Figure 7: **WSD vs Cosine Pretrain Loss across model sizes**

## D.2 Learning-Forgetting Pareto

### D.2.1 Across Datasets

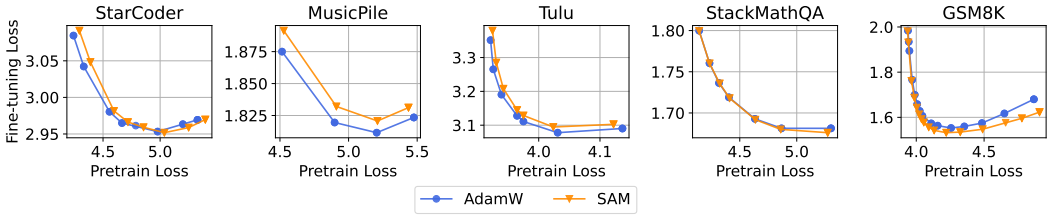


Figure 8: **AdamW vs SAM Learning-Forgetting frontier for OLMo-20M across datasets at 4B tokens**

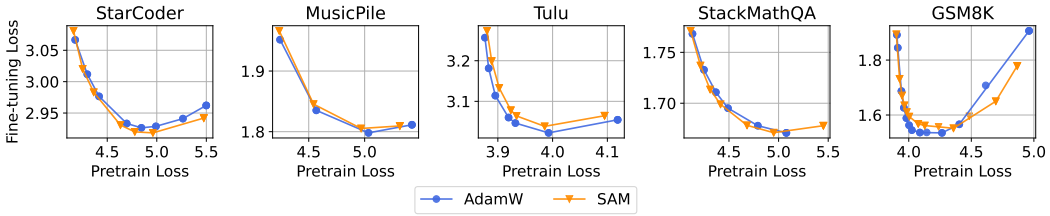


Figure 9: **AdamW vs SAM Learning-Forgetting frontier for OLMo-20M across datasets at 8B tokens**

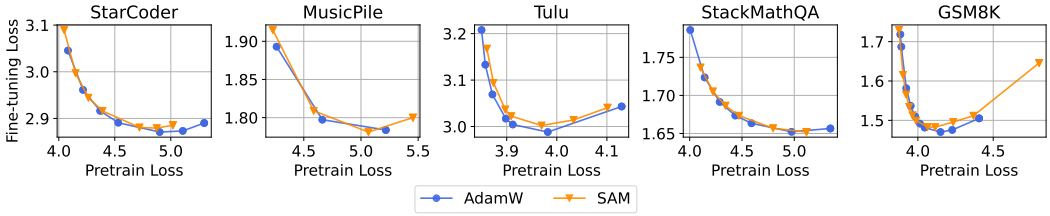


Figure 10: **AdamW vs SAM Learning-Forgetting frontier for OLMo-20M across datasets at 16B tokens**

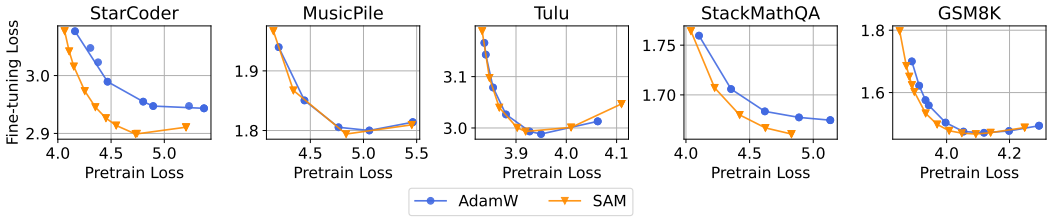


Figure 11: **AdamW vs SAM Learning-Forgetting frontier for OLMo-20M across datasets at 32B tokens**

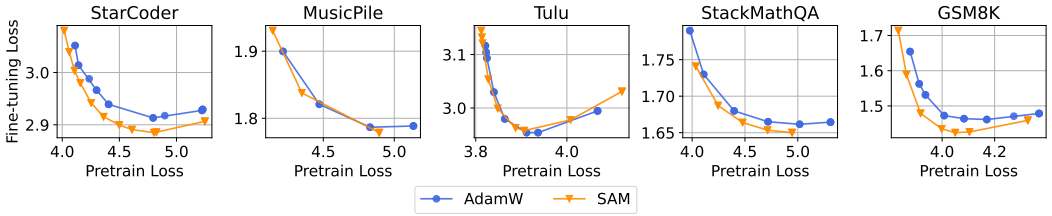


Figure 12: **AdamW vs SAM Learning-Forgetting frontier for OLMo-20M across datasets at 64B tokens**

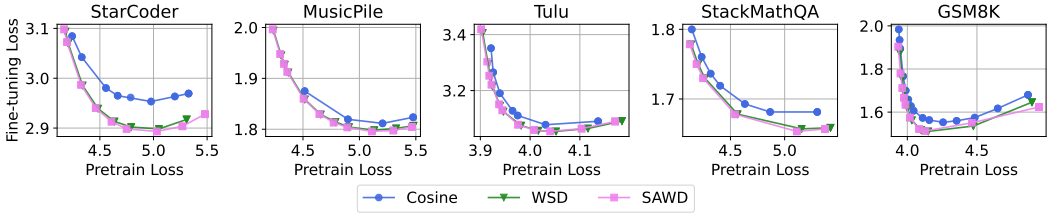


Figure 13: **Cosine vs WSD Learning-Forgetting frontier for OLMo-20M across datasets at 4B tokens**

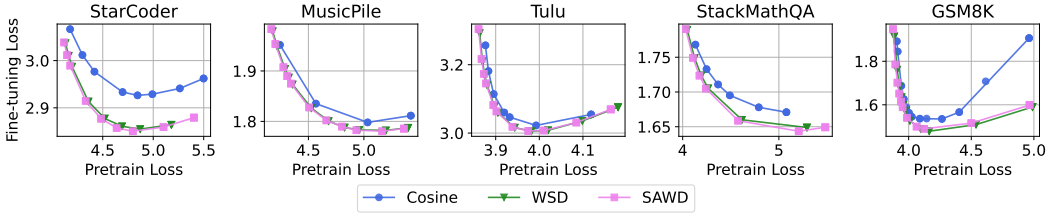


Figure 14: **Cosine vs WSD Learning-Forgetting frontier for OLMo-20M across datasets at 8B tokens**

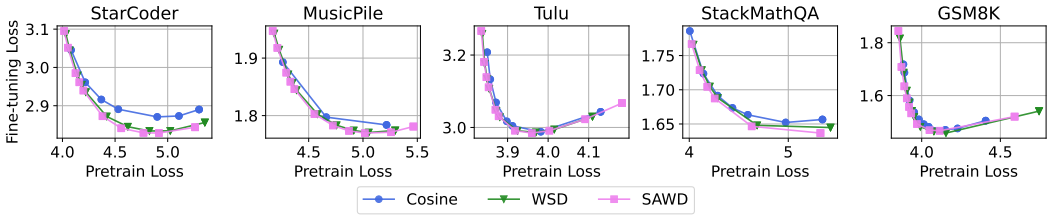


Figure 15: **Cosine vs WSD Learning-Forgetting frontier for OLMo-20M across datasets at 16B tokens**

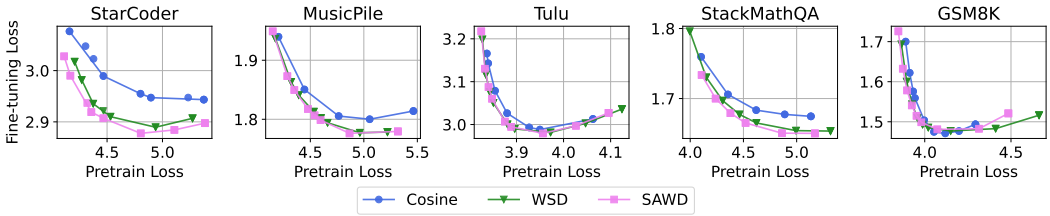


Figure 16: **Cosine vs WSD Learning-Forgetting frontier for OLMo-20M across datasets at 32B tokens**

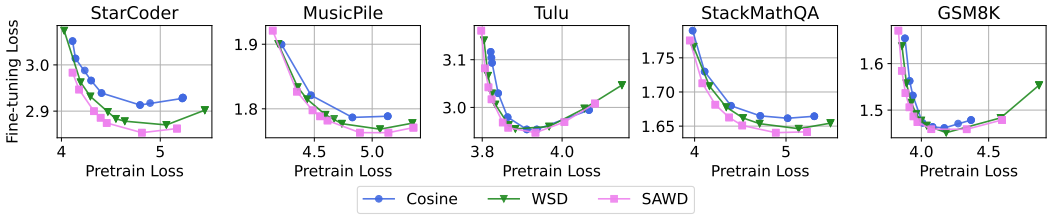


Figure 17: **Cosine vs WSD Learning-Forgetting frontier for OLMo-20M across datasets at 64B tokens**

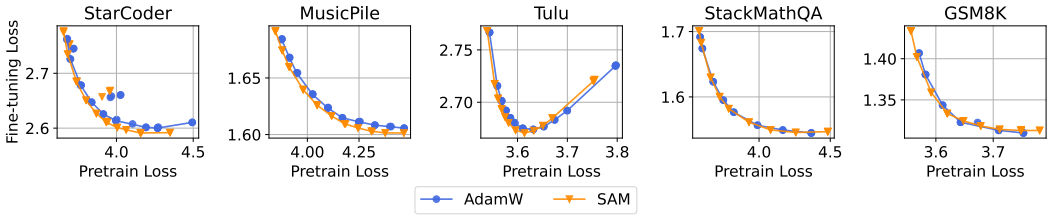


Figure 18: **AdamW vs SAM Learning-Forgetting frontier for OLMo-60M across datasets at 12B tokens**

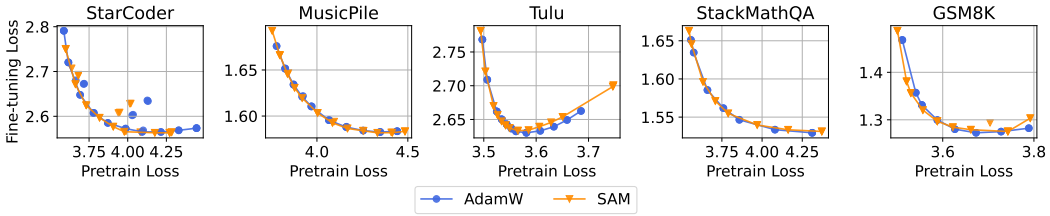


Figure 19: **AdamW vs SAM Learning-Forgetting frontier for OLMo-60M across datasets at 24B tokens**

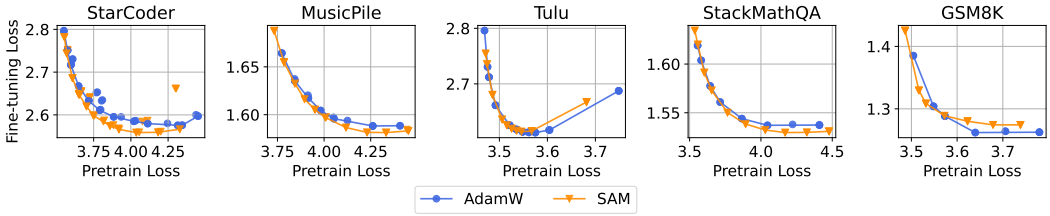


Figure 20: **AdamW vs SAM Learning-Forgetting frontier for OLMo-60M across datasets at 48B tokens**

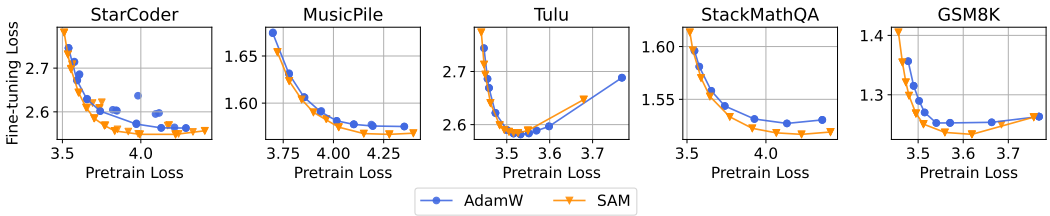


Figure 21: **AdamW vs SAM Learning-Forgetting frontier for OLMo-60M across datasets at 96B tokens**

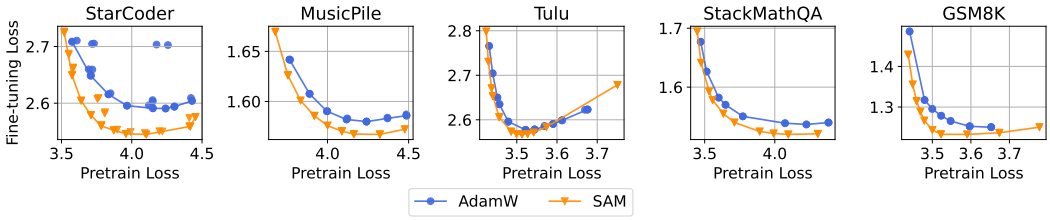


Figure 22: **AdamW vs SAM Learning-Forgetting frontier for OLMo-60M across datasets at 192B tokens**

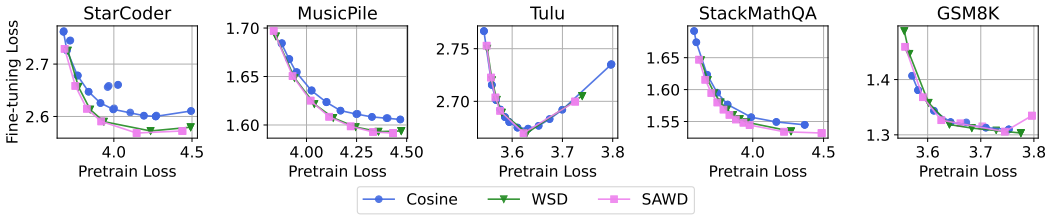


Figure 23: **Cosine vs WSD Learning-Forgetting frontier for OLMo-60M across datasets at 12B tokens**

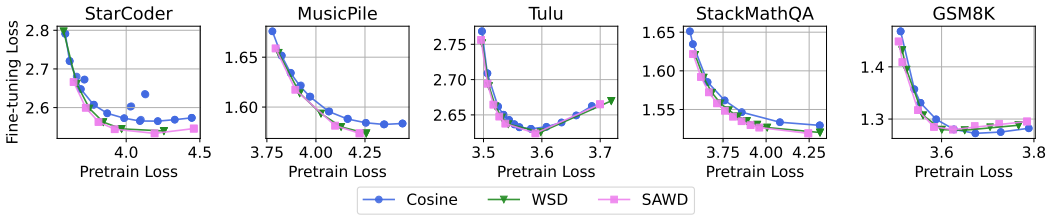


Figure 24: **Cosine vs WSD Learning-Forgetting frontier for OLMo-60M across datasets at 24B tokens**

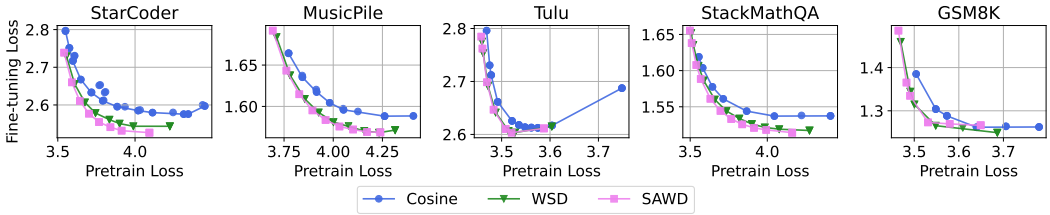


Figure 25: **Cosine vs WSD Learning-Forgetting frontier for OLMo-60M across datasets at 48B tokens**

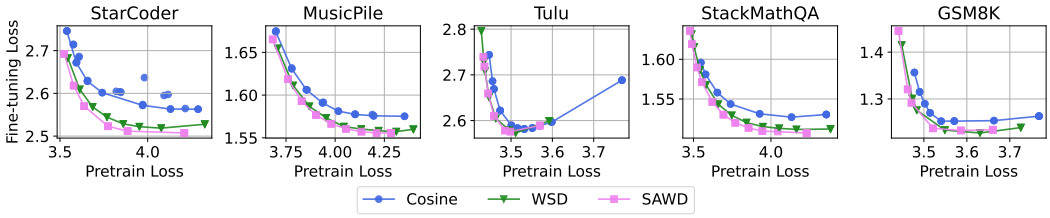


Figure 26: **Cosine vs WSD Learning-Forgetting frontier for OLMo-60M across datasets at 96B tokens**

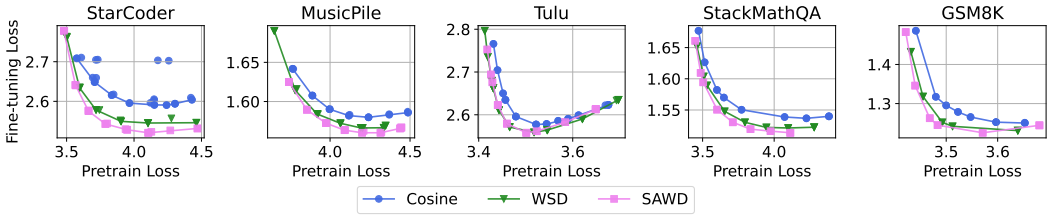


Figure 27: **Cosine vs WSD Learning-Forgetting frontier for OLMo-60M across datasets at 192B tokens**

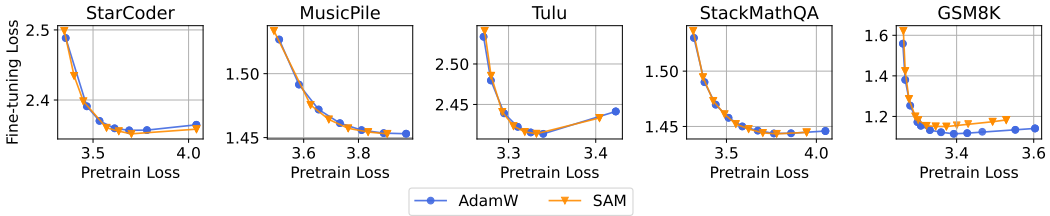


Figure 28: **AdamW vs SAM Learning-Forgetting frontier for OLMo-150M across datasets at 15B tokens**

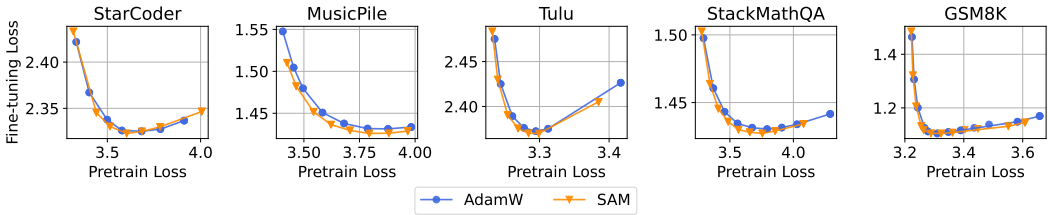


Figure 29: **AdamW vs SAM Learning-Forgetting frontier for OLMo-150M across datasets at 30B tokens**

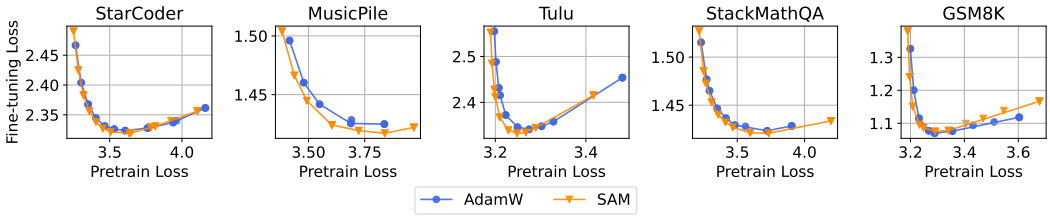


Figure 30: **AdamW vs SAM Learning-Forgetting frontier for OLMo-150M across datasets at 60B tokens**

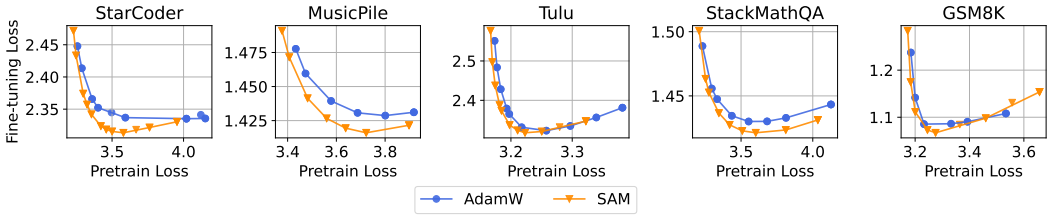


Figure 31: **AdamW vs SAM Learning-Forgetting frontier for OLMo-150M across datasets at 120B tokens**

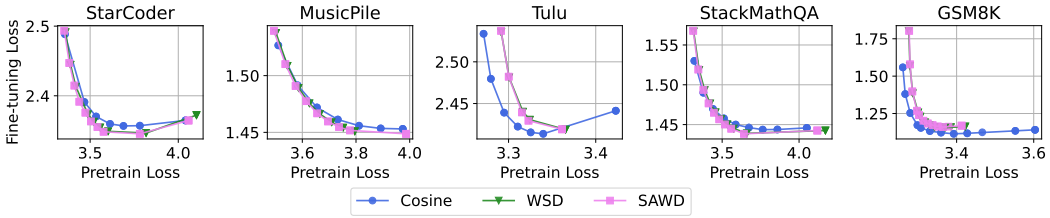


Figure 32: **Cosine vs WSD Learning-Forgetting frontier for OLMo-150M across datasets at 15B tokens**

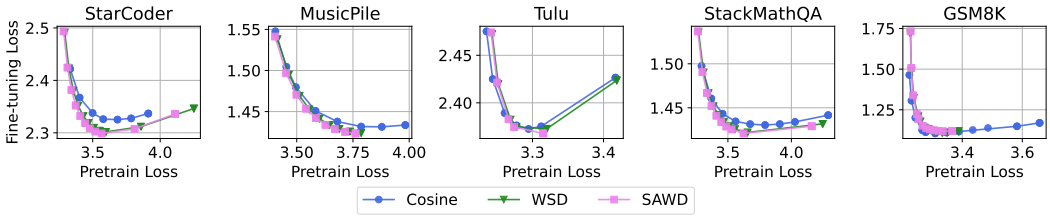


Figure 33: **Cosine vs WSD Learning-Forgetting frontier for OLMo-150M across datasets at 30B tokens**

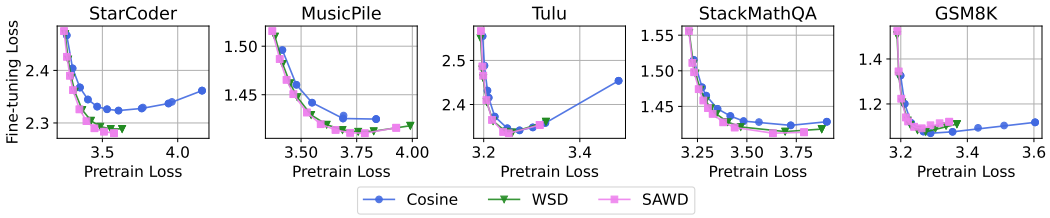


Figure 34: **Cosine vs WSD Learning-Forgetting frontier for OLMo-150M across datasets at 60B tokens**

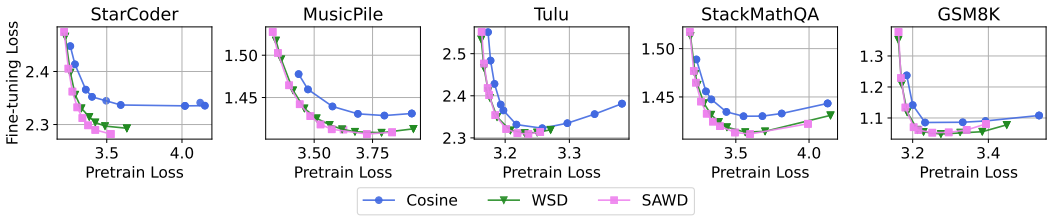


Figure 35: **Cosine vs WSD Learning-Forgetting frontier for OLMo-150M across datasets at 120B tokens**

### D.2.2 Scaling Tokens

We investigate whether benefits persist as we scale data and model size. In this section, we compare learning–forgetting frontiers for all pretrained checkpoints trained using different configurations of optimizers (AdamW, SAM), learning rate schedule (Cosine, WSD), and model sizes (20M, 60M, 150M) in a token-matched setting. The performance gap between SAM and AdamW *widens* as tokens increase. While Springer et al. (2025) report that AdamW models become increasingly brittle with prolonged training, SAM mitigates this degradation, demonstrating its strongest advantage in high-token regimes. We further see similar trends when comparing WSD and Cosine schedules.

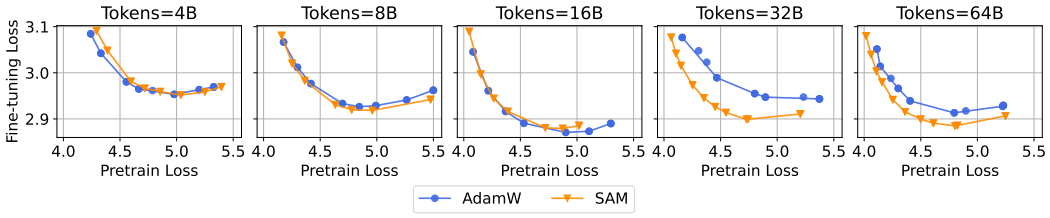


Figure 36: **AdamW vs SAM Starcoder 20M**

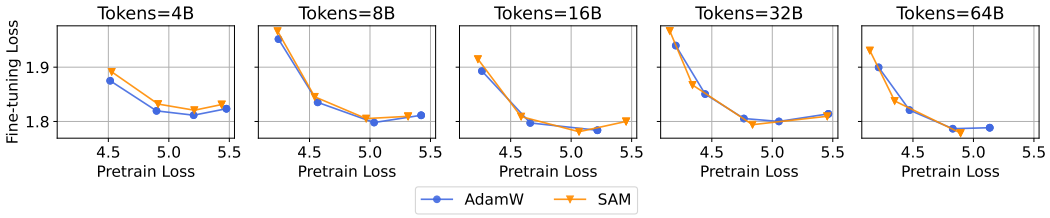


Figure 37: **AdamW vs SAM Musicpile 20M**

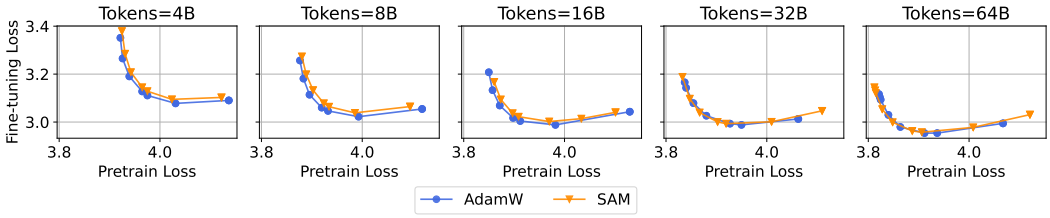


Figure 38: **AdamW vs SAM Tulu 20M**

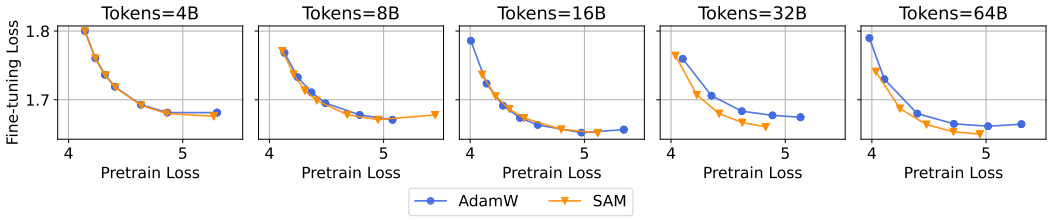


Figure 39: **AdamW vs SAM StackmathQA 20M**

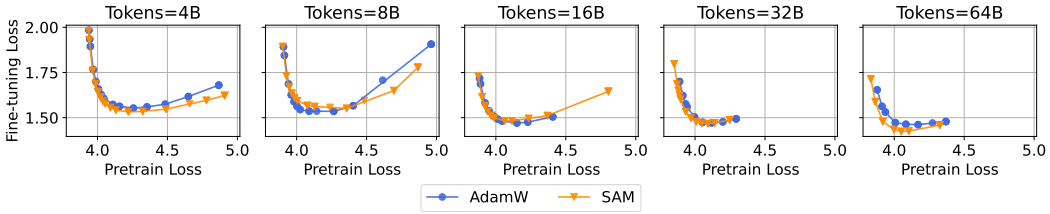


Figure 40: **AdamW vs SAM GSM8K 20M**

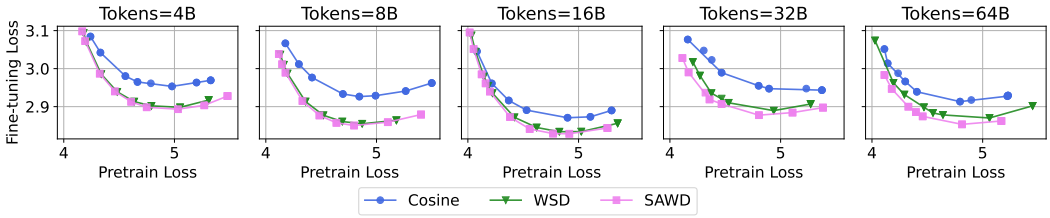


Figure 41: **WSD vs Cosine Starcoder 20M**

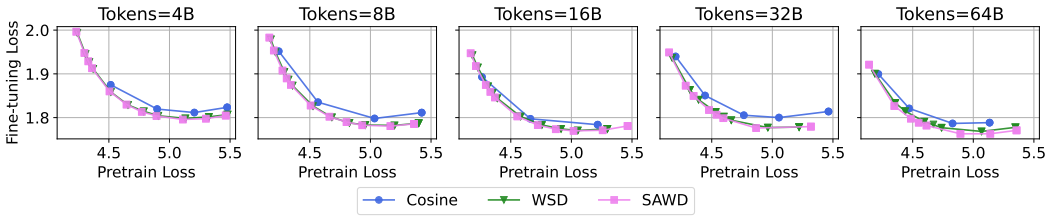


Figure 42: **WSD vs Cosine Musicpile 20M**

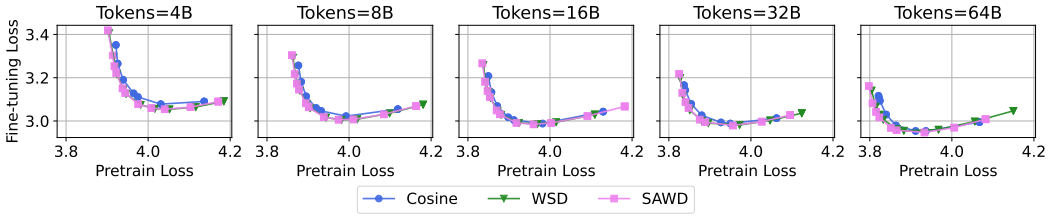


Figure 43: **WSD vs Cosine Tulu 20M**

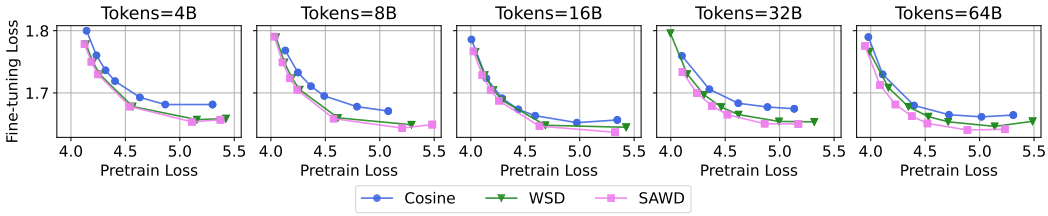


Figure 44: **WSD vs Cosine StackmathQA 20M**

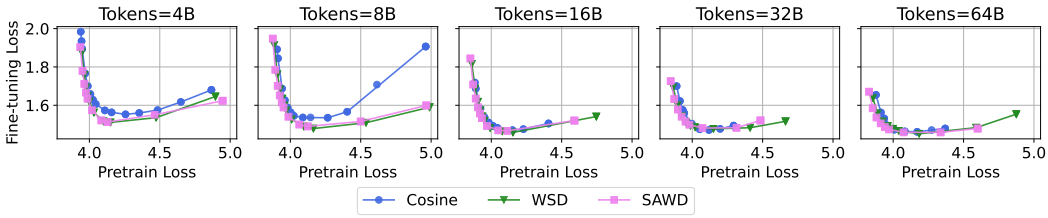


Figure 45: **WSD vs Cosine GSM8K 20M**

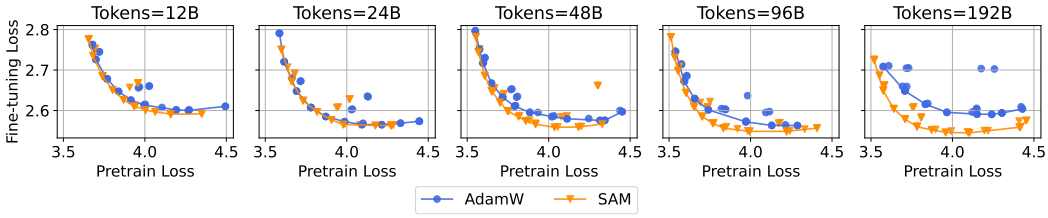


Figure 46: **AdamW vs SAM Starcoder 60M**

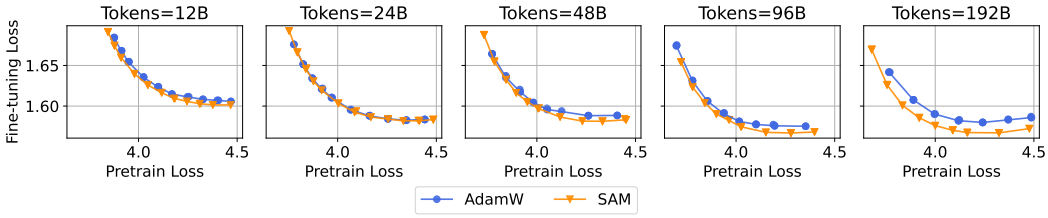


Figure 47: **AdamW vs SAM Musicpile 60M**

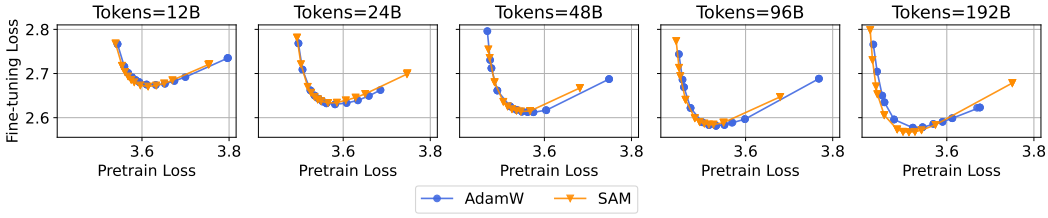


Figure 48: **AdamW vs SAM Tulu 60M**

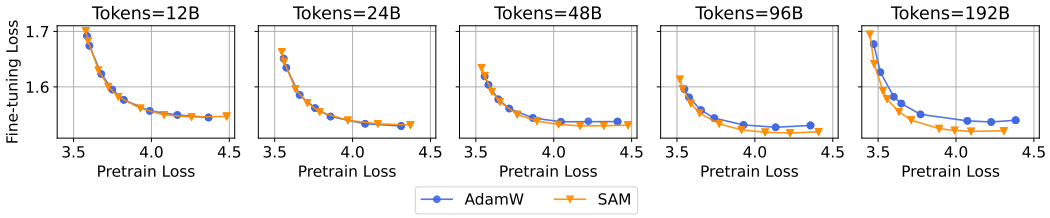


Figure 49: **AdamW vs SAM StackmathQA 60M**

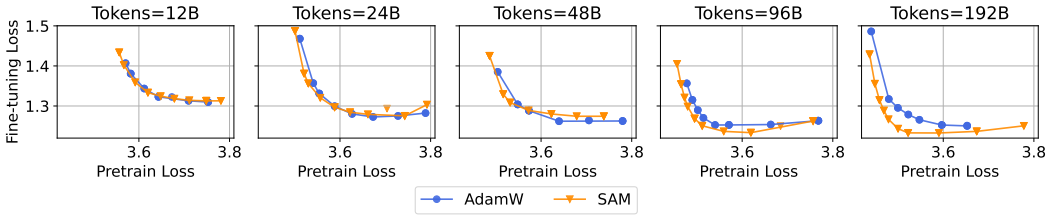


Figure 50: **AdamW vs SAM GSM8K 60M**

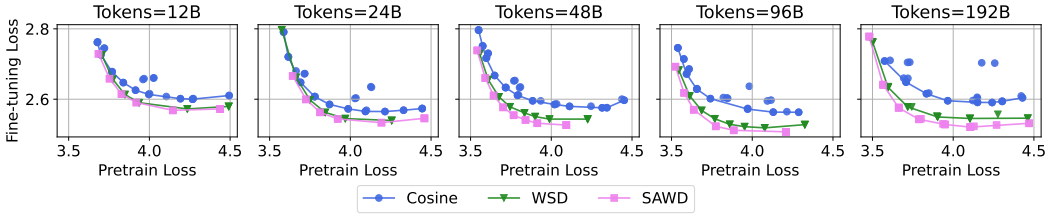


Figure 51: **WSD vs Cosine Starcoder 60M**

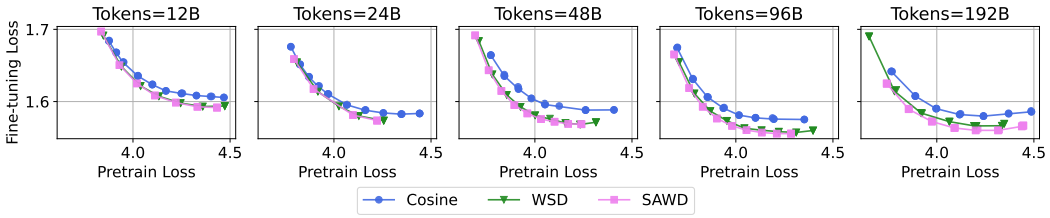


Figure 52: **WSD vs Cosine Musicpile 60M**

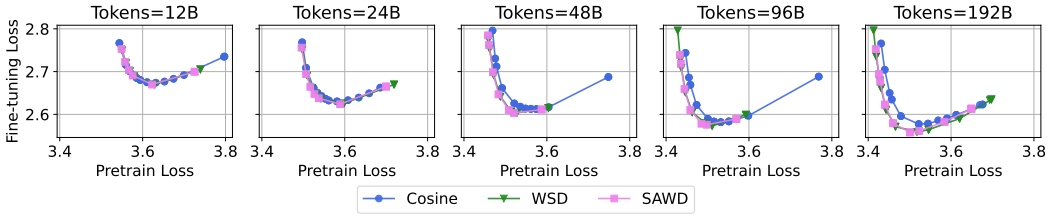


Figure 53: **WSD vs Cosine Tulu 60M**

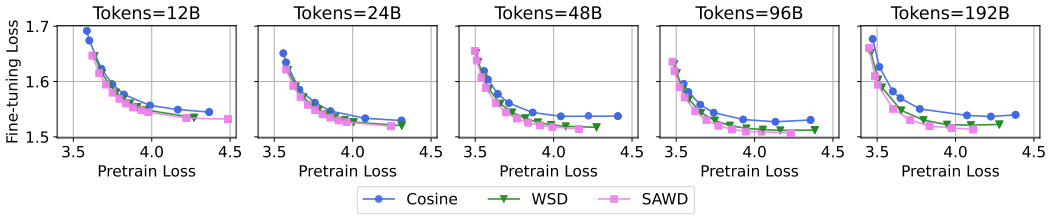


Figure 54: **WSD vs Cosine StackmathQA 60M**

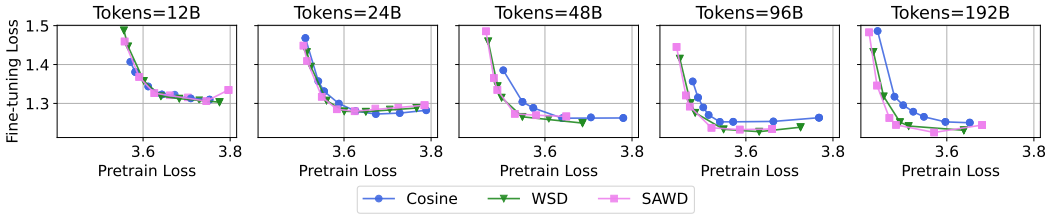


Figure 55: **WSD vs Cosine GSM8K 60M**

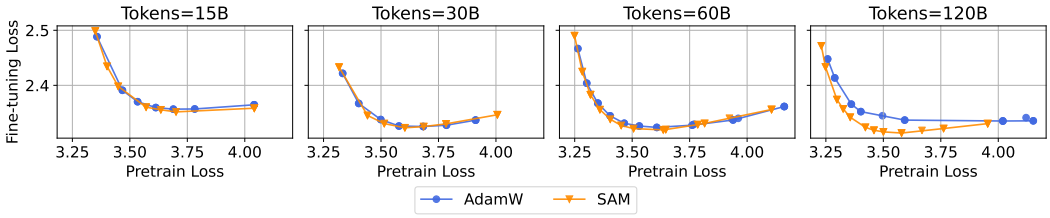


Figure 56: **AdamW vs SAM Starcoder 150M**

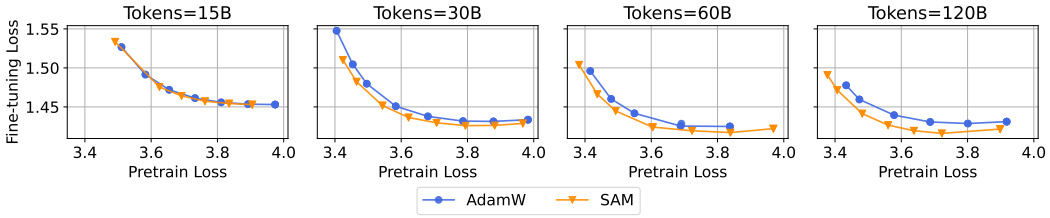


Figure 57: **AdamW vs SAM Musicpile 150M**

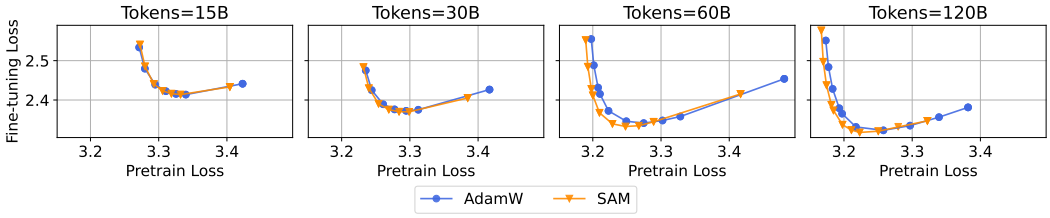


Figure 58: **AdamW vs SAM Tulu 150M**

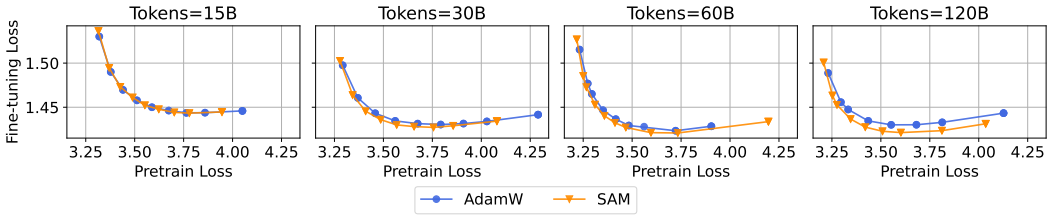


Figure 59: **AdamW vs SAM StackmathQA 150M**

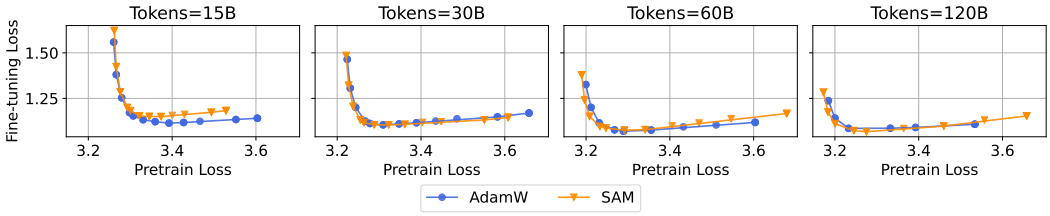


Figure 60: **AdamW vs SAM GSM8K 150M**

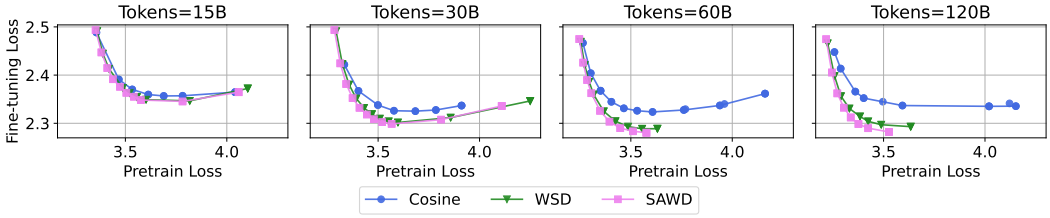


Figure 61: **WSD vs Cosine Starcoder 150M**

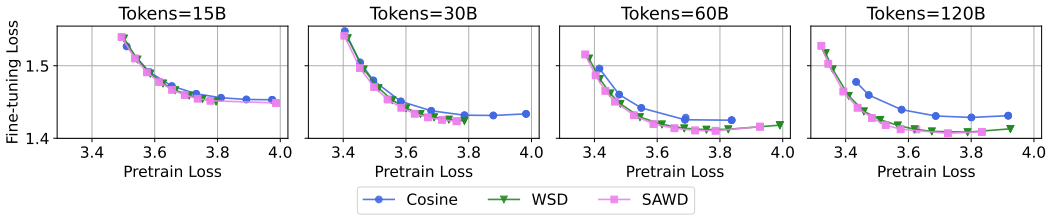


Figure 62: **WSD vs Cosine Musicpile 150M**

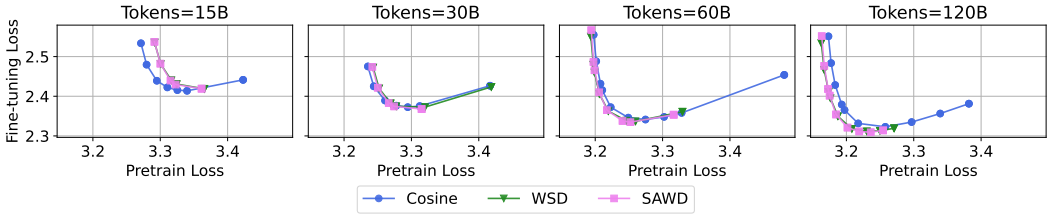


Figure 63: **WSD vs Cosine Tulu 150M**

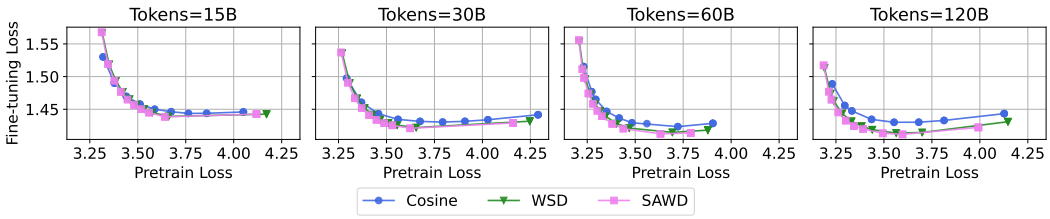


Figure 64: **WSD vs Cosine StackmathQA 150M**

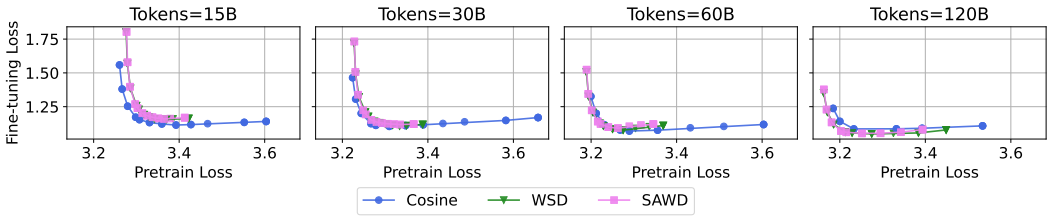


Figure 65: **WSD vs Cosine GSM8K 150M**

### D.2.3 COMPUTE MATCHED

Since SAM's two-step update doubles per-iteration compute cost, we also compare SAM and AdamW in a compute-matched setting, where the SAM models are trained on half the tokens to equalize total FLOPs. Even under this stricter comparison, SAM often maintains competitive or superior learning–forgetting frontiers, particularly at larger model sizes and higher token-to-parameter ratios.

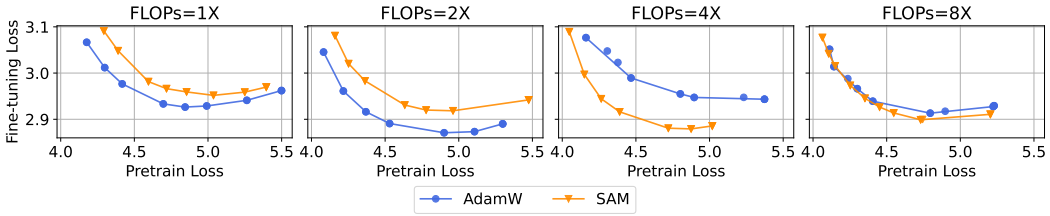


Figure 66: **AdamW vs SAM Starcoder 20M (Compute Matched)**

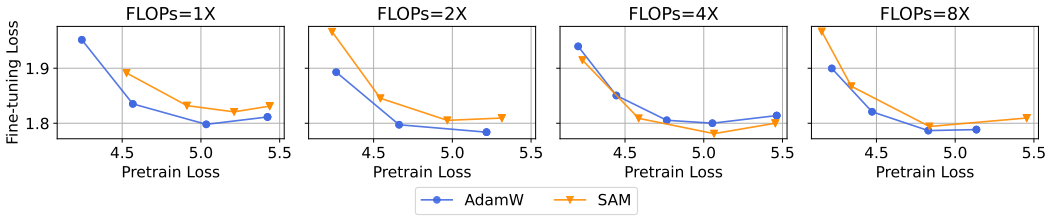


Figure 67: **AdamW vs SAM Musicpile 20M (Compute Matched)**

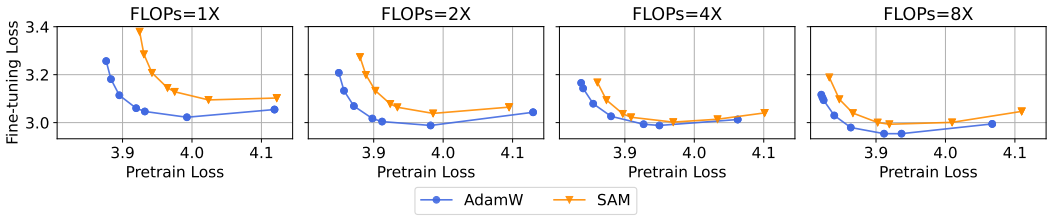


Figure 68: **AdamW vs SAM Tulu 20M (Compute Matched)**

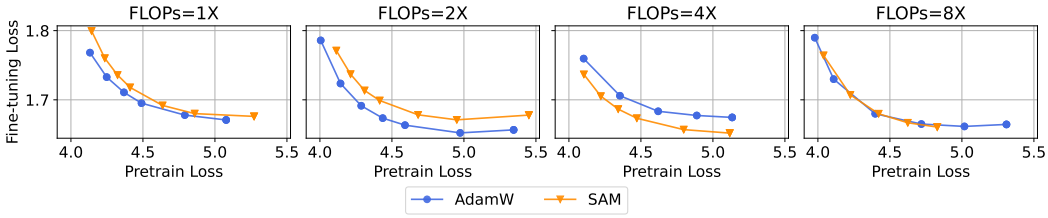


Figure 69: **AdamW vs SAM StackmathQA 20M (Compute Matched)**

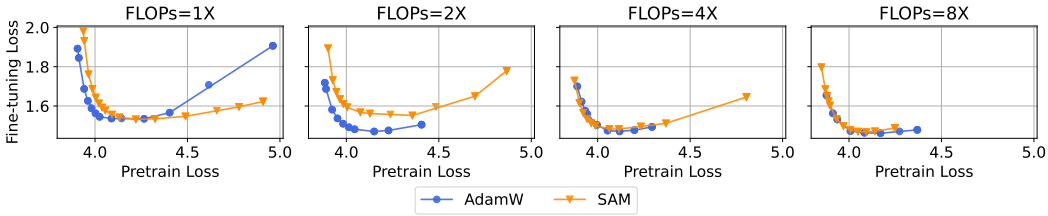


Figure 70: **AdamW vs SAM GSM8K 20M (Compute Matched)**

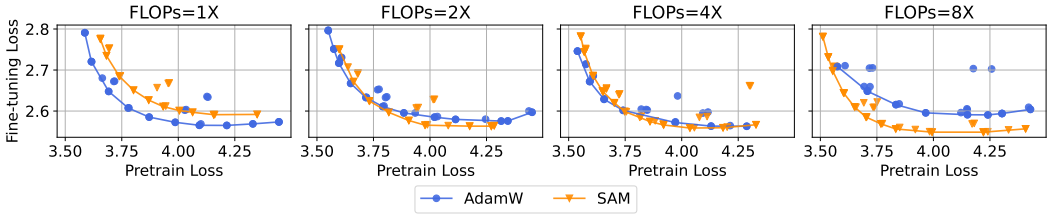


Figure 71: **AdamW vs SAM Starcoder 60M (Compute Matched)**

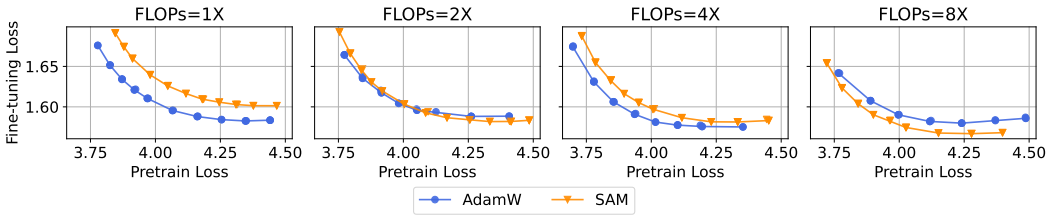


Figure 72: **AdamW vs SAM Musicpile 60M (Compute Matched)**

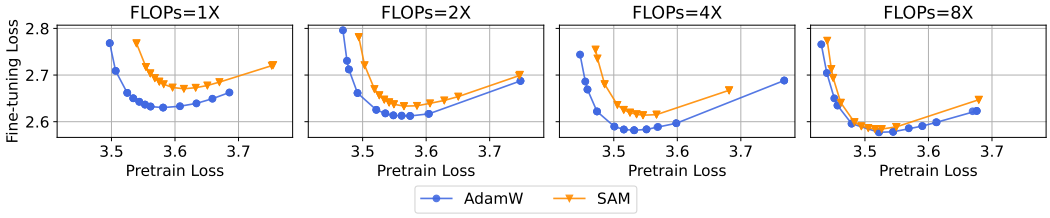


Figure 73: **AdamW vs SAM Tulu 60M (Compute Matched)**

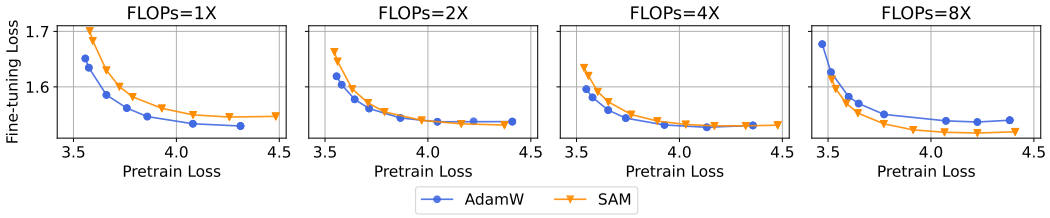


Figure 74: **AdamW vs SAM StackmathQA 60M (Compute Matched)**

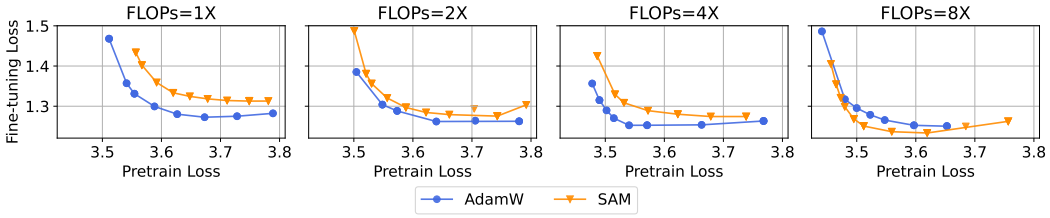


Figure 75: **AdamW vs SAM GSM8K 60M (Compute Matched)**

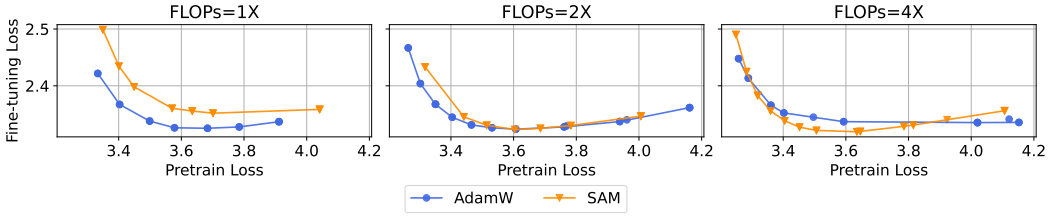


Figure 76: **AdamW vs SAM Starcoder 150M (Compute Matched)**

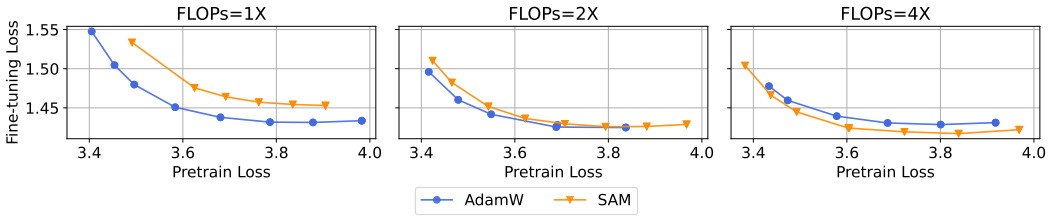


Figure 77: **AdamW vs SAM Musicpile 150M (Compute Matched)**

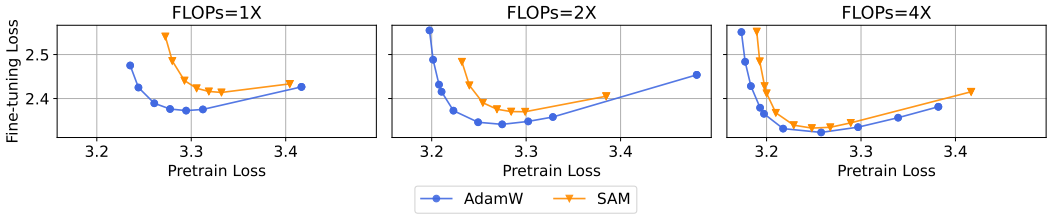


Figure 78: **AdamW vs SAM Tulu 150M (Compute Matched)**

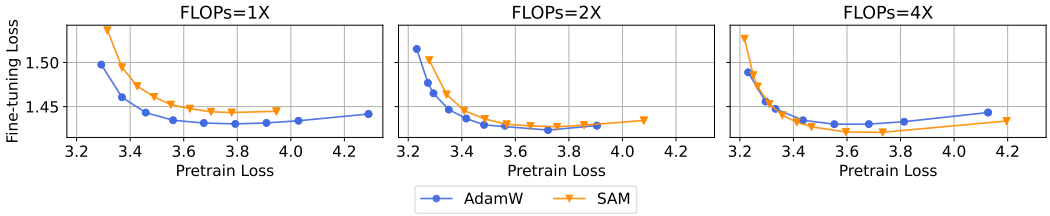


Figure 79: **AdamW vs SAM StackmathQA 150M (Compute Matched)**

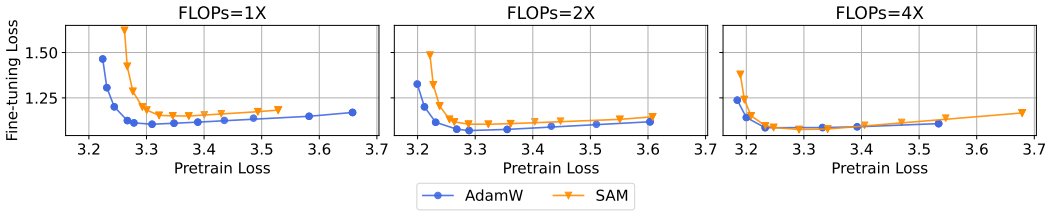


Figure 80: **AdamW vs SAM GSM8K 150M (Compute Matched)**

#### D.2.4 SCALING MODEL SIZE

We analyze whether benefits persist as model size increases. In this sction, we plot learning–forgetting frontiers across model sizes at multiple fixed *token-per-parameter* ratios (200, 400, 800). The performance gap between SAM and AdamW remains consistent and often *widens* at larger scales, suggesting benefits do not diminish but become more pronounced.

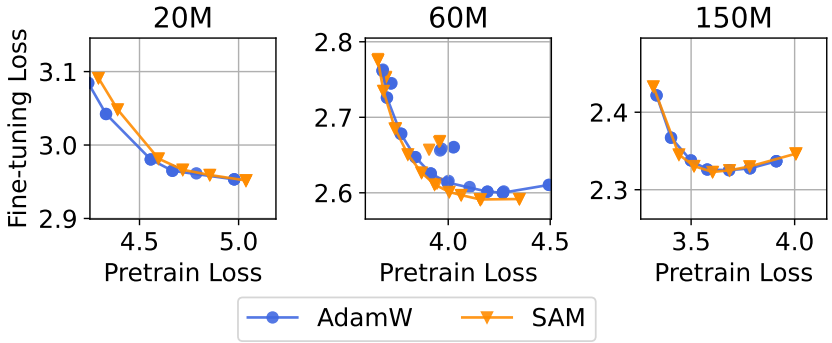


Figure 81: **AdamW vs SAM Learning forgetting frontier across Model Sizes at 200 token / param for Starcoder**

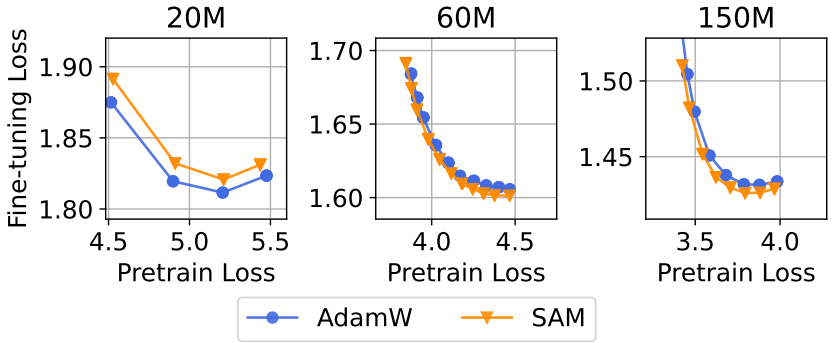


Figure 82: **AdamW vs SAM Learning forgetting frontier across Model Sizes at 200 token / param for Musicpile**

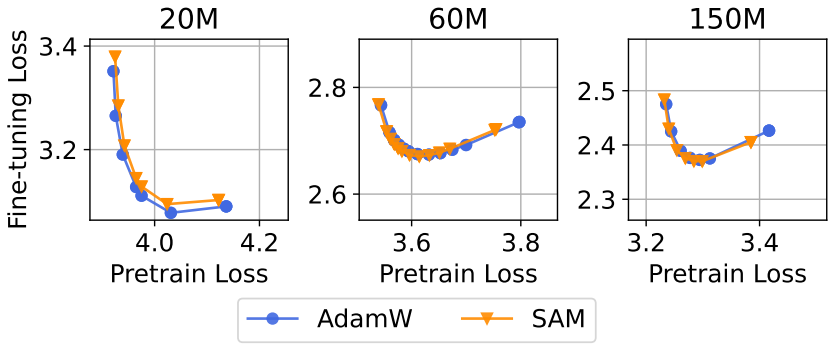


Figure 83: **AdamW vs SAM Learning forgetting frontier across Model Sizes at 200 token / param for Tulu**

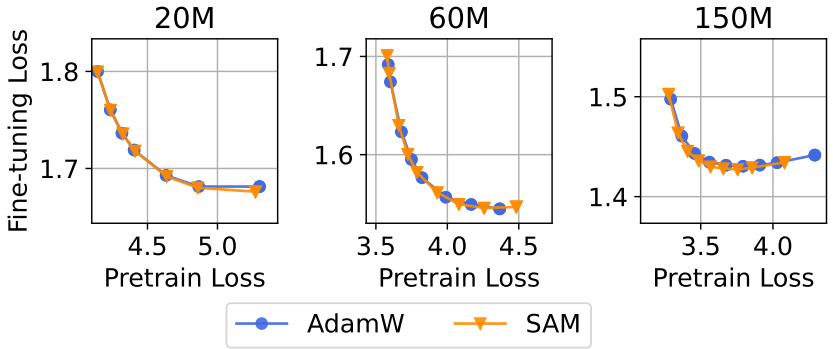


Figure 84: **AdamW vs SAM Learning forgetting frontier across Model Sizes at 200 token / param for StackmathQA**

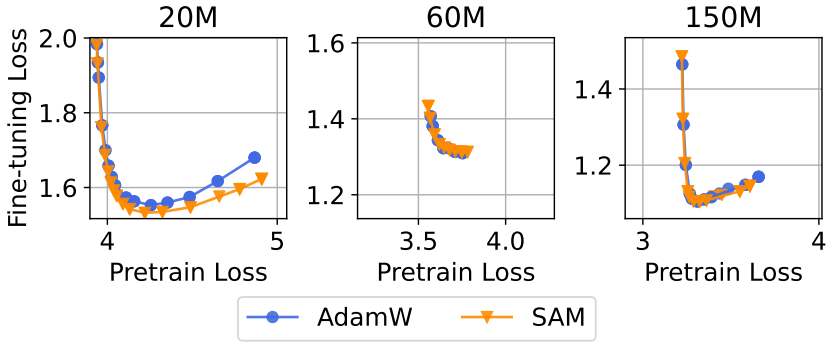


Figure 85: **AdamW vs SAM Learning forgetting frontier across Model Sizes at 200 token / param for GSM8K**

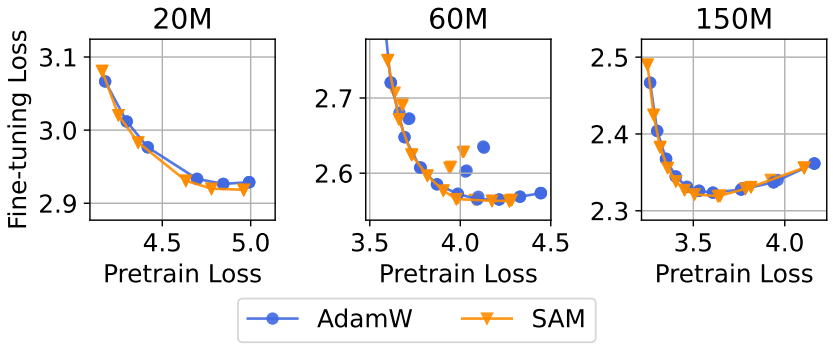


Figure 86: **AdamW vs SAM Learning forgetting frontier across Model Sizes at 400 token / param for Starcoder**

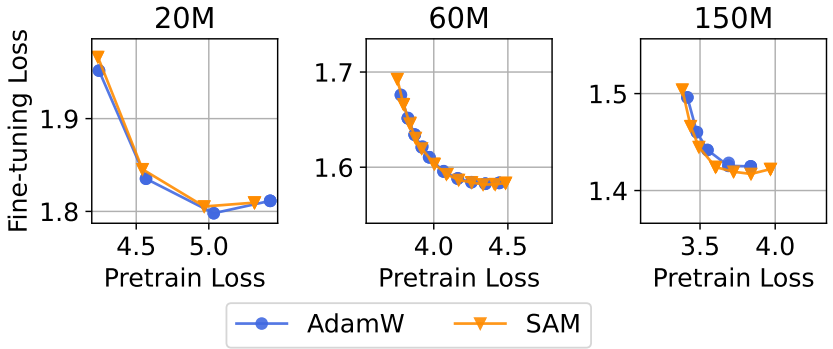


Figure 87: **AdamW vs SAM Learning forgetting frontier across Model Sizes at 400 token / param for Musicpile**

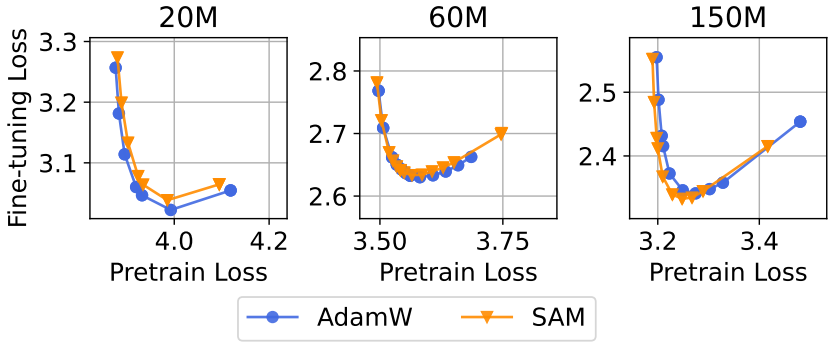


Figure 88: **AdamW vs SAM Learning forgetting frontier across Model Sizes at 400 token / param for Tulu**

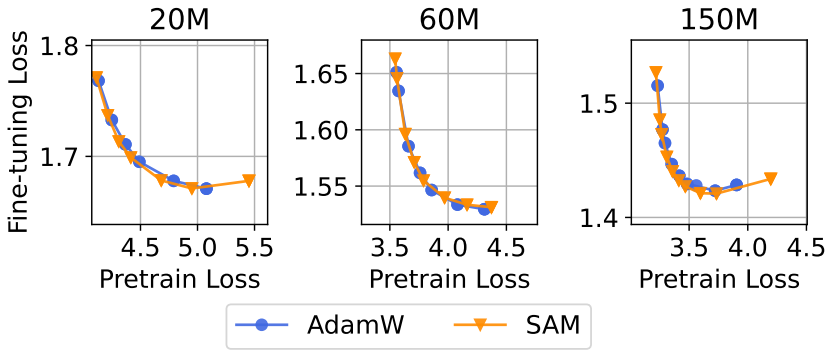


Figure 89: **AdamW vs SAM Learning forgetting frontier across Model Sizes at 400 token / param for StackmathQA**

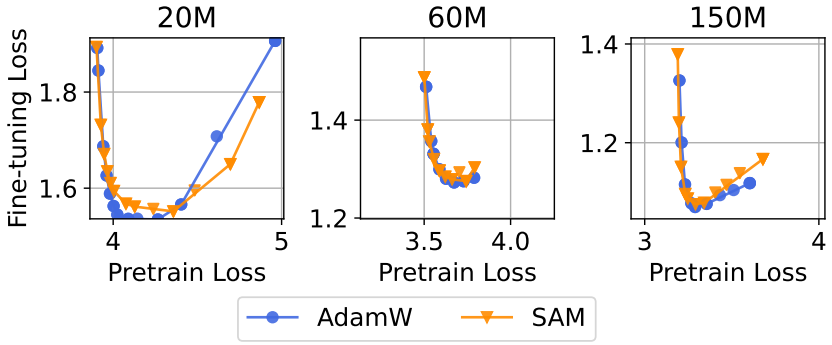


Figure 90: **AdamW vs SAM Learning forgetting frontier across Model Sizes at 400 token / param for GSM8K**

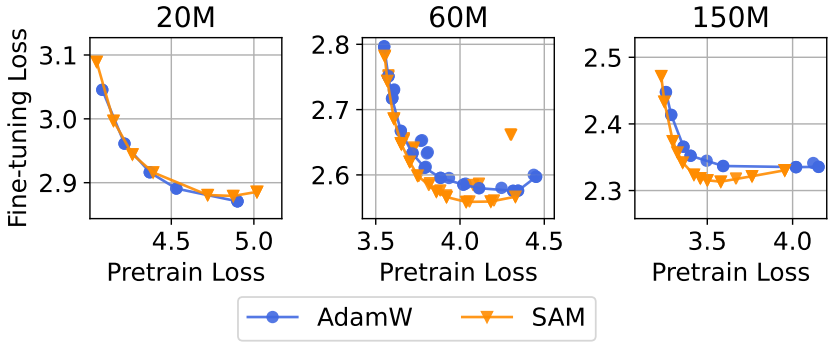


Figure 91: **AdamW vs SAM Learning forgetting frontier across Model Sizes at 800 token / param for Starcoder**

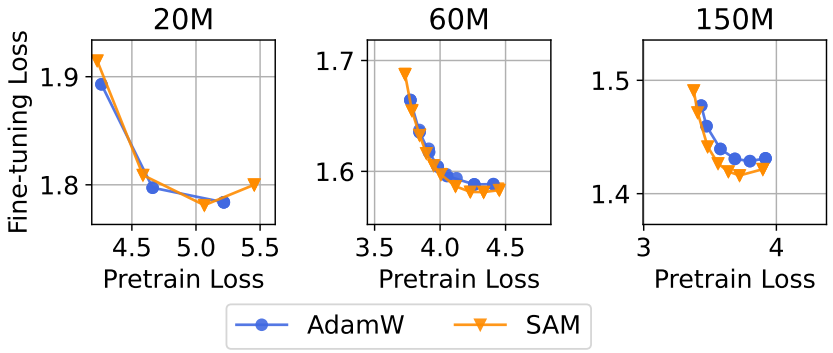


Figure 92: **AdamW vs SAM Learning forgetting frontier across Model Sizes at 800 token / param for Musicpile**

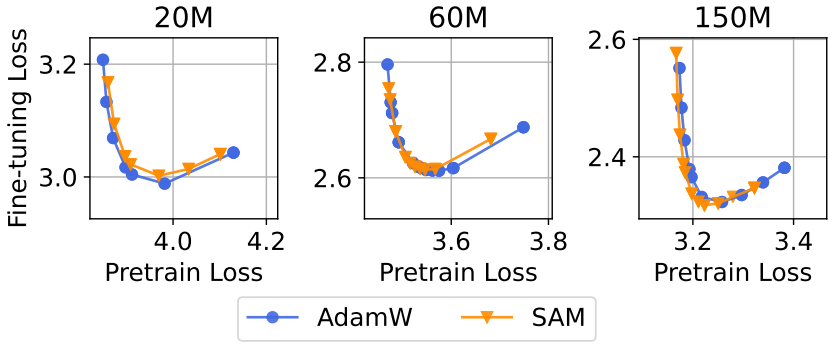


Figure 93: **AdamW vs SAM Learning forgetting frontier across Model Sizes at 800 token / param for Tulu**

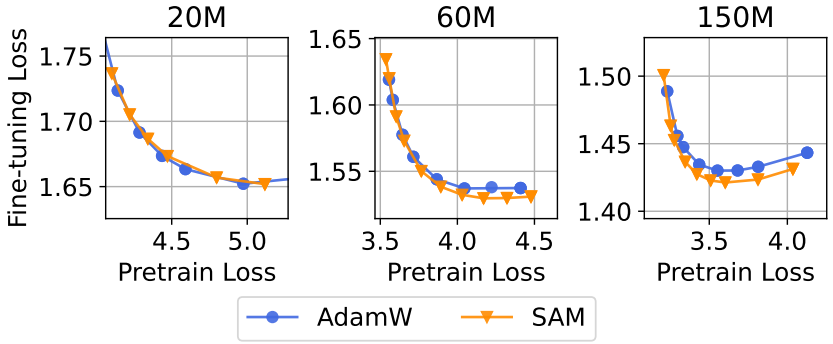


Figure 94: **AdamW vs SAM Learning forgetting frontier across Model Sizes at 800 token / param for StackmathQA**

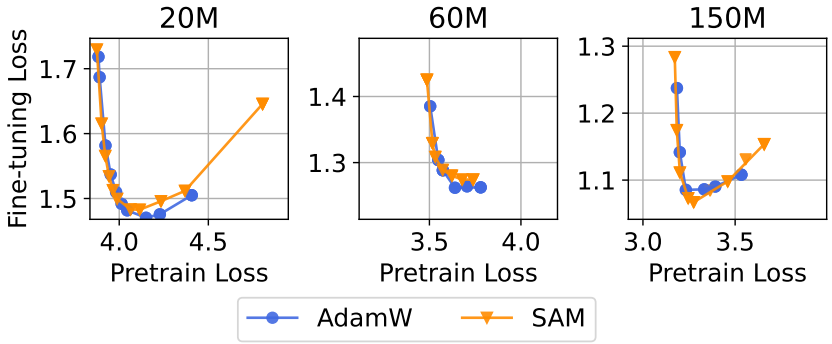


Figure 95: **AdamW vs SAM Learning forgetting frontier across Model Sizes at 800 token / param for GSM8K**

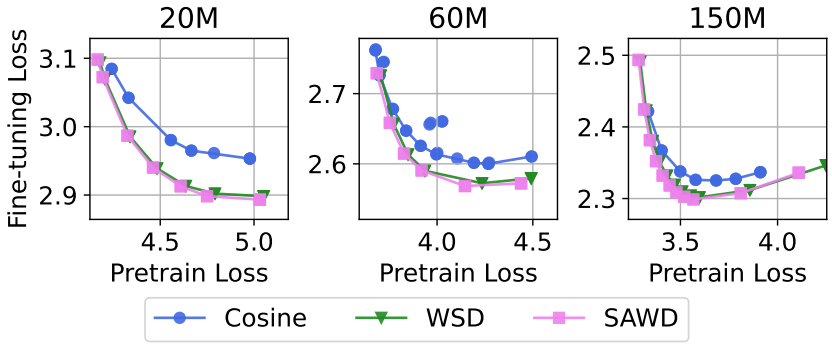


Figure 96: **Cosine vs WSD Learning forgetting frontier across Model Sizes at 200 token / param for Starcoder**

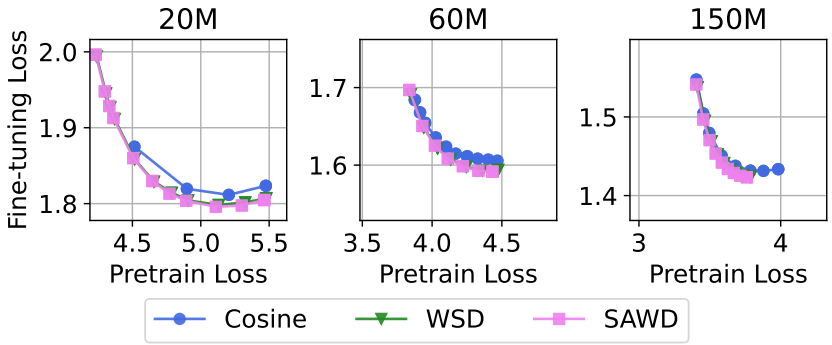


Figure 97: **Cosine vs WSD Learning forgetting frontier across Model Sizes at 200 token / param for Musicpile**

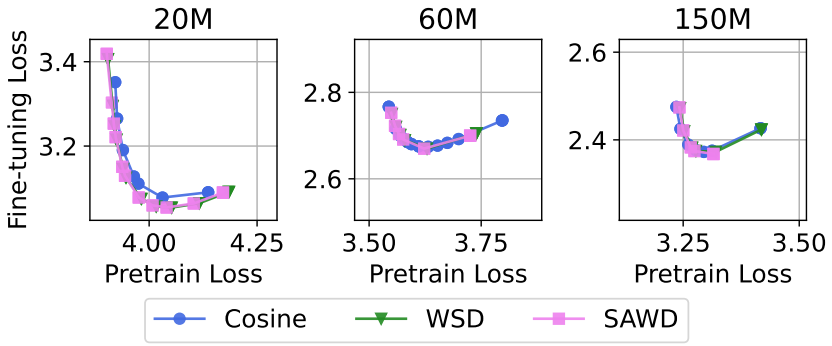


Figure 98: **Cosine vs WSD Learning forgetting frontier across Model Sizes at 200 token / param for Tulu**

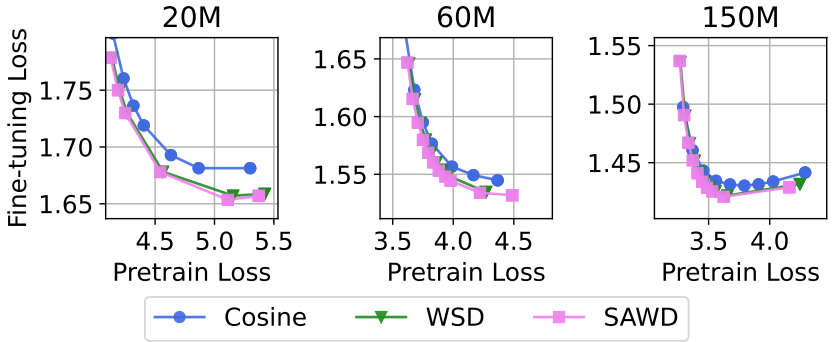


Figure 99: **Cosine vs WSD Learning forgetting frontier across Model Sizes at 200 token / param for StackmathQA**

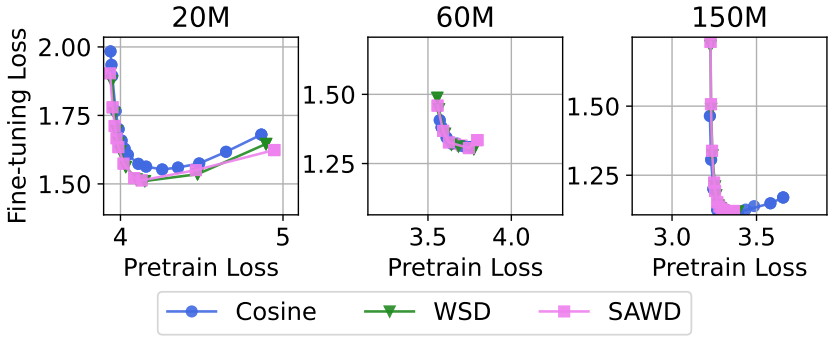


Figure 100: **Cosine vs WSD Learning forgetting frontier across Model Sizes at 200 token / param for GSM8K**

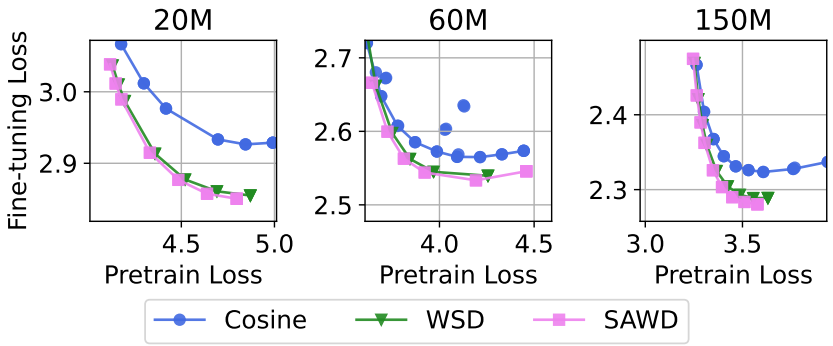


Figure 101: **Cosine vs WSD Learning forgetting frontier across Model Sizes at 400 token / param for Starcoder**

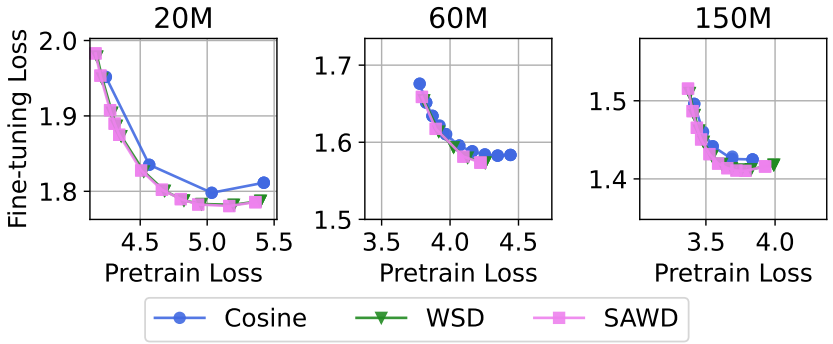


Figure 102: **Cosine vs WSD Learning forgetting frontier across Model Sizes at 400 token / param for Musicpile**

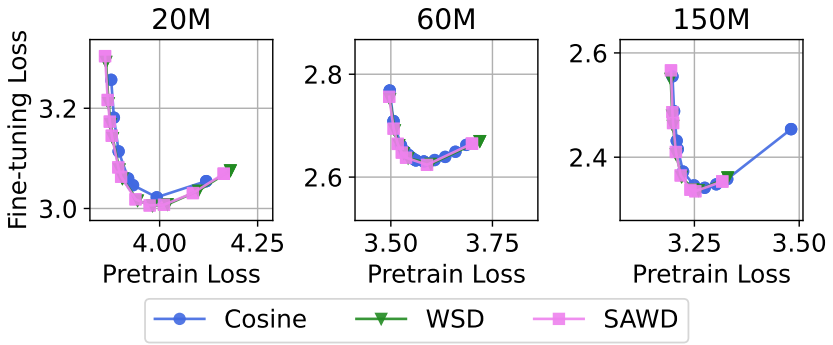


Figure 103: **Cosine vs WSD Learning forgetting frontier across Model Sizes at 400 token / param for Tulu**

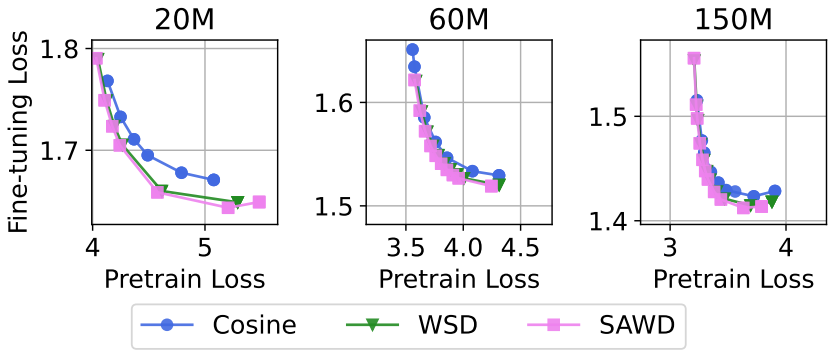


Figure 104: **Cosine vs WSD Learning forgetting frontier across Model Sizes at 400 token / param for StackmathQA**

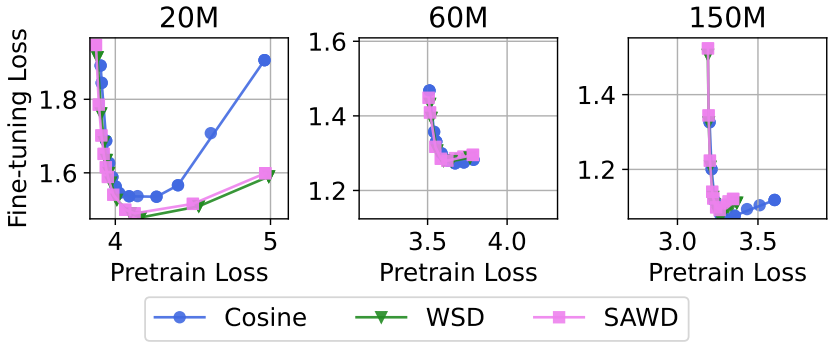


Figure 105: **Cosine vs WSD Learning forgetting frontier across Model Sizes at 400 token / param for GSM8K**

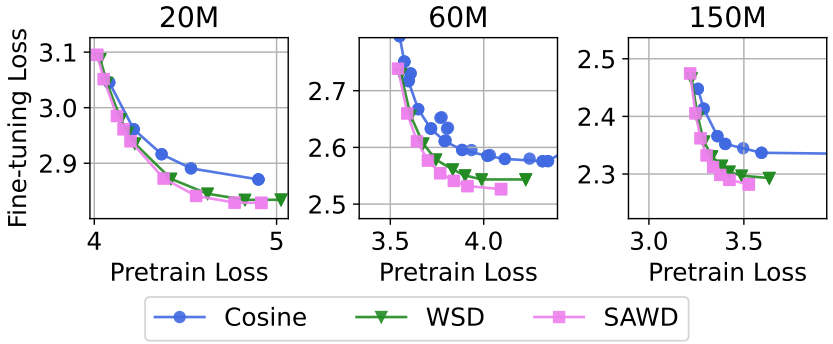


Figure 106: **Cosine vs WSD Learning forgetting frontier across Model Sizes at 800 token / param for Starcoder**

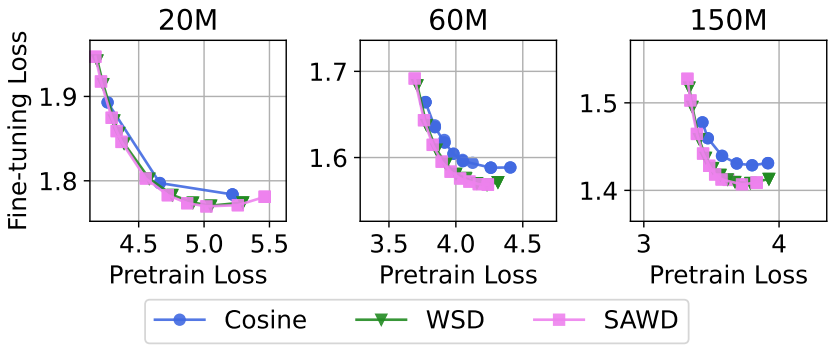


Figure 107: **Cosine vs WSD Learning forgetting frontier across Model Sizes at 800 token / param for Musicpile**

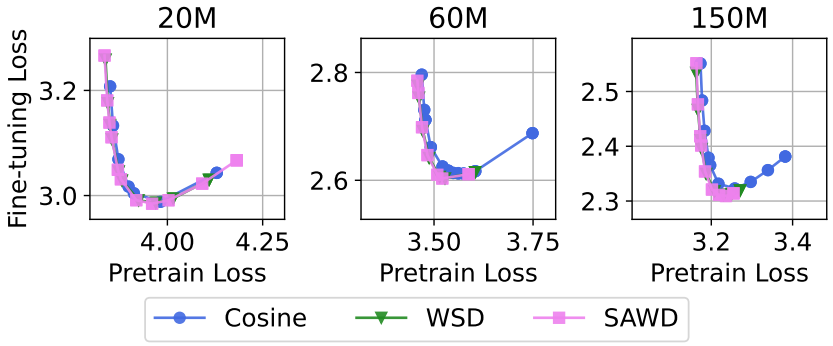


Figure 108: **Cosine vs WSD Learning forgetting frontier across Model Sizes at 800 token / param for Tulu**

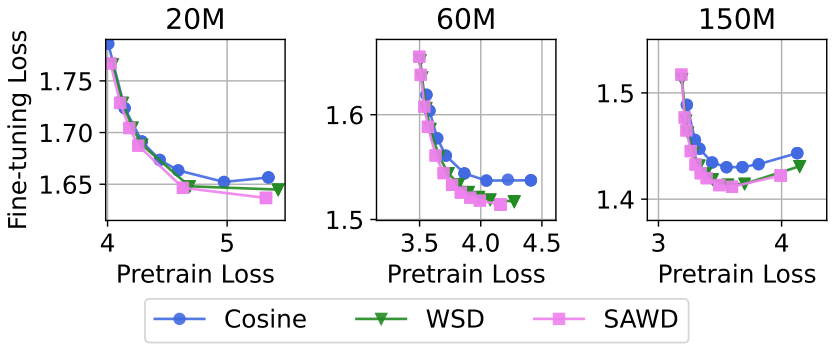


Figure 109: **Cosine vs WSD Learning forgetting frontier across Model Sizes at 800 token / param for StackmathQA**

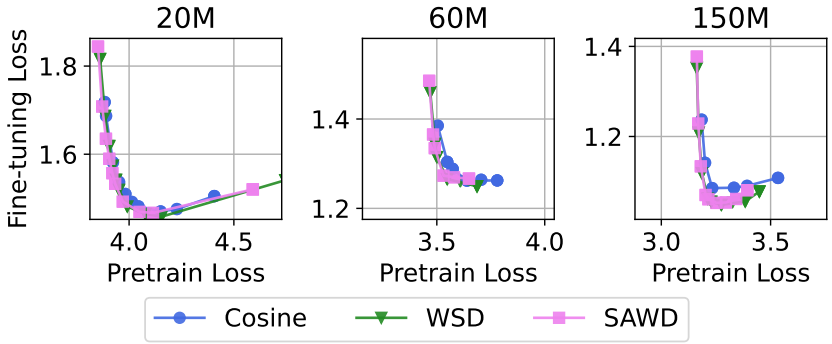


Figure 110: **Cosine vs WSD Learning forgetting frontier across Model Sizes at 800 token / param for GSM8K**

### D.3 Learning Rate Schedules

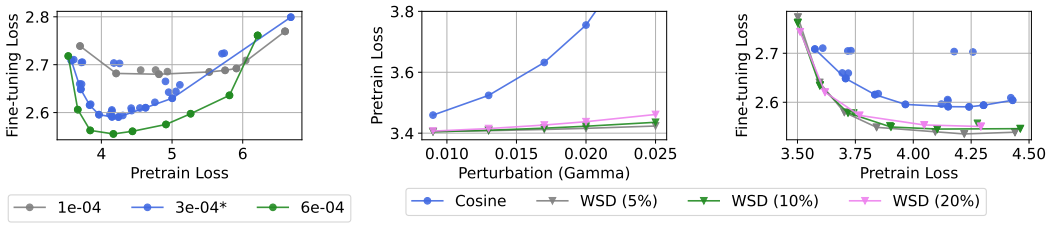


Figure 111: **Learning-rate schedules with shorter decay phases mitigate forgetting.** OLMo-60M models trained for 192B tokens with cosine schedules at varying peak learning rates (left) and WSD schedules with different annealing fractions (middle/right) and fine-tuned on StarCoder. Higher peak learning rates and shorter decay phases yield better learning–forgetting tradeoffs.

### D.4 CATASTROPHIC OVER-TRAINING TRADEOFF

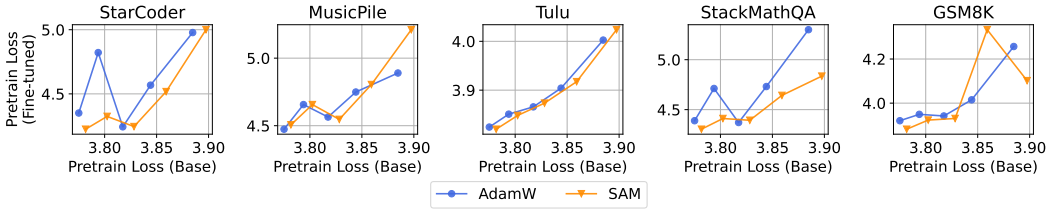


Figure 112: **AdamW vs SAM Catastrophic overtraining tradeoff for OLMo-20M across datasets**

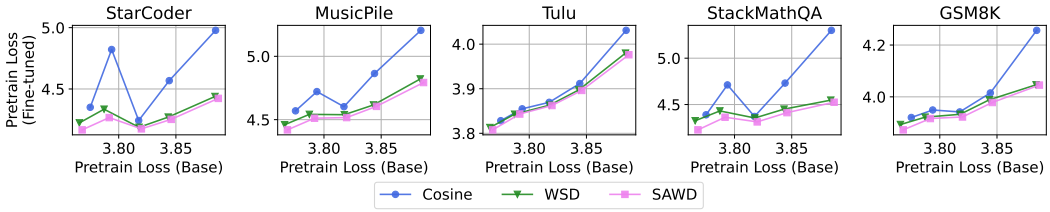


Figure 113: **WSD vs Cosine Catastrophic overtraining tradeoff for OLMo-20M across datasets**

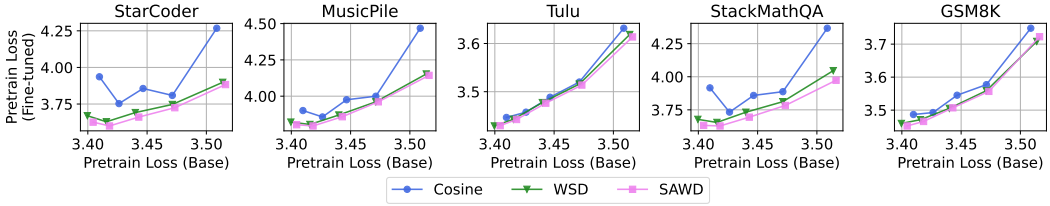


Figure 114: **WSD vs Cosine Catastrophic overtraining tradeoff for OLMo-60M across datasets**

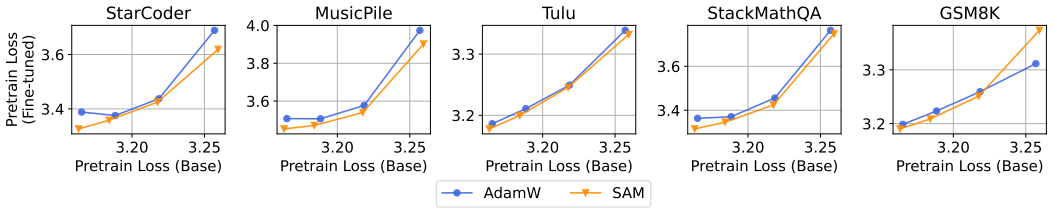


Figure 115: **AdamW vs SAM Catastrophic overtraining tradeoff for OLMo-150M across datasets**

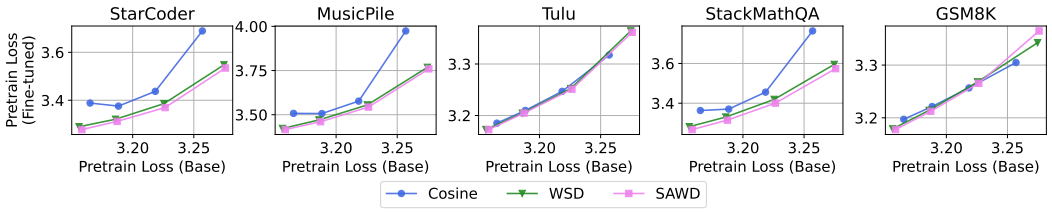


Figure 116: **WSD vs Cosine Catastrophic overtraining tradeoff for OLMo-150M across datasets**

### D.5 Gaussian Parameter Perturbations

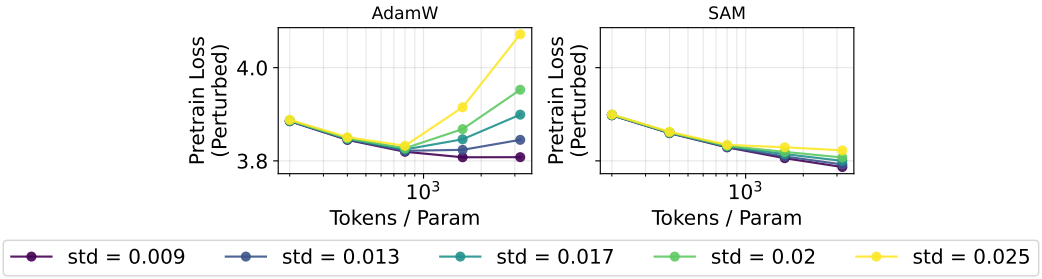


Figure 117: **AdamW vs SAM Gaussian Perturbation OLMo-20M**

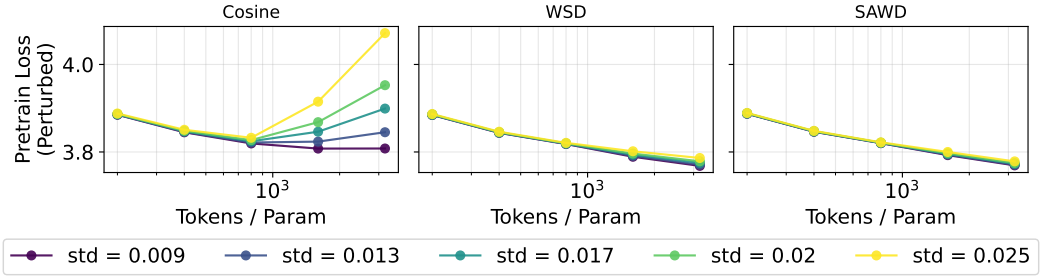


Figure 118: **WSD vs Cosine Gaussian Perturbation OLMo-20M**

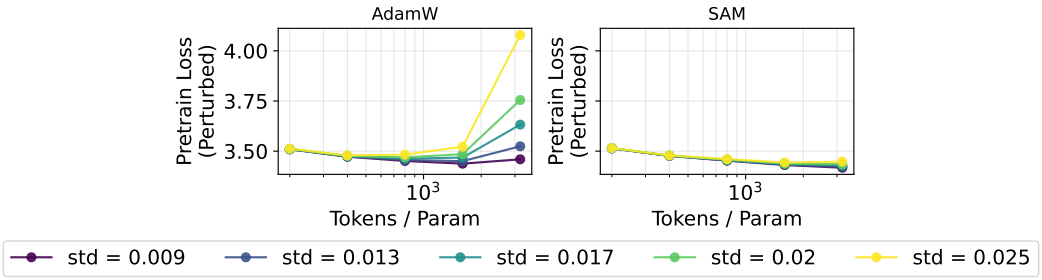


Figure 119: **AdamW vs SAM Gaussian Perturbation OLMo-60M**

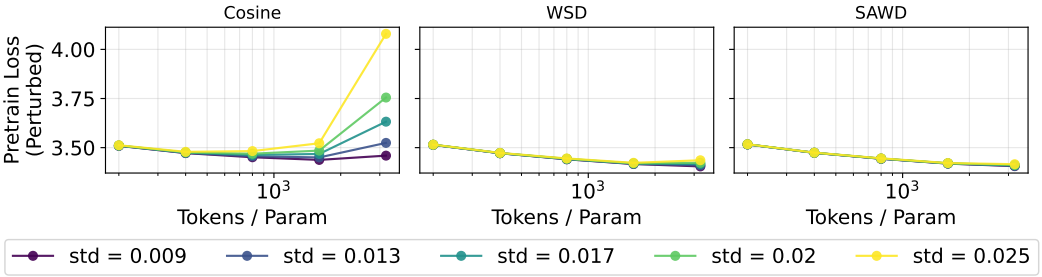


Figure 120: **WSD vs Cosine Gaussian Perturbation OLMo-60M**

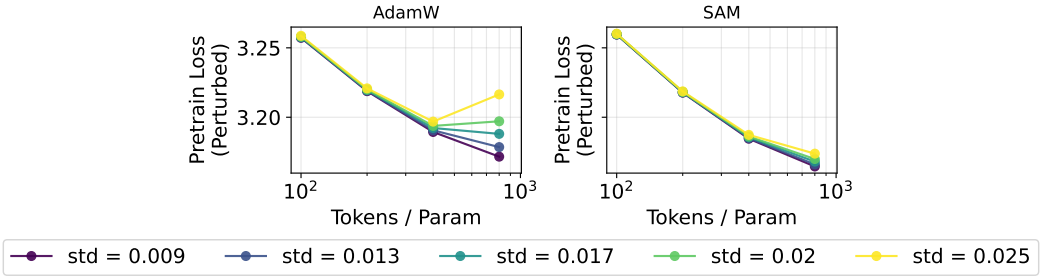


Figure 121: **AdamW vs SAM Gaussian Perturbation OLMo-150M**

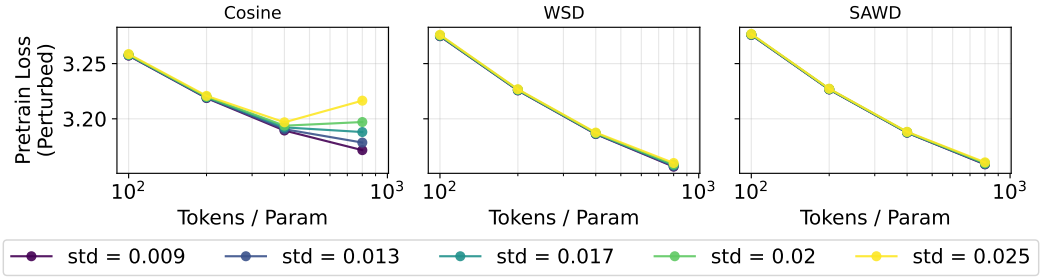


Figure 122: **WSD vs Cosine Gaussian Perturbation OLMo-150M**

### D.6 Post Training Quantization

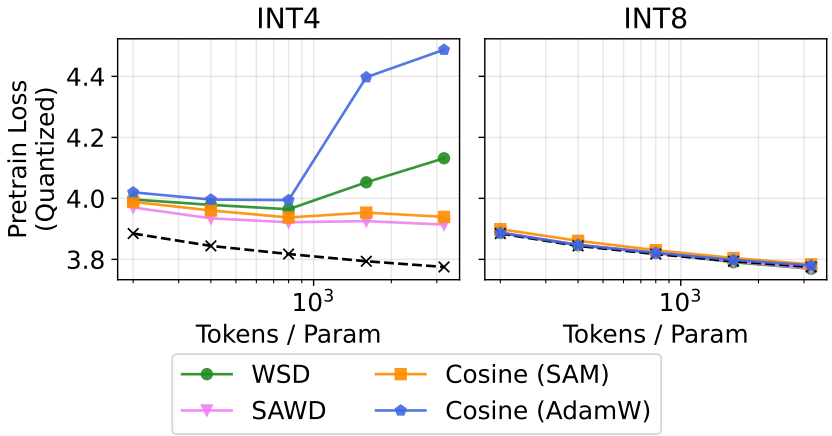


Figure 123: **Different pretraining configs PTQ performance for OLMo-20M**

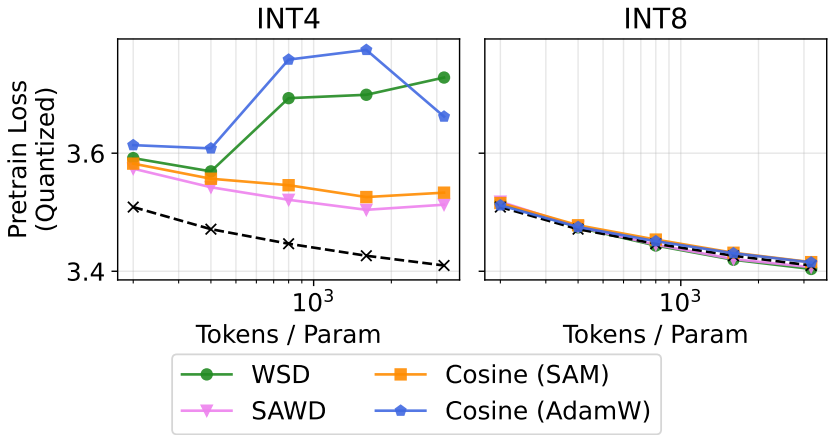


Figure 124: **Different pretraining configs PTQ performance for OLMo-60M**

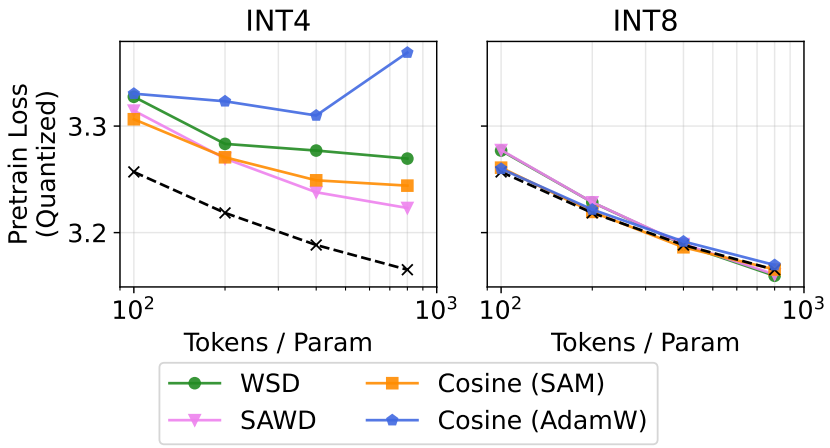


Figure 125: **Different pretraining configs PTQ performance for OLMo-150M**