

IMU-1: Sample-Efficient Pre-training of Small Language Models

George Grigorev
 Independent Researcher
 deezchannel@gmail.com

Abstract

We present IMU-1, a 430M-parameter language model trained on 72B tokens that approaches the benchmark performance of models trained on $56 \times$ more data. We describe a validated training recipe combining recent architectural interventions (QK-norm attention, per-head gating, value residuals, LayerNorm scaling) with optimization advances (NorMuon with cautious weight decay, μ P parametrization) and a three-stage training schedule with post-hoc checkpoint EMA. We provide ablations for each component and release code, weights and data to enable reproduction: https://huggingface.co/thepowerfuldeez/imu1_base

1 Introduction

The training of large language models (LLMs) has traditionally been characterized by ever-increasing compute budgets, with state-of-the-art models requiring trillions of tokens and thousands of GPU-hours. However, recent work has demonstrated that careful attention to architecture, optimization, and data selection can substantially improve *sample efficiency*—the quality achieved per training token Allal et al. [2025], Li et al. [2024b], Shah et al. [2025].

This paper presents IMU-1, a 430M-parameter language model trained on 72B tokens that surpasses SmoLM-360M (600B tokens) and approaches SmoLM2-360M (4T tokens) on standard benchmarks. Rather than proposing novel techniques, we provide a validated recipe that combines multiple recent advances into a reproducible training pipeline:

- **Architectural interventions:** QK-norm attention for stability Henry et al. [2020], per-head gated attention for improved expressivity and attention sink mitigation Qiu et al. [2025], value residual connections for improved gradient flow Zhou et al. [2024], and LayerNorm scaling to address depth-related training pathologies.
- **Optimization advances:** NorMuon optimizer with Triton-accelerated orthogonalization Li et al. [2025], cautious weight decay for selective regularization Chen et al. [2025], and μ P parametrization for hyperparameter transfer Yang et al. [2022].
- **Training dynamics:** Warmup-Stable-Decay (WSD) learning rate schedules with flexible decay timing Wen et al. [2024], and post-hoc exponential moving average (EMA) of checkpoints for improved final performance.

We examine each intervention through ablations (§7), document our data mixture (§4), and release code, weights, and configurations (§8).

Contributions.

1. A validated training recipe for sample-efficient small-LM pretraining, combining known architectural and optimization techniques.
2. Ablations isolating the contribution of each intervention on a 70M proxy model.
3. A complete, reproducible training framework with code, weights, data, and configurations.

2 Related Work

Sample-efficient pretraining. Recent work demonstrates that small models can achieve strong performance through careful data curation and training strategies. SmoLM2 Allal et al. [2025] documents a data-centric approach using multi-stage mixtures of web text, math, code, and instruction data, achieving state-of-the-art results at the 360M–1.7B scale. DataComp-LM Li et al. [2024b] provides controlled dataset experimentation with standardized evaluation, while RefinedWeb Penedo et al. [2023] demonstrates that careful web filtering alone can match curated datasets. However, most prior work relies on cosine learning rate schedules and conventional optimizers. Our work combines data-centric strategies with architectural and optimization advances that further improve sample efficiency.

Learning rate schedules. Cosine decay remains the dominant schedule for LLM pretraining, but it requires specifying the total compute budget in advance. This constraint hinders practitioners with limited or uncertain compute, since the schedule cannot be adjusted based on intermediate evaluation results. Warmup-Stable-Decay (WSD) Wen et al. [2024] addresses this by maintaining a constant learning rate during a “stable” phase, with decay applied at a configurable cutoff. This flexibility enables mid-training decisions based on benchmark performance, and recent work shows WSD interacts favorably with data mixture changes during training Luo et al. [2025].

Checkpoint averaging improves final model quality when applied during the decay phase Tian et al. [2025]. We adopt post-hoc EMA of weights.

Small language model architectures. Several 2025 releases target the sub-500M parameter range: Gemma-3-270M Gemma Team [2025] from Google, LFM2-350M Liquid AI [2025] from Liquid AI using hybrid Mamba-attention, Granite-4.0-H-350M IBM Research [2025] from IBM also using hybrid architectures, and Baguettotron Pleias [2025] trained on synthetic data. These models train on 10–14 trillion tokens. In contrast, we demonstrate that combining multiple architectural interventions—QK-norm, per-head gating, value residuals, and LayerNorm scaling—with modern optimizers enables similar quality at 72B tokens.

Optimization advances. Muon-style orthogonalized updates Shah et al. [2025] have emerged as a promising alternative to Adam for LLM training. NorMuon Li et al. [2025] improves scalability through neuron-wise normalization, while Cautious Weight Decay Chen et al. [2025] provides selective regularization based on gradient-weight alignment. Most prior small model work uses AdamW; we adopt NorMuon with cautious weight decay for improved training dynamics.

3 Method

We present an approach to improving sample efficiency in language model pretraining through architectural and optimization interventions. Our method addresses two complementary goals: (1) improving training stability to enable higher learning rates, and (2) improving gradient signal quality to accelerate convergence. Each intervention is validated through controlled ablations (§7), with combined improvements yielding 5.21% relative reduction in training loss at matched tokens and iterations.

3.1 Model Architecture

IMU-1 is a 430M-parameter decoder-only transformer with the following configuration: $d_{\text{model}} = 1152$, 30 layers, 18 attention heads, and grouped-query attention Ainslie et al. [2023] with 6 KV heads. We use RMSNorm Zhang and Sennrich [2019] for normalization, SwiGLU Shazeer

[2020] for the feed-forward network, and rotary position embeddings (RoPE) Su et al. [2021]. The vocabulary size is 49,152 tokens using the SmoLLM2-360M tokenizer Allal et al. [2025].

Ablation model. For ablations (§7), we use a smaller 70M-parameter model ($d_{\text{model}} = 768$, 8 layers, 12 heads, 4 KV heads) with a custom 32,768-token BPE tokenizer to enable rapid iteration.

3.2 Architectural Interventions

We apply four architectural modifications targeting attention stability, gradient flow, and depth scaling. Our ablations (§7.1) show that while some interventions provide isolated benefits, their combined effect exceeds the sum of parts.

3.2.1 QK-Norm Attention

Standard scaled dot-product attention computes:

$$\text{Attention}(Q, K, V) = \text{softmax} \left(\frac{QK^\top}{\sqrt{d_h}} \right) V \quad (1)$$

where d_h is the head dimension. As training progresses, the norms of Q and K can grow unboundedly, leading to large logits that saturate the softmax and produce high-kurtosis attention distributions Dehghani et al. [2023], Wortsman et al. [2023].

Following Henry et al. [2020], we normalize queries and keys using RMS normalization before computing attention:

$$\text{Attention}(Q, K, V) = \text{softmax} \left(\gamma \cdot \frac{Q}{\text{RMS}(Q)} \cdot \frac{K^\top}{\text{RMS}(K)} \right) V \quad (2)$$

where $\text{RMS}(x) = \sqrt{\frac{1}{d_h} \sum_i x_i^2}$ and $\gamma \in \mathbb{R}$ is a learnable gain parameter initialized to 1. Normalization bounds attention logit magnitudes, preventing saturation regardless of Q and K scales.

We fuse QK-Norm into a custom FlashAttention Dao et al. [2022] kernel for efficiency.

3.2.2 Per-Head Gated Attention

Transformers trained with causal attention develop “attention sinks”—early tokens that accumulate disproportionate attention mass regardless of semantic relevance Xiao et al. [2023]. This wastes model capacity and creates artifacts in streaming inference.

Following Qiu et al. [2025], we introduce learnable per-head gates that modulate attention output:

$$\text{out}_h = 2 \cdot \sigma(g_h) \cdot \text{Attention}_h(Q, K, V) \quad (3)$$

where $g \in \mathbb{R}^{n_h}$ is computed via projection $g = W_g x$ with $W_g \in \mathbb{R}^{d \times n_h}$, and g_h is the scalar gate logit for head h . The factor of 2 ensures the expected output magnitude matches standard attention when $g_h = 0$ (i.e., $\sigma(0) = 0.5$).

3.2.3 Normalized Value Residual Learning

Deep transformers suffer from gradient degradation in the value stream, as values pass through many layers of attention-weighted averaging before reaching the output Zhou et al. [2024]. This “rank collapse” reduces the effective expressivity of deep networks.

We extend the original value residual formulation with explicit normalization and disentangled scaling:

$$V^{(l)} = s \cdot \frac{\alpha_1 V_{\text{local}}^{(l)} + \alpha_2 V^{(1)}}{\sqrt{\alpha_1^2 + \alpha_2^2}} \quad (4)$$

where $V_{\text{local}}^{(l)} = W_V^{(l)}x$ is the current layer’s value projection and $V^{(1)}$ is the first layer’s value projection. We introduce three modifications: (1) normalization by $\sqrt{\alpha_1^2 + \alpha_2^2}$ preserves output magnitude as the residual weight changes, (2) a separate scaling factor s decouples magnitude control from the mixing ratio, and (3) initialization $(s, \alpha_1, \alpha_2) = (1, 1, 0)$ starts from standard attention and learns the residual contribution.

3.2.4 LayerNorm Scaling

Sun et al. [2025] identify that deeper transformer layers contribute less to the output due to accumulated normalization effects—the “curse of depth.” Later layers’ contributions are suppressed relative to earlier layers, limiting the effective depth of the network.

We apply depth-dependent scaling to LayerNorm outputs:

$$\text{LN}_l(x) = \frac{1}{\sqrt{l}} \cdot \text{LayerNorm}(x) \quad (5)$$

where $l \in \{1, \dots, L\}$ is the layer index. This rebalances layer contributions, allowing deeper layers to have proportional impact on the output.

LayerNorm Scaling may become more impactful at greater depth.

3.3 Optimization

Beyond architecture, we apply optimization techniques that improve gradient utilization and regularization.

3.3.1 NorMuon Optimizer

AdamW applies element-wise adaptive learning rates, which can be suboptimal for weight matrices where parameters interact through matrix multiplication Shah et al. [2025]. Muon-style optimizers instead orthogonalize gradients before applying updates, ensuring updates remain on the Stiefel manifold of orthonormal matrices.

We use NorMuon Li et al. [2025], which addresses norm imbalance after orthogonalization through neuron-wise normalization:

$$W_{t+1} = W_t - \eta \cdot \text{NeuronNorm}(\text{Ortho}(G_t)) \quad (6)$$

where G_t is the gradient, $\text{Ortho}(\cdot)$ applies Newton-Schulz iterations for orthogonalization, and $\text{NeuronNorm}(\cdot)$ normalizes each output neuron’s update.

We implement orthogonalization using Polar Express constants Amsel et al. [2025] with 7 Newton-Schulz steps, and use the Dion Ahn et al. [2025] Triton kernel for efficiency. Muon tolerates higher learning rates than AdamW due to the implicit preconditioning from orthogonalization; we use $\eta = 0.0235$ for 2D parameters (weight matrices) and $\eta = 0.007$ for 1D parameters. Following standard practice Shah et al. [2025], 1D parameters include: (1) all parameters with $\text{ndim} < 2$ (biases, LayerNorm gains), (2) embedding weights, and (3) the output projection (`lm_head`). These are optimized with AdamW while weight matrices use NorMuon.

3.3.2 Cautious Weight Decay

Standard weight decay applies uniform L_2 regularization: $\Delta w = -\lambda w$. However, decay can conflict with gradient updates, pushing weights in the opposite direction from the loss gradient Chen et al. [2025].

Cautious Weight Decay (CWD) applies decay only when it aligns with the update direction:

$$\Delta w_{\text{CWD}} = \begin{cases} -\lambda w & \text{if } \text{sign}(u) = \text{sign}(w) \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

where $u = \text{NeuronNorm}(\text{Ortho}(G_t))$ is the orthogonalized update (not the raw gradient). This prevents decay from counteracting beneficial updates while still regularizing weights that the optimizer is not actively using.

3.3.3 Z-Loss Regularization

Following Chowdhery et al. [2022], we apply auxiliary Z-loss to the logits:

$$\mathcal{L}_z = \lambda_z \cdot \log^2 \left(\sum_i \exp(z_i) \right) \quad (8)$$

where z is the logit vector and $\lambda_z = 10^{-4}$. Z-loss penalizes large logit magnitudes, improving numerical stability in softmax computation without affecting the argmax.

3.4 Learning Rate Schedule

We explore two learning rate schedules: cosine decay and Warmup-Stable-Decay (WSD).

Cosine schedule. Our baseline uses cosine decay Loshchilov and Hutter [2017] from peak learning rate to $\eta_{\min} = 0.01 \cdot \eta_{\max}$ over the training horizon, with linear warmup for the first 1,000 steps.

WSD schedule. WSD Wen et al. [2024] maintains a stable learning rate after warmup, then decays in the final phase. This enables checkpoint re-use: a model trained with WSD stable phase can be continued with additional data before decaying. We use $1 - \sqrt{t}$ decay profile and set stable-phase LR to 55% of peak cosine LR based on preliminary experiments (0.013 for Muon 2D params, 0.0039 for 1D params). Our ablations (§7.3) evaluate decay fractions of 10–30%.

3.5 Implementation

We implement all techniques in PyTorch with custom Triton kernels for QK-Norm attention and NorMuon orthogonalization. Training uses bfloat16 mixed precision with gradient checkpointing. We apply μP parametrization Yang et al. [2022] for hyperparameter transfer across model scales. Full implementation details and hyperparameters are provided in Appendix A.3.

4 Data

We use a mixture of web text (DCLM-edu, Cosmopedia), code (Stack-edu), math (FineMath), PDFs (FinePDFs), and wiki data (FineWiki), with progressively tighter quality filters in later stages Allal et al. [2025].

4.1 Data sources and filtering

Web data. DCLM-edu is filtered from DCLM Li et al. [2024b] using the FineWeb-edu classifier, which predicts educational quality on a 0–5 scale. We use threshold > 2.75 for Stage 1, increasing to > 3.2 for Stage 2. Cosmopedia-v2 synthetic textbooks are similarly filtered with the FineWeb-edu classifier (threshold > 2.0 for Stage 1, > 2.3 for Stage 2).

Code data. We follow The Stack V2 process Allal et al. [2025]: scraping repositories from the latest available date, then filtering to Python-only files. Educational quality is scored using the Stack-edu classifier with thresholds > 3.75 (Stage 1) and > 4.1 (Stage 2).

Math data. FineMath is filtered with threshold > 3.7 (Stage 1) increasing to > 4.1 (Stage 2). We include MegaMath and other math-focused corpora in the mixture.

PDF and wiki data. FinePDFs are filtered with threshold > 1.75 (Stage 1) to > 2.1 (Stage 2). We include FineWiki as a high-quality knowledge source.

4.2 Quality thresholds by stage

Table 1 summarizes filtering thresholds by stage.

Source	Stage 1	Stage 2	Stage 3
DCLM-edu	> 2.75	> 3.2	—
Cosmopedia	> 2.0	> 2.3	> 2.5
FineMath	> 3.7	> 4.1	> 4.25
Stack-edu	> 3.75	> 4.1	> 4.25
FinePDFs	> 1.75	> 2.1	> 2.4

Table 1: Educational score thresholds by training stage.

4.3 Stage 3: Midtrain

Stage 3 additionally filters by document length (> 4000 characters) and includes instruction-formatted data with chat templates. We use synthetic reasoning data from Pleias SYNTH Pleias [2024] filtered with threshold > 1.65 (Stage 1) to > 2.1 (Stage 3).

DCLM-edu-boolq. We prepare a subset of DCLM-edu for Boolean question answering via model-based filtering. An LLM identifies passages containing verifiable factual claims suitable for BoolQ/NLI-style tasks (Appendix A.5), then we train a fastText classifier on these samples to label the full corpus.

4.4 Training mixture by stage

Table 2 shows the available token pool for each training stage. Training samples from these pools, consuming approximately 29B, 28B, and 14B tokens respectively (72B total).

5 Evaluation

We evaluate on standard benchmarks following the DCLM protocol Li et al. [2024b]: HellaSwag (commonsense reasoning), ARC-Easy/Challenge (science QA), PIQA (physical intuition), and Lambada (language modeling). All evaluations use fixed prompting templates with deterministic decoding. Full benchmark results and evaluation code are provided in Appendix A.

Source	Stage 1 (B)	Stage 2 (B)	Stage 3 (B)
DCLM-edu	27.0	5.1	—
FineWiki	8.4	7.5	—
FinePDFs-edu	8.0	5.3	4.2
Python-edu	12.0	1.4	—
FineMath	5.0	2.0	—
MegaMath-web-pro	5.0	5.1	1.3
Zyda-2	4.3	4.4	4.0
Cosmopedia-edu	2.4	4.0	1.2
Stack (code)	2.0	—	—
Datashop-science-qa	1.0	2.1	0.4
arXiv	—	2.4	—
SYNTH	—	4.8	1.0
StackExchange	—	2.2	0.6
Legal	—	0.3	—
DCLM-edu-boolq	—	—	0.6
Total	75.1	46.6	13.3

Table 2: Data mixture by training stage (token counts in billions). Stage 1 emphasizes web and code data; Stage 2 adds synthetic and domain-specific sources; Stage 3 focuses on high-quality subsets with instruction formatting.

6 Results

6.1 Main results

We train IMU-1 (430M parameters) in three stages totaling 265k iterations on 72B tokens: Stage 1 (100k iterations, 29B tokens) uses standard pre-training data, Stage 2 (100k iterations, 28B tokens) applies decay with tighter quality filters, and Stage 3 (65k iterations, 14B tokens) incorporates instruction-formatted and synthetic reasoning data. Table 3 compares our model against SmoLM baselines.

Model	Params	Tokens	HellaSwag	ARC-E	ARC-C	PIQA	Lambada	Avg
SmoLM-135M	135M	600B	0.422	0.576	0.276	0.693	0.304	0.454
SmoLM-360M	360M	600B	0.540	0.676	0.351	0.726	0.509	0.560
SmoLM2-360M	360M	4T	0.554	0.697	0.411	0.736	0.532	0.586
<i>IMU-1 (430M) training progression</i>								
Stage 1 (100k)	430M	29B	0.393	0.615	0.333	0.647	0.317	0.461
Stage 2 (200k)	430M	57B	0.451	0.689	0.381	0.682	0.405	0.522
Stage 3 (265k)	430M	72B	0.503	0.697	0.413	0.703	0.482	0.560
+ EMA	430M	72B	0.511	0.714	0.428	0.702	0.513	0.574

Table 3: Benchmark comparison. IMU-1 trained on 72B tokens approaches SmoLM-360M (600B tokens) and SmoLM2-360M (4T tokens) performance. Bold indicates best in column.

Key findings.

- IMU-1 trained on 72B tokens approaches SmoLM-360M (600B tokens) on average benchmark score, using **8× fewer tokens**.
- At similar parameter count, IMU-1 approaches SmoLM2-360M (0.574 vs 0.586 avg) with **56× fewer tokens**.
- Three-stage training shows consistent improvements: avg $0.461 \rightarrow 0.522 \rightarrow 0.560$, with EMA adding $+0.014$.

6.2 Training efficiency

Table 4 summarizes training compute for each stage.

Stage	Iterations	Batch	Context	Wall Time (h)
Stable	100,000	384	768	13.4
Decay	100,000	312	896	13.9
Midtrain	65,000	192	1,152	9.3
Total	265,000	—	—	36.6

Table 4: Training compute breakdown. Total training completed in under 37 hours on a single 8×H200 node.

Steps reported are training iterations (forward-backward passes); with gradient accumulation of 2, optimizer updates occur every 2 iterations (yielding $50k + 50k + 32.5k = 132.5k$ optimizer updates total). Effective tokens per iteration: $\sim 295k$ (Stable), $\sim 280k$ (Decay), $\sim 221k$ (Midtrain).

Throughput. Peak throughput reaches 1.8M tokens/sec with Model FLOPs Utilization (MFU) of 26–36% depending on stage (longer context lengths reduce MFU due to increased attention cost relative to parameter FLOPs). NorMuon uses 7 Newton-Schulz iterations for orthogonalization Amsel et al. [2025], adding $\sim 3\%$ overhead compared to AdamW.

6.3 Benchmark details

We report accuracy on standard benchmarks following the DCLM evaluation protocol:

- **CORE**: Aggregate score across held-out tasks
- **HellaSwag**: Commonsense reasoning (4-way)
- **ARC-Easy/Challenge**: Science QA
- **PIQA**: Physical intuition
- **Lambada**: Language modeling / word prediction

Additional benchmarks (Winograd, CommonsenseQA, BoolQ, etc.) are reported in Appendix A.

6.4 Training dynamics

Figure 1 shows training loss across the three stages.

Combined intervention effect. Training the full IMU-1 architecture with all interventions disabled yields final loss 2.438; with all interventions enabled, the loss is 2.328—a 4.5% relative improvement at matched tokens and iterations. This validates the combined recipe on the production model, complementing the ablations on the 70M proxy model (§7).

7 Ablations

We conduct ablations to measure the contribution of each intervention. All ablations use a 70M parameter model ($d=768$, 8 layers, 12 heads, vocab 32,768) with a custom BPE tokenizer trained on 1.4B tokens from DCLM-edu Li et al. [2024a], representing $20\times$ the parameter count (Chinchilla optimal Hoffmann et al. [2022]). Training uses AdamW with cosine schedule over

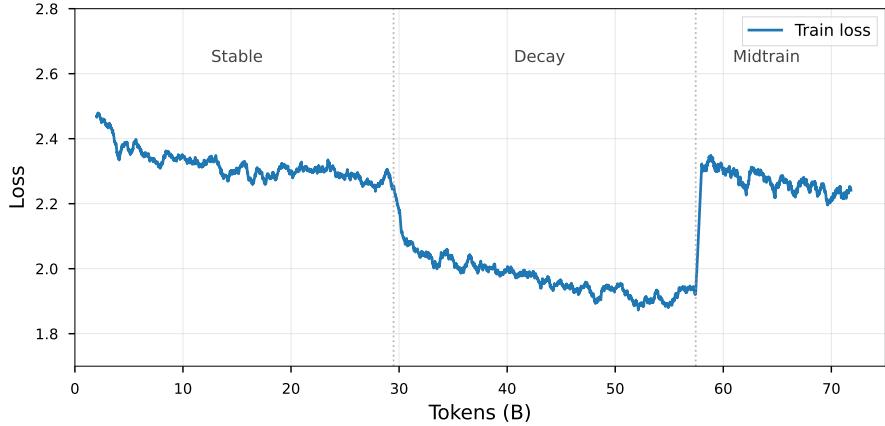


Figure 1: Training loss vs. tokens. Vertical lines mark stage transitions (29B, 57B).

9,000 iterations, batch size 307,200 tokens, learning rate 0.002 with 1,000 warmup iterations and $\eta_{\min}/\eta_{\max} = 0.01$. We apply Z-loss Chowdhery et al. [2022] with coefficient 10^{-4} for numerical stability. Note: the production IMU-1 model uses a different architecture (30 layers, $d=1152$) and the SmollM2-360M tokenizer (vocab 49,152); see §3 for details.

7.1 Architectural Interventions

Table 5 shows the effect of each architectural intervention in isolation.

Intervention	Train Loss	Δ Loss	Δ %
Baseline (AdamW only)	3.247	—	—
+ QK-Norm	3.227	-0.020	-0.63%
+ Per-Head Gating	3.245	-0.002	-0.05%
+ Norm. Value Residual	3.234	-0.013	-0.38%
+ LayerNorm Scaling	3.235	-0.012	-0.36%
All interventions	3.194	-0.053	-1.64%

Table 5: Architectural ablations. Each row enables a single intervention versus the AdamW baseline. QK-Norm shows the largest individual benefit; the combined effect exceeds the sum of parts, suggesting positive interactions.

QK-Norm provides the largest individual improvement (-0.63%), followed by Normalized Value Residual (-0.38%) and LayerNorm Scaling (-0.36%). Per-Head Gating shows minimal isolated benefit. However, all interventions combined yield -1.64% improvement, exceeding the sum of individual effects. This suggests synergistic interactions: gating may help primarily when combined with QK-Norm, and LayerNorm Scaling may become more impactful at greater depth.

QK-Norm reduces activation kurtosis. Figure 2(d) shows that QK-Norm substantially reduces kurtosis (fourth central moment) across all layers. High kurtosis indicates heavy-tailed activation distributions that can cause training instability Wortsman et al. [2023]. The kurtosis reduction is consistent across layers, supporting the stability benefits of QK-Norm.

7.2 Optimization Interventions

Building on the combined architectural interventions, we ablate optimizer choices.

Configuration	Train Loss	Δ vs Arch	Δ vs Baseline
All Arch (AdamW)	3.250	—	-0.047 (-1.42%)
+ NorMuon	3.156	-0.094 (-2.88%)	-0.141 (-4.27%)
+ Cautious WD	3.125	-0.125 (-3.85%)	-0.172 (-5.21%)

Table 6: Optimization ablations. NorMuon provides substantial improvement over AdamW. Cautious Weight Decay adds further gains. Muon uses higher learning rate (0.0235 for 2D params, 0.007 for 1D params).

Switching from AdamW to NorMuon yields -2.88% relative improvement on the architectural baseline. Muon tolerates higher learning rates; we use 0.0235 for 2D parameters and 0.007 for 1D parameters (embeddings, biases). Adding Cautious Weight Decay provides an additional -0.97% relative gain.

Total improvement. Combining architectural and optimization interventions yields **5.21% relative improvement** in train loss ($3.297 \rightarrow 3.125$) at matched tokens and iterations.

7.3 WSD Schedule

We evaluate Warmup-Stable-Decay (WSD) schedule variants against cosine baseline. During stable phase, we use 55% of peak cosine LR (0.013 for Muon, 0.0039 for AdamW 1D params).

Schedule	Train Loss	Δ vs Cosine
Cosine	3.125	—
WSD Stable only	3.188	+0.063 (+2.0%)
WSD Decay 10%	3.234	+0.109 (+3.5%)
WSD Decay 20%	3.125	+0.000 (0.0%)
WSD Decay 30%	3.172	+0.047 (+1.5%)

Table 7: WSD schedule ablations with $1 - \sqrt{t}$ decay profile. WSD with 20% decay matches cosine performance.

WSD with 20% decay matches cosine exactly (3.125), while shorter decay fractions underperform. This suggests decay duration is critical—too little decay (10%) leaves the model undertrained, while excessive decay (30%) may overshoot. We adopt WSD for production training due to its flexibility: stable-phase checkpoints can be continued with additional data before applying final decay, enabling iterative data curation without retraining from scratch.

Key findings.

- Architectural interventions provide 1.42% relative improvement, with QK-Norm contributing the most individually.
- NorMuon with Cautious WD provides an additional 3.85% relative improvement over AdamW.
- Combined interventions yield **5.21% relative improvement** in train loss at matched tokens and iterations.
- QK-Norm measurably reduces activation kurtosis across all layers.

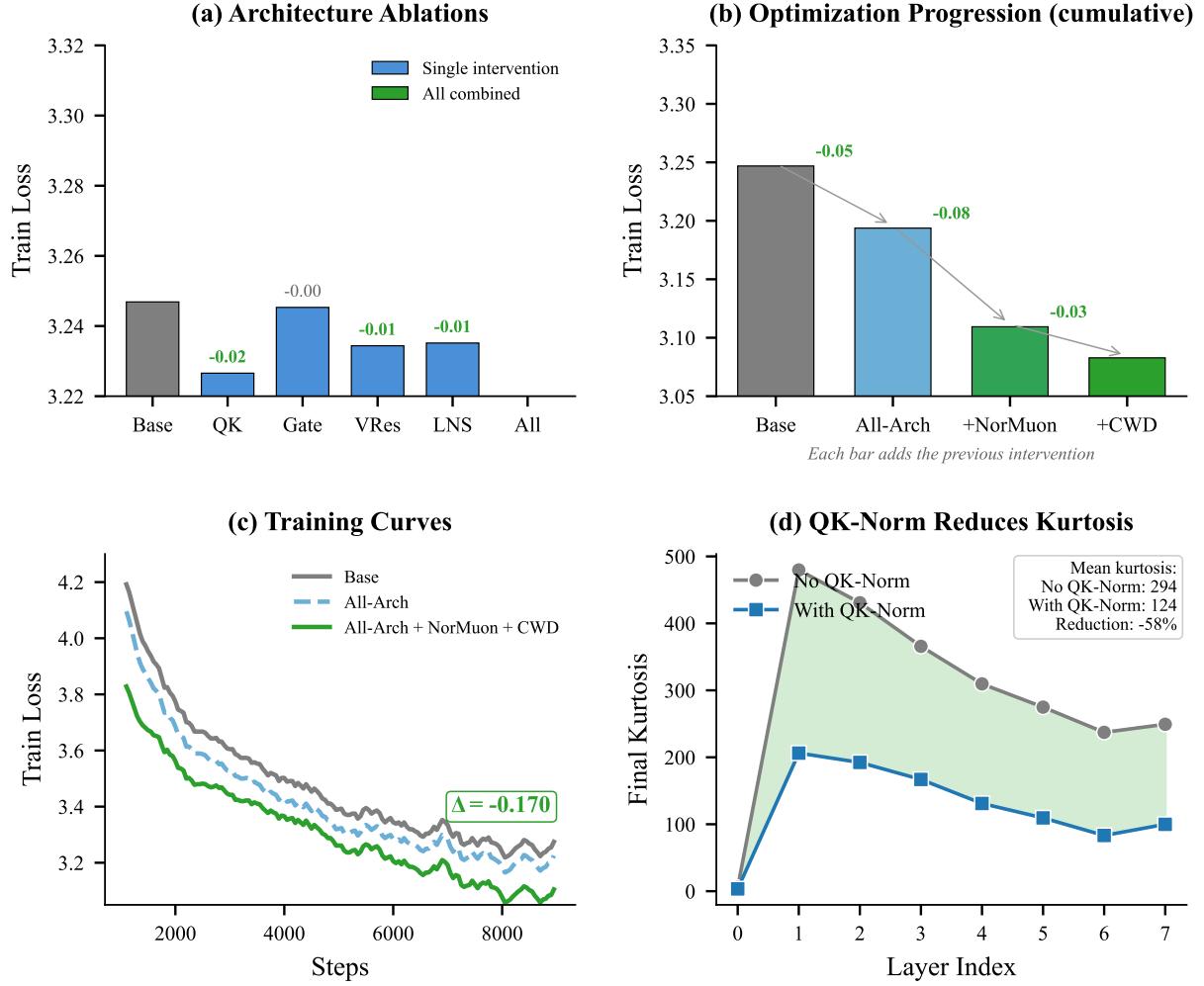


Figure 2: Ablation results. (a) Architectural interventions versus baseline. (b) Optimization progression from baseline through NorMuon with CWD. (c) Training curves comparing baseline versus all architectural interventions combined. (d) QK-Norm effect on activation kurtosis across layers—lower kurtosis indicates more stable activations.

8 Release and Reproducibility

We release (i) model weights, (ii) tokenizer, (iii) training and evaluation code, and (iv) exact configuration files and run manifests. Training and evaluation are implemented in `sample_efficient_gpt` [thepowerfuldeez]. We additionally provide inference wrappers (Hugging Face / vLLM) and scripts to reproduce all figures and tables from logged metrics.

Artifacts.

- **Model:** https://huggingface.co/thepowerfuldeez/imu1_base (base checkpoint with EMA).
- **Code:** https://github.com/thepowerfuldeez/sample_efficient_gpt.
- **Data:** https://huggingface.co/datasets/thepowerfuldeez/1218_imu1_base_stable_corpus, https://huggingface.co/datasets/thepowerfuldeez/1226_imu1_base_decay_corpus.

9 Limitations

Our experiments focus on sub-billion parameter models (440M) and a specific data mixture. While μ P parametrization is designed for hyperparameter transfer, we have not validated that all interventions provide consistent benefits at larger scales or with different data compositions.

References

- Kwangjun Ahn, Byron Xu, Natalie Abreu, Ying Fan, Gagik Magakyan, Pratyusha Sharma, Zheng Zhan, and John Langford. Dion: Distributed orthonormalized updates, 2025.
- Joshua Ainslie, James Lee-Thorp, Michiel de Jong, Yury Zemlyanskiy, Federico Lebron, and Sumit Sanghai. Gqa: Training generalized multi-query transformer models from multi-head checkpoints, 2023.
- Loubna Ben Allal, Anton Lozhkov, Elie Bakouch, Gabriel Martín Blázquez, Guilherme Penedo, Lewis Tunstall, et al. Smollm2: When smol goes big – data-centric training of a small language model, 2025.
- Noah Amsel, David Persson, Christopher Musco, and Robert M. Gower. The polar express: Optimal matrix sign methods and their application to the muon algorithm, 2025.
- Lizhang Chen, Jonathan Li, Kaizhao Liang, Baiyu Su, Cong Xie, Nuo Wang Pierse, Chen Liang, Ni Lao, and Qiang Liu. Cautious weight decay, 2025.
- Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, et al. Palm: Scaling language modeling with pathways, 2022. Z-loss regularization.
- Tri Dao, Daniel Y. Fu, Stefano Ermon, Atri Rudra, and Christopher Ré. Flashattention: Fast and memory-efficient exact attention with io-awareness, 2022.
- Mostafa Dehghani, Josip Djolonga, Basil Mustafa, Piotr Padlewski, Jonathan Heek, Justin Gilmer, et al. Scaling vision transformers to 22 billion parameters, 2023. QK-Norm for ViT stability.
- Gemma Team. Gemma 3 technical report, 2025. URL <https://ai.google.dev/gemma/docs/core>. Google DeepMind.
- Alex Henry, Prudhvi Raj Dachapally, Shubham Pawar, and Yuxuan Chen. Query-key normalization for transformers, 2020.
- Jordan Hoffmann, Sebastian Borgeaud, Arthur Mensch, Elena Buchatskaya, Trevor Cai, Eliza Rutherford, et al. Training compute-optimal large language models, 2022.
- IBM Research. Granite 4.0: Hyper-efficient, high performance hybrid models for enterprise, 2025. URL <https://huggingface.co/ibm-granite/granite-4.0-h-350m-base>.
- Jeffrey Li, Alex Fang, Georgios Smyrnis, Maor Ivgi, Matt Jordan, Samir Gadre, et al. Datacomp-lm: In search of the next generation of training sets for language models, 2024a.
- Jeffrey Li, Alex Fang, Georgios Smyrnis, Maor Ivgi, Matt Jordan, Samir Gadre, et al. Datacomp-lm: In search of the next generation of training sets for language models, 2024b.
- Zichong Li, Liming Liu, Chen Liang, Weizhu Chen, and Tuo Zhao. Normuon: Making muon more efficient and scalable, 2025.
- Liquid AI. Lfm2 technical report, 2025.

Ilya Loshchilov and Frank Hutter. Sgdr: Stochastic gradient descent with warm restarts. In *International Conference on Learning Representations*, 2017. URL <https://openreview.net/forum?id=Skq89Scxx>.

Kairong Luo, Zhenbo Sun, Haodong Wen, Xinyu Shi, Jiarui Cui, Chenyi Dang, Kaifeng Lyu, and Wenguang Chen. How learning rate decay wastes your best data in curriculum-based llm pretraining, 2025.

Guilherme Penedo, Quentin Malartic, Daniel Hesslow, Ruxandra Cojocaru, Alessandro Cappelli, Hamza Alobeidli, Baptiste Pannier, Ebtesam Almazrouei, and Julien Launay. The refinedweb dataset for falcon llm: Outperforming curated corpora with web data, and web data only, 2023.

Pleias. Synth: the new data frontier, 2024. URL <https://pleias.fr/blog/blogsynth-the-new-data-frontier>. Blog post.

Pleias. Baguettotron: A 321m reasoning model, 2025. URL <https://huggingface.co/PleIAS/Baguettotron>. Trained on SYNTH dataset.

Zihan Qiu, Zekun Wang, Bo Zheng, Zeyu Huang, Kaiyue Wen, Songlin Yang, Rui Men, Le Yu, Fei Huang, Suozhi Huang, Dayiheng Liu, Jingren Zhou, and Junyang Lin. Gated attention for large language models: Non-linearity, sparsity, and attention-sink-free, 2025.

Ishaan Shah, Anthony M. Polloreno, Karl Stratos, Philip Monk, Adarsh Chaluvaraju, Andrew Hojel, Andrew Ma, Anil Thomas, Ashish Tanwer, Darsh J Shah, Khoi Nguyen, Kurt Smith, Michael Callahan, Michael Pust, Mohit Parmar, Peter Rushton, Platon Mazarakis, Ritvik Kapila, Saurabh Srivastava, Somanshu Singla, Tim Romanski, Yash Vanjani, and Ashish Vaswani. Practical efficiency of muon for pretraining, 2025.

Noam Shazeer. Glu variants improve transformer, 2020.

Jianlin Su, Yu Lu, Shengfeng Pan, Ahmed Murtadha, Bo Wen, and Yunfeng Liu. Roformer: Enhanced transformer with rotary position embedding, 2021.

Wenfang Sun, Xinyuan Song, Pengxiang Li, Lu Yin, Yefeng Zheng, and Shiwei Liu. The curse of depth in large language models, 2025.

George Grigorev (thepowerfuldeez). sample_efficient_gpt: Training framework for sample-efficient llm pretraining, 2026. URL https://github.com/thepowerfuldeez/sample_efficient_gpt.

Changxin Tian, Jiapeng Wang, Qian Zhao, Kunlong Chen, Jia Liu, Ziqi Liu, Jiaxin Mao, Wayne Xin Zhao, Zhiqiang Zhang, and Jun Zhou. Wsm: Decay-free learning rate schedule via checkpoint merging for llm pre-training, 2025.

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, 2024.

Mitchell Wortsman, Peter J. Liu, Lechao Xiao, Katie Everett, Alex Alemi, Ben Adlam, John D. Co-Reyes, Izzeddin Gur, Abhishek Kumar, Roman Novak, Jeffrey Pennington, Jascha Sohl-Dickstein, Kelvin Xu, Jaehoon Lee, Justin Gilmer, and Simon Kornblith. Stable training of large language models with adaptive gradient methods, 2023.

Guangxuan Xiao, Yuandong Tian, Beidi Chen, Song Han, and Mike Lewis. Efficient streaming language models with attention sinks, 2023.

Greg Yang, Edward J. Hu, Igor Babuschkin, Szymon Sidor, Xiaodong Liu, David Farhi, Nick Ryder, Jakub Pachocki, Weizhu Chen, and Jianfeng Gao. Tensor programs v: Tuning large neural networks via zero-shot hyperparameter transfer, 2022.

Biao Zhang and Rico Sennrich. Root mean square layer normalization, 2019.

Zhanchao Zhou, Tianyi Wu, Zhiyun Jiang, Fares Obeid, and Zhenzhong Lan. Value residual learning, 2024.

A Additional Results

A.1 Full benchmark scores

Table 8 provides complete benchmark results for IMU-1 at each training stage.

Benchmark	100k (stable)	200k (decay)	265k (midtrain)	EMA
HellaSwag (0-shot)	0.393	0.451	0.503	0.511
Jeopardy	0.128	0.224	0.268	0.288
BigBench QA WikiData	0.516	0.560	0.582	0.599
ARC-Easy	0.615	0.689	0.697	0.714
ARC-Challenge	0.333	0.381	0.413	0.411
COPA	0.630	0.720	0.700	0.690
CommonsenseQA	0.260	0.400	0.421	0.430
PIQA	0.647	0.682	0.703	0.702
OpenBookQA	0.342	0.372	0.386	0.382
Lambada (OpenAI)	0.317	0.405	0.482	0.513
Winograd	0.659	0.674	0.722	0.747
WinoGrande	0.523	0.552	0.547	0.552
BigBench Dyck Languages	0.198	0.144	0.147	0.162
AGI Eval LSAT AR	0.252	0.274	0.235	0.261
BigBench CS Algorithms	0.395	0.455	0.437	0.439
BigBench Operators	0.243	0.300	0.271	0.338
BigBench Repeat Copy Logic	0.031	0.063	0.063	0.063
SQuAD	0.094	0.224	0.263	0.319
CoQA	0.209	0.288	0.316	0.353
BoolQ	0.532	0.460	0.520	0.595
BigBench Language ID	0.250	0.255	0.264	0.269
CORE (centered)	0.192	0.249	0.276	0.302

Table 8: Full benchmark results for IMU-1 across training stages.

For context, Granite-4.0-350M Dense IBM Research [2025] reports AGIEval aggregate of 28.97 (20 tasks) and BBH aggregate of 32.19 (23 tasks with CoT); our DCLM evaluation includes LSAT-AR (26.09) and Dyck Languages (16.20) as individual tasks from these suites. Granite uses 14.5T tokens (200 \times more than our 72B).

A.2 Model architecture

A.3 Hyperparameters

Table 10 lists key hyperparameters for each training stage.

Step and token accounting. “Steps” refers to training iterations (forward-backward passes), not optimizer steps. With gradient accumulation of 2, optimizer updates occur every 2 iterations. Effective tokens per iteration: Stable = $384 \times 768 = 295\text{k}$, Decay = $312 \times 896 = 280\text{k}$, Midtrain = $192 \times 1152 = 221\text{k}$. Total tokens: $100\text{k} \times 295\text{k} + 100\text{k} \times 280\text{k} + 65\text{k} \times 221\text{k} \approx 72\text{B}$.

Checkpoint EMA. We apply exponential moving average to checkpoints post-hoc with $\beta = 0.8$ over the final 10 checkpoints (saved every 5k steps during decay phase). The reported “+ EMA” results use this averaged checkpoint.

Parameter	Value
Hidden dimension (d_{model})	1,152
Number of layers	30
Number of heads	18
Head dimension	64
FFN hidden dimension	3,072
Vocabulary size	49,152
KV heads (GQA)	6
Total parameters	$\sim 440M$
<i>Architectural features</i>	
QK-norm	Yes (learnable scale)
Per-head gating	Yes (sigmoid)
Value residual	Yes
LayerNorm scaling	Yes (depth-dependent)
Position encoding	RoPE ($\theta = 10000$)
Activation	SwiGLU

Table 9: Model architecture details.

Parameter	Stable	Decay	Midtrain
Steps	100,000	100,000	65,000
Batch size	384	312	192
Context length	768	896	1,152
Muon LR	0.011	0.0115	0.003
Embed LR	0.006	0.006	0.002
Muon WD	0.1	0.1	0.1
LR min ratio	0.01	0.25	0.33
Warmup steps	2,500	0	0
Grad accum	2	2	2
Z-loss weight Chowdhery et al. [2022]	10^{-4}	10^{-4}	10^{-4}

Table 10: Training hyperparameters by stage.

A.4 WSD schedule comparison

Each stage uses Warmup-Stable-Decay (WSD) with $1 - \sqrt{t}$ decay profile. The stable phase uses 55% of peak cosine LR. Decay begins at 80% of total stage steps (i.e., 20% decay fraction based on ablations).

Schedule	Decay %	Steps	Final Loss
Cosine	100%	9,000	3.125
WSD	0% (stable only)	9,000	3.188
WSD	10%	9,000	3.234
WSD	20%	9,000	3.125
WSD	30%	9,000	3.172

Table 11: WSD schedule comparison on 70M model with NorMuon+CWD. WSD with 20% decay matches cosine performance while enabling checkpoint re-use for multi-stage training.

A.5 DCLM-edu-boolq filtering prompt

The following prompt identifies passages suitable for Boolean question answering. An LLM processes batches of 50 samples and returns indices of qualifying passages; these are used to train

a fastText classifier.

You are selecting text samples suitable for training Boolean question answering and textual entailment models (BoolQ / NLI style).

A sample qualifies ONLY IF ALL conditions hold:

- 1) The passage contains at least one explicit or implicit factual CLAIM whose truth value can be determined from the passage itself.
- 2) That claim could naturally be turned into a YES/NO question (e.g., involving negation, exceptions, quantifiers, or exclusivity).
- 3) The passage provides sufficient EVIDENCE to verify or falsify the claim. (No external knowledge required.)
- 4) Preference is given to passages involving: negation (not, no, never, except, unless); quantifiers (all, some, only, at least, none); contradictions or contrastive statements; factual verification.
- 5) EXCLUDE passages that are: purely descriptive or narrative; definitions without verifiable truth conditions; open-ended discussion without decidable claims; opinion or speculative text.

If NO samples qualify, return an EMPTY LINE. Output ONLY the numbers of qualifying samples as a comma-separated list.