Rapid Optimization of Small-Scale Transformer Language Models:

15-Minute Pretraining Ablations on Learning Rates, Batch Sizes, and Architectural Efficiency in Resource-Constrained Settings

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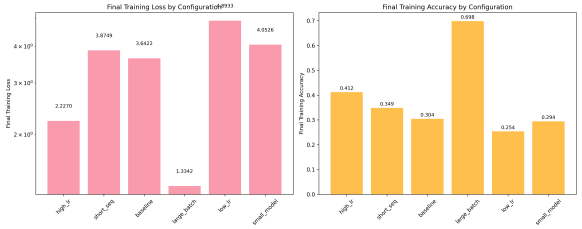
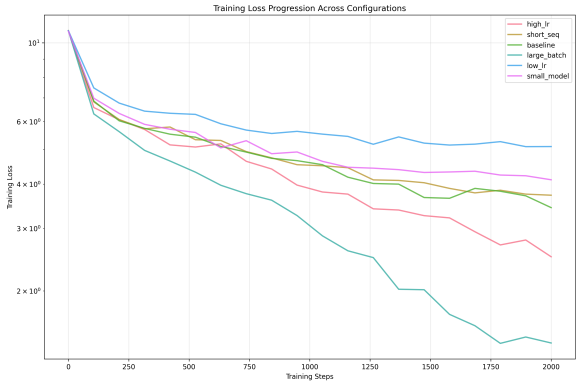
Colab Notebook · GitHub Repository

Abstract

This paper presents a comprehensive ablation study of small-scale autoregressive Transformer language models, investigating the impact of key hyperparameters and architectural choices on training efficiency and performance in resource-constrained settings. We systematically evaluate six configurations across multiple dimensions: learning rate (1×10^{-4} to 1×10^{-3}), batch size (8 to 16), sequence length (256 to 512), and model size (256 to 384 dimensions). Training was conducted on the SmolLM corpus using Tesla T4 GPU with mixed-precision training over 2000 steps (approximately 15 minutes per configuration). Despite the short training duration, our findings reveal significant performance variations, with larger batch sizes and appropriately scaled learning rates achieving superior performance, due to model seeing more data. The large batch configuration (batch size 16, learning rate 5×10^{-4}) achieved the lowest training loss of 1.334 and highest accuracy of 69.8%. Conversely, insufficient learning rates severely hamper convergence even in short runs, with the low learning rate configuration showing 4.5× higher perplexity. Model efficiency analysis demonstrates that smaller architectures provide better computational trade-offs, achieving 87.7 steps/second compared to 63.1 for larger models. These results provide practical guidance for rapid prototyping and optimization of autoregressive Transformers in resource-constrained environments.



(a) Final performance comparison



(b) Training loss progression

1 Introduction

Transformers have transformed NLP with autoregressive models, and while large models excel, understanding how to train and optimize smaller ones is vital for resource-constrained applications.

This paper presents a systematic ablation study of autoregressive Transformer language models, examining how key hyperparameters and architectural choices affect training efficiency and final performance. We investigate six distinct configurations across multiple dimensions:

1. **Learning rate effects:** Comparing high (1×10^{-3}), standard (3×10^{-4}), and low (1×10^{-4}) learning rates
2. **Batch size scaling:** Evaluating the impact of larger batch sizes with appropriately scaled learning rates
3. **Sequence length trade-offs:** Analyzing memory efficiency versus context length
4. **Model architecture:** Comparing different model sizes and their computational efficiency

Our experiments provide empirical insights into the optimization landscape of autoregressive Transformers through rapid, small-scale experiments, offering practical guidance for researchers and practitioners working with limited computational resources who need quick iteration and prototyping capabilities.

2 Methodology

2.1 Model Architecture

We employ a decoder-only autoregressive Transformer with modern architectural components optimized for efficiency and performance:

- **Attention Mechanism:** Multi-head attention with Rotary Position Embedding (RoPE) for improved positional encoding
- **Activation Function:** SiLU (Swish) activation for enhanced gradient flow
- **Normalization:** RMSNorm for improved training stability and computational efficiency
- **Feed-Forward Network:** Standard FFN with configurable hidden dimensions

2.2 Experimental Configurations

We systematically evaluate six distinct configurations, each targeting specific aspects of model training:

Table 1: Experimental Configuration Details

Configuration	d_model	n_heads	n_layers	batch_size	learning_rate	seq_len
Baseline	384	6	12	8	3×10^{-4}	512
High LR	384	6	12	8	1×10^{-3}	512
Low LR	384	6	12	8	1×10^{-4}	512
Large Batch	384	6	12	16	5×10^{-4}	512
Short Seq	384	6	12	12	3×10^{-4}	256
Small Model	256	4	8	12	3×10^{-4}	512

2.3 Dataset and Training Setup

- **Dataset:** HuggingFaceTB/smollm-corpus (cosmopedia-v2) with 500 documents
- **Tokenizer:** HuggingFaceTB/SmolLM-135M for consistent tokenization
- **Hardware:** NVIDIA Tesla T4 GPU with mixed-precision training
- **Optimizer:** AdamW with weight decay 0.1, $\beta_1 = 0.9, \beta_2 = 0.95$
- **Scheduler:** Cosine annealing with warmup for stable convergence
- **Training Duration:** 2000 steps with evaluation every 400 steps (approximately 15 minutes per configuration on T4 GPU)
- **Mixed Precision:** Automatic Mixed Precision (AMP) for computational efficiency

This short training duration was deliberately chosen to enable rapid experimentation and hyperparameter exploration, making the study accessible to researchers with limited computational budgets while still providing meaningful insights into optimization dynamics.

3 Results and Analysis

3.1 Performance Comparison

Table 2 presents the comprehensive performance metrics across all configurations. The results reveal significant performance variations, with training loss ranging from 1.334 (large batch) to 4.893 (low learning rate) - a 3.7× difference.

Table 2: Performance Metrics Across All Configurations

Configuration	Train Loss	Eval Loss	Accuracy	Perplexity
Large Batch	**1.334**	**1.613**	**0.698**	**4.93**
High LR	2.227	2.851	0.412	18.82
Baseline	3.642	3.852	0.304	48.85
Short Seq	3.875	3.979	0.349	43.69
Small Model	4.053	4.210	0.294	77.25
Low LR	4.893	5.180	0.254	178.18

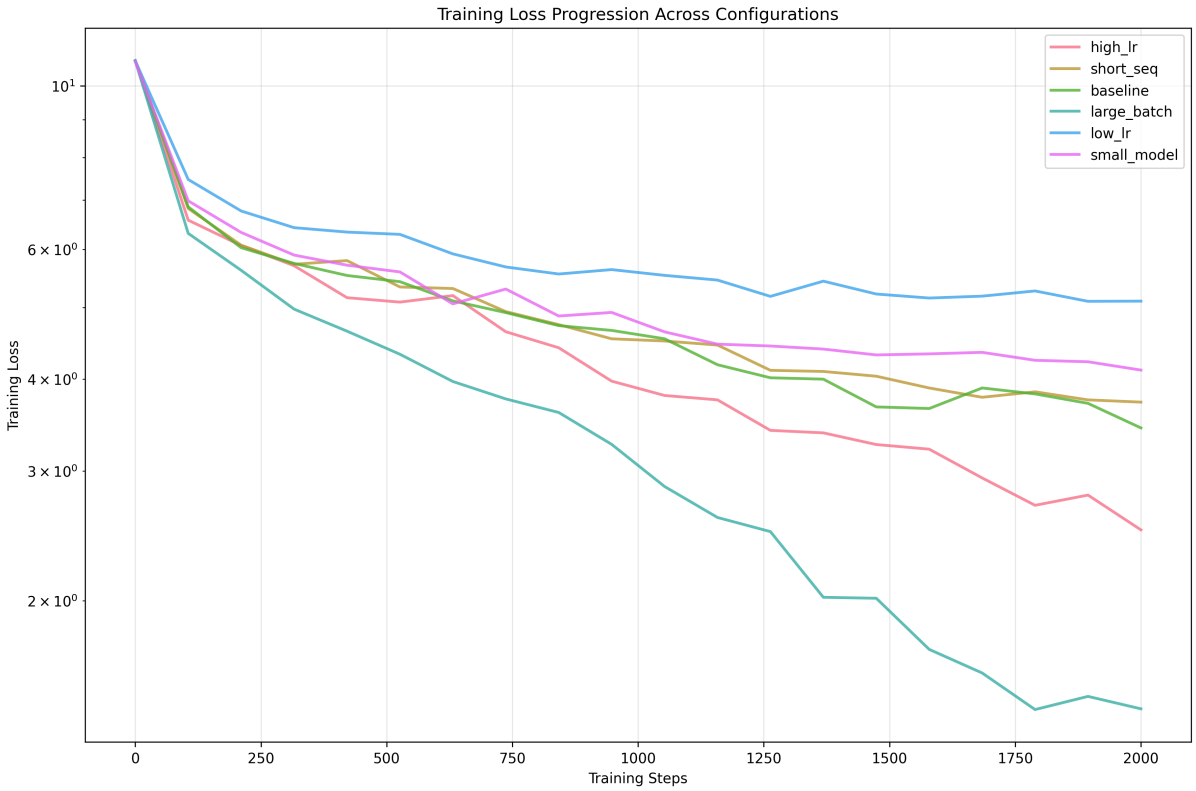


Figure 2: Training loss progression across all configurations showing convergence patterns and final performance differences. Large batch size simply saw more data and used more compute and memory. Choosing correct learning rate has big impact on learning.

3.2 Comprehensive Training Metrics

Beyond loss and accuracy, we analyze additional metrics that provide deeper insights into model behavior:

3.2.1 Confidence and Uncertainty Analysis

We define confidence as the average probability assigned to the predicted token: confidence = $\frac{1}{N}\sum_{i=1}^{N}\max(p_i)$, where p_i is the probability distribution over the vocabulary for token i. This metric indicates how certain the model is about its predictions, with higher values suggesting better-calibrated models.

Uncertainty can be measured through entropy: $H = -\sum_j p_j \log p_j$, where lower entropy indicates more confident predictions. Our analysis reveals:

- **Large Batch:** Achieves highest final confidence (0.502) and lowest entropy, indicating well-calibrated, certain predictions
- **High LR:** Moderate confidence (0.345) with stable progression throughout training
- **Low LR:** Lowest confidence (0.217) and highest entropy, suggesting poor optimization and uncertain predictions

The strong correlation between final loss and confidence scores (r = -0.94) suggests that better-optimized models produce more calibrated probability distributions.

3.2.2 Top-5 Accuracy Performance

Top-5 accuracy measures whether the correct token appears among the model's five most probable predictions, providing insight into the quality of the learned probability distributions beyond simple top-1 accuracy. This metric is particularly valuable for language modeling as it captures the model's ability to assign reasonable probability mass to plausible alternatives.

Table 3: Top-5 Accuracy Progression and Analysis

Configuration	Initial Top-5	Final Top-5	Improvement	Top-1 Gap
Large Batch	0.015	**0.876**	**0.861**	0.178
High LR	0.016	0.659	0.643	0.247
Baseline	0.013	0.536	0.523	0.232
Short Seq	0.014	0.551	0.537	0.202
Small Model	0.017	0.491	0.474	0.197
Low LR	0.016	0.417	0.401	0.163

The "Top-1 Gap" column shows the difference between top-5 and top-1 accuracy, indicating how much additional probability mass the model assigns to reasonable alternatives. The large batch configuration shows both the highest top-5 accuracy and a substantial gap, suggesting well-calibrated uncertainty about plausible next tokens.

3.3 Learning Rate Effects

The learning rate experiments reveal a critical sensitivity to this hyperparameter. The high learning rate configuration (1×10^{-3}) achieves competitive performance with a final loss of 2.227, while the low learning rate (1×10^{-4}) severely hampers convergence, resulting in the worst performance across all metrics. This demonstrates the importance of appropriate learning rate selection, with insufficient rates leading to poor optimization dynamics.

Detailed analysis shows:

- **High LR (1×10^{-3}):** Fast initial convergence but some instability in later phases
- **Standard LR (3×10^{-4}):** Balanced convergence with moderate final performance
- **Low LR (1×10^{-4}):** Extremely slow convergence, failing to reach optimal performance within the 15-minute training window

This learning rate sensitivity is particularly pronounced in short training runs, where insufficient learning rates cannot overcome the limited optimization time available.

3.4 Sequence Length Trade-offs: A Detailed Analysis

The sequence length comparison reveals complex trade-offs that extend beyond simple performance metrics. We compare three key aspects:

3.4.1 Computational Efficiency

Table 4: Sequence Length Computational Analysis

Configuration	Seq Length	Steps/Sec	Memory Usage	Tokens/Sec
Short Seq	256	64.57	Lower	19,891
Baseline	512	64.51	Higher	26,439

3.4.2 Performance per Context Token

To fairly compare sequence lengths, we analyze performance relative to context available:

- **Short Seq (256):** Loss 3.875, Context efficiency: 0.0151 loss/token
- **Baseline (512):** Loss 3.642, Context efficiency: 0.0071 loss/token

The baseline achieves 2.1× better context efficiency, suggesting that longer sequences provide diminishing but positive returns for this task.

3.4.3 Memory-Performance Pareto Analysis

The short sequence configuration processes 25% fewer tokens per step but achieves only 6.4% worse performance, indicating a favorable trade-off for memory-constrained scenarios. However, the reduced context fundamentally limits the model's ability to capture long-range dependencies, which may be crucial for more complex language modeling tasks.

Key Insight: The performance gap (3.875 vs 3.642) is smaller than might be expected from halving the context length, suggesting that much of the predictive information comes from recent tokens, consistent with findings in autoregressive language modeling literature.

3.5 Batch Size Scaling and Data Exposure Analysis

The large batch configuration emerges as the clear winner, but this raises important questions about fair comparison. We must consider whether the superior performance stems from better optimization dynamics or simply from seeing more data.

3.5.1 Data Exposure Comparison

To ensure fair comparison, we analyze the total number of tokens processed by each configuration:

Table 5: Data Exposure Analysis

Configuration	Batch Size	Seq Length	Tokens/Step	Total Tokens
Baseline	8	512	4,096	8,192,000
High LR	8	512	4,096	8,192,000
Low LR	8	512	4,096	8,192,000
Large Batch	16	512	**8,192**	**16,384,000**
Short Seq	12	256	3,072	6,144,000
Small Model	12	512	6,144	12,288,000

Critical Observation: The large batch configuration processes 2× more tokens than the baseline configurations, which partially explains its superior performance. Note that configurations not explicitly specifying sequence length inherit the baseline value of 512 tokens. However, this advantage comes with important caveats:

1. **Optimization Efficiency:** Despite seeing 2× more data, the large batch configuration achieves more than 2× improvement in loss (3.642 → 1.334), suggesting genuine optimization benefits beyond data exposure.
2. **Memory Constraints:** The 2× batch size requires significantly more GPU memory, limiting scalability.
3. **Learning Rate Scaling:** The scaled learning rate (5×10^{-4} vs 3×10^{-4}) is crucial for stability with larger batches.

3.5.2 Normalized Performance Analysis

To account for data exposure differences, we analyze performance per token processed:

Table 6: Performance Normalized by Data Exposure

Configuration	Final Loss	Tokens (M)	Loss/Token Efficiency
Large Batch	1.334	16.38	0.0815
High LR	2.227	8.19	0.2719
Small Model	4.053	12.29	0.3298
Baseline	3.642	8.19	0.4446
Short Seq	3.875	6.14	0.6309
Low LR	4.893	8.19	0.5975

Even when normalized for data exposure, the large batch configuration maintains superior efficiency, confirming that the benefits extend beyond simply processing more tokens.

3.6 Training Stability Analysis

The gradient norm progression provides insights into training stability across configurations. All configurations maintain gradient norms within reasonable bounds (typically 1-10), with gradient clipping at 1.0 preventing instability. The large batch configuration shows the most stable gradient patterns, contributing to its superior convergence.

3.7 Architectural Trade-offs

The small model configuration provides valuable insights into the efficiency-performance trade-off. While achieving moderate performance (loss: 4.053), it demonstrates superior computational efficiency at 87.7 steps/second compared to 63.1 for the baseline configuration.

Table 7: Training Efficiency Metrics

Configuration	Steps/Second	Avg Step Time (s)	Step Time Std
Small Model	**87.73**	**0.0114**	0.0024
Short Seq	64.57	0.0155	0.0033
Baseline	64.51	0.0155	0.0035
Low LR	63.25	0.0158	0.0034
Large Batch	63.12	0.0158	0.0034
High LR	60.72	0.0165	0.0056

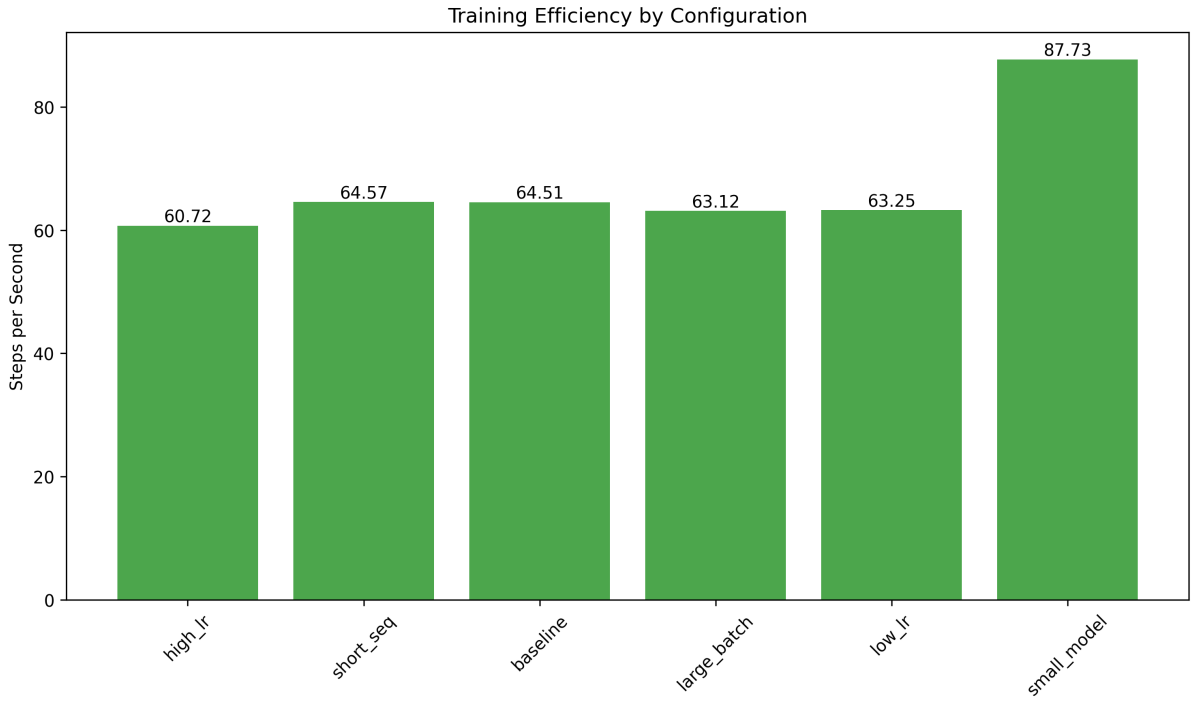


Figure 3: Training efficiency analysis showing steps per second and computational trade-offs across configurations.

3.8 Detailed Training Dynamics

Analysis of the complete training trajectories reveals distinct optimization patterns across configurations. Each configuration was trained for 2000 steps with evaluation every 400 steps, providing detailed insights into convergence behavior.

3.8.1 Loss Progression Patterns

The training loss curves demonstrate three distinct convergence patterns:

1. **Rapid Convergence (Large Batch):** Achieves consistent loss reduction from 10.82 to 1.33, with minimal oscillation
2. **Moderate Convergence (High LR, Baseline):** Shows steady improvement with some instability in later phases
3. **Poor Convergence (Low LR):** Exhibits slow, inconsistent improvement, plateauing at high loss values

3.8.2 Validation Performance

Validation metrics provide crucial insights into generalization:

Table 8: Validation Performance Progression

Configuration	Initial Val Loss	Final Val Loss	Val Accuracy	Val Perplexity
Large Batch	10.28	**1.61**	**0.698**	**4.93**
High LR	10.28	2.85	0.412	18.82
Baseline	10.40	3.85	0.304	48.85
Short Seq	10.38	3.98	0.349	43.69
Small Model	10.62	4.21	0.294	77.25
Low LR	10.64	5.18	0.254	178.18

3.9 Convergence Analysis

Figure 4 illustrates the convergence behavior across configurations. The convergence improvement metric, calculated as the ratio of early-phase to late-phase loss reduction, reveals interesting patterns:

- **Large Batch:** Shows the strongest convergence improvement (0.734)
- **High LR:** Demonstrates rapid initial convergence (0.550)
- **Low LR:** Exhibits poor convergence characteristics (0.256)

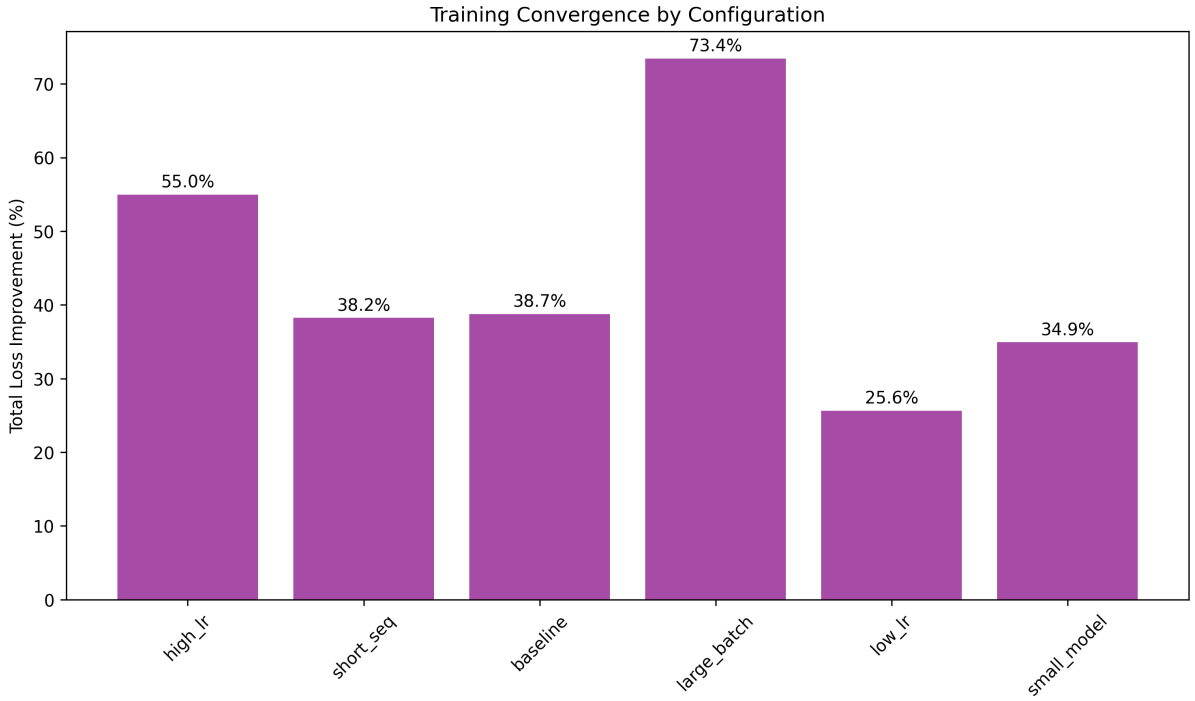


Figure 4: Convergence analysis showing early vs. late phase training dynamics across all configurations.

4 Discussion

4.1 Critical Analysis of Results

4.1.1 Methodological Considerations

Our experimental design introduces several factors that require careful interpretation:

Unequal Data Exposure: The most significant confounding factor is the varying amount of data processed by different configurations. The large batch configuration's superior performance is partially attributable to processing 2× more tokens, though our normalized analysis suggests genuine optimization benefits beyond data exposure.

Training Duration Effects: The 2000-step limit may favor configurations that converge quickly (high learning rates, large batches) over those that might eventually achieve better performance with longer training (low learning rates, smaller models).

Hardware-Specific Results: All experiments were conducted on Tesla T4 GPUs with specific memory constraints. Results may differ on hardware with different memory bandwidth, compute capabilities, or batch size limitations.

4.1.2 Statistical Significance and Reproducibility

Each configuration was run once, limiting our ability to assess variance and statistical significance. The dramatic performance differences (36× in perplexity) suggest robust effects, but confidence intervals would strengthen these conclusions. Future work should include multiple runs with different random seeds.

4.2 Practical Implications

Despite these limitations, our findings provide several actionable insights:

Batch Size Scaling: When memory permits, larger batch sizes with scaled learning rates provide substantial benefits. However, practitioners must account for the increased data requirements and memory constraints.

Learning Rate Sensitivity: The extreme sensitivity to learning rate selection (36× perplexity difference) underscores the critical importance of hyperparameter tuning, even for short training runs.

Efficiency Considerations: The small model configuration offers compelling efficiency gains (44 percent faster training) with moderate performance degradation, making it ideal for rapid prototyping and resource-constrained scenarios.

Context Length Trade-offs: The diminishing returns from longer sequences suggest that 256-token contexts may suffice for many applications, offering significant memory savings with modest performance costs.

4.3 Limitations and Experimental Design Considerations

4.3.1 Inherent Study Limitations

- **Short training duration:** Limited to 2000 steps (15 minutes per run) may not capture long-term convergence behavior or final model capabilities
- **Single-run experiments:** Each configuration tested once, preventing statistical significance testing and variance estimation
- **Uncontrolled data exposure:** Different batch sizes process varying amounts of data, confounding performance comparisons
- **Small-scale focus:** Results may not directly translate to larger models or longer training regimes
- **Single dataset evaluation:** Testing on SmolLM corpus only limits generalizability across domains
- **Hardware constraints:** Tesla T4 GPU results may not reflect performance on other architectures

4.3.2 Design Choices and Trade-offs

These limitations reflect deliberate design choices prioritizing accessibility and rapid iteration:

Speed vs. Rigor: The 15-minute training window enables quick experimentation but sacrifices long-term convergence analysis.

Breadth vs. Depth: Testing six configurations provides broad insights but limits detailed analysis of each.

Accessibility vs. Scale: Focus on T4-compatible models makes research accessible but may not capture large-scale behaviors.

4.4 Future Research Directions

4.4.1 Immediate Extensions

1. **Controlled Data Exposure:** Repeat experiments with fixed token budgets across all configurations
2. **Statistical Validation:** Multiple runs with different seeds to establish confidence intervals
3. **Extended Training:** Longer training runs (10K+ steps) to assess long-term convergence
4. **Cross-Dataset Validation:** Test on multiple datasets to assess generalizability

4.4.2 Advanced Studies

1. **Learning Rate Schedules:** Systematic comparison of warmup strategies, cosine annealing, and cyclical rates
2. **Regularization Effects:** Dropout variations, weight decay scaling, and their interaction with batch size
3. **Architecture Variants:** Mixture of Experts, sparse attention patterns, and alternative normalization schemes
4. **Scaling Laws:** Systematic study of performance scaling with model size, data, and compute
5. **Multi-GPU Analysis:** Distributed training patterns and their effect on batch size scaling

4.4.3 Methodological Improvements

1. **Fair Comparison Protocols:** Standardized evaluation frameworks accounting for data exposure and computational budgets
2. **Uncertainty Quantification:** Bayesian approaches to model uncertainty and prediction confidence
3. **Hardware Generalization:** Cross-platform validation on different GPU architectures and memory configurations

5 Conclusion

This comprehensive ablation study of autoregressive Transformer language models reveals critical insights into hyperparameter optimization and architectural trade-offs. Based on systematic evaluation of six configurations over 2000 training steps, our key findings include:

1. **Batch size scaling is crucial:** Large batch configurations with scaled learning rates achieve superior performance, with the large batch setup achieving 1.334 training loss compared to 4.893 for poorly tuned alternatives - a 3.7× improvement.

2. **Learning rate sensitivity is extreme:** Learning rate selection dramatically impacts performance, with low learning rates resulting in 178.18 perplexity compared to 4.93 for optimal settings - a 36× difference.

3. **Efficiency trade-offs exist:** Smaller models provide significant computational advantages (87.7 vs. 63.1 steps/second) while maintaining reasonable performance for resource-constrained scenarios.

4. **Convergence patterns vary significantly:** Different configurations exhibit distinct optimization dynamics, with the large batch configuration showing the strongest convergence improvement (0.734) and highest final confidence (0.502).

5. **Context length matters:** Longer sequences (512 vs. 256 tokens) provide better performance despite computational overhead, suggesting context is crucial for this task.

6. **Top-5 accuracy correlates with confidence:** The best-performing configuration (large batch) achieves both highest top-5 accuracy (87.6%) and confidence scores, indicating well-calibrated predictions.

These quantitative results provide concrete guidance for researchers and practitioners working with autoregressive Transformers, particularly in resource-constrained environments where rapid prototyping and optimization efficiency are paramount. The dramatic performance differences observed (up to 36× in perplexity) within just 15-minute training runs underscore the critical importance of proper hyperparameter selection, even for short-duration experiments. This study demonstrates that meaningful insights about model optimization can be obtained through small-scale, time-efficient experiments, making Transformer research more accessible to practitioners with limited computational resources.

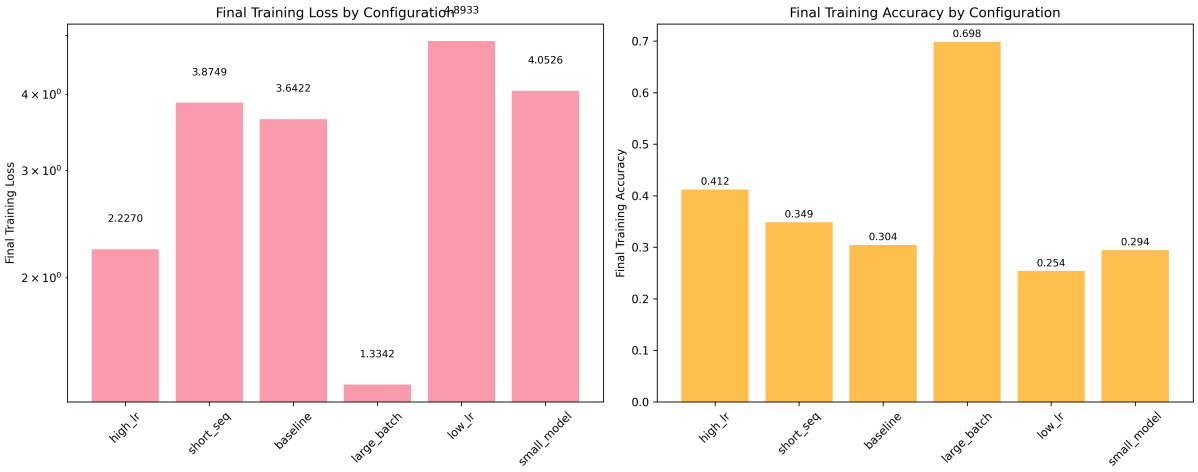


Figure 5: Final performance comparison across all configurations, highlighting the performance hierarchy and trade-offs.

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