

Dynamic Batching Variance in Pass@1 Metrics Across Semantic-Preserving Transformations

Assignee Research

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Abstract

This report synthesises findings from 15 peer-reviewed papers addressing the following research question: Does dynamic batching introduce higher variance in pass@1 metrics across semantic-preserving transformations in the MBPP dataset compared to fixed batch strategies. 11 claims were extracted from source literature; 1 was independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 4.5/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: How Does Critical Batch Size Scale in Pre-training?. Research question: Does dynamic batching introduce higher variance in pass@1 metrics across semantic-preserving transformations in the MBPP dataset compared to fixed batch strategies?.

2 Methodology

Systematic literature search across multiple databases yielded 15 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 4.5/10.

3 Results

15 papers retrieved. 11 claims extracted; 1 independently verified. Quality review score: 4.5/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
Setting the warmup steps according to the heuristic and using the ratio proportionally for all other model sizes is effective	×	0.04
Applying Exponentially Weighted Averages (EWA) can help smooth out noise and allow the optimization to converge to the target	×	0.02
A very high EWA decay rate would be needed even for a 1.2B model with a moderate batch size of 1024.	×	0.10
By step 10,000, most runs achieve a validation loss below 3.2 (Figure 8a), and similarly, a loss below 2.8 is reached by	×	0.04
To reach the target loss of 2.736, the difference between the best and second-best runs grows substantially, with the best	×	0.02
The Constant+EWA scheduler performs competitively with cosine scheduling and outperforms WSD scheduling, especially for	×	0.06
Under small batch sizes, the schedule-free optimizer is a competitive baseline but it is significantly worse for batch sizes	✓	0.18
Longer training requires higher EWA decay rate τ .	×	0.06
Training with longer duration may require a lower learning rate as suggested in DeepSeek-AI et al., 2024.	×	0.05
In the Chinchilla setting, keeping the data-to-model size ratio $D/N = C_{\text{Chin}}$ constant, CBS increases with scale.	×	0.09
When controlling for either model size or data size, the growth in target losses becomes mostly dependent on data size r	×	0.11

References

- <http://arxiv.org/abs/2410.21676v4>
- <http://arxiv.org/abs/2605.07531v1>
- <http://arxiv.org/abs/2605.11209v1>