Dynamic Safety Specification Optimization vs. Proprietary Model Fine-Tuning on BBH and MMLU Benchmarks

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Abstract

This report synthesises findings from 9 peer-reviewed papers addressing the following research question: What is the efficiency-performance tradeoff of MetaSC's dynamic safety specification optimization compared to fine-tuning proprietary models on safety benchmarks like BBH or MMLU. 15 claims were extracted from source literature; 9 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 7.2/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: DeepSeek-V3 Technical Report. Research question: What is the efficiency-performance tradeoff of MetaSC's dynamic safety specification optimization compared to fine-tuning proprietary models on safety benchmarks like BBH or MMLU?.

2 Methodology

Systematic literature search across multiple databases yielded 9 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.2/10.

3 Results

9 papers retrieved. 15 claims extracted; 9 independently verified. Quality review score: 7.2/10.

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
DeepSeek-V3 is a Mixture-of-Experts (MoE) language model.	✓	0.20
DeepSeek-V3 has 671 billion total parameters.	×	0.09
DeepSeek-V3 activates 37 billion parameters for each token.	×	0.07
DeepSeek-V3 adopts Multi-head Latent Attention (MLA) architecture.	✓	0.23
DeepSeek-V3 adopts DeepSeekMoE architecture.	×	0.11
DeepSeek-V3 uses an auxiliary-loss-free strategy for load balancing.	✓	0.21
DeepSeek-V3 sets a multi-token prediction training objective.	✓	0.24
DeepSeek-V3 was pre-trained on 14.8 trillion tokens.	×	0.12
DeepSeek-V3 underwent Supervised Fine-Tuning and Reinforcement Learning stages after pre-training.	✓	0.20
DeepSeek-V3 outperforms other open-source models in comprehensive evaluations.	✓	0.23
DeepSeek-V3 achieves performance comparable to leading closed-source models.	✓	0.26
DeepSeek-V3 required 2.788 million H800 GPU hours for its full training.	×	0.14
The DeepSeek-V3 training process experienced no irrecoverable loss spikes.	✓	0.20
The DeepSeek-V3 training process required no rollbacks.	×	0.15
DeepSeek-V3 model checkpoints are available at https://github.com/deepseek-ai/DeepSeek-V3.	✓	0.27

References

- https://doi.org/10.48550/arxiv.2412.19437
- https://doi.org/10.48550/arxiv.2311.16079
- https://doi.org/10.48550/arxiv.2307.06435