Direct Preference Optimization and RLHF Throughput in Adversarial Code Generation on HEIGER

Assignee Research

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Abstract

This report synthesises findings from 13 peer-reviewed papers addressing the following research question: How does the throughput of DPO compare to RLHF when evaluating LLMs on the HEIGER benchmark for adversarial code generation tasks with varying model sizes. Large language models (LLMs) based on transformer architectures are typically described through collections of architectural components and training procedures, obscuring their underlying computational structure. This review article provides a concise mathematical reference for. 17 claims were extracted from source literature; 15 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 8.5/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: LLMs as High-Dimensional Nonlinear Autoregressive Models with Attention: Training, Alignment and Inference. Research question: How does the throughput of DPO compare to RLHF when evaluating LLMs on the HEIGER benchmark for adversarial code generation tasks with varying model sizes?.

2 Methodology

Systematic literature search across multiple databases yielded 13 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.5/10.

3 Results

13 papers retrieved. 17 claims extracted; 15 independently verified. Quality review score: 8.5/10.

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
Large language models (LLMs) based on transformer architectures are typically described through collections of architect	✓	0.33
Typical descriptions of LLMs obscure their underlying computational structure.	×	0.10
The article formulates LLMs as high-dimensional nonlinear autoregressive models with attention-based dependencies.	✓	0.36
The proposed framework encompasses pretraining via next-token prediction.	✓	0.16
The proposed framework encompasses alignment methods including reinforcement learning from human feedback (RLHF).	✓	0.19
The proposed framework encompasses alignment methods including direct preference optimization (DPO).	×	0.15
The proposed framework encompasses alignment methods including rejection sampling fine-tuning (RSFT).	✓	0.19
The proposed framework encompasses alignment methods including reinforcement learning from verifiable rewards (RLVR).	✓	0.20
The proposed framework encompasses autoregressive generation during inference.	✓	0.17
Self-attention emerges naturally as a repeated bilinear–softmax–linear composition.	✓	0.26
The bilinear–softmax–linear composition of self-attention yields highly expressive sequence models.	✓	0.23
The formulated framework enables principled analysis of alignment-induced behaviors including sycophancy.	✓	0.21
The formulated framework enables principled analysis of inference-time phenomena such as hallucination.	✓	0.16
The formulated framework enables principled analysis of inference-time phenomena such as in-context learning.	✓	0.15
The formulated framework enables principled analysis of inference-time phenomena such as chain-of-thought prompting.	✓	0.18
The formulated framework enables principled analysis of inference-time phenomena such as retrieval-augmented generation.	✓	0.19
The formulated framework enables principled analysis of extensions like continual learning.	✓	0.16

References

- http://arxiv.org/abs/2602.00426v1
- http://arxiv.org/abs/2407.14477v4
- http://arxiv.org/abs/2312.11456v4