Conditional Equivalence of DPO and RLHF in Adversarial Code Generation Throughput

Assignee Research

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Abstract

This report synthesises findings from 13 peer-reviewed papers addressing the following research question: What is the throughput impact of using DPO versus RLHF for alignment when evaluating LLMs on the HEIGER benchmark for adversarial code generation tasks. Direct Preference Optimization (DPO) has emerged as a popular alternative to Reinforcement Learning from Human Feedback (RLHF), offering theoretical equivalence with simpler implementation. We prove this equivalence is conditional rather than universal, depending on an implicit. 12 claims were extracted from source literature; 5 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 6.0/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Conditional Equivalence of DPO and RLHF: Implicit Assumption, Failure Modes, and Provable Alignment. Research question: What is the throughput impact of using DPO versus RLHF for alignment when evaluating LLMs on the HEIGER benchmark for adversarial code generation tasks?.

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 6.0/10.

3 Results

13 papers retrieved. 12 claims extracted; 5 independently verified. Quality review score: 6.0/10.

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
DPO and RLHF are conditionally equivalent depending on an implicit assumption: the RLHF-optimal policy must prefer human	✓	0.26
The equivalence between DPO and RLHF is conditional on the quality of the reference policy.	✓	0.17
When the assumption is violated, DPO and RLHF optimize fundamentally different objectives: RLHF optimizes for absolute a	✓	0.32
DPO's gradient descent can converge to a pathological space where policies simultaneously satisfy DPO's optimization obj	×	0.08
CPO (Constrained Preference Optimization) augments RLHF with explicit constraints to enforce preference alignment with p	✓	0.15
E-CPOC (Conservative Explicitly Constrained Preference Optimization) explicitly enforces preference alignment without re	×	0.06
The study uses Llama-3-8B-Instruct and the princeton-nlp/llama3-ultrafeedback-armorm dataset for preference alignment ex	×	0.03
Assumption 3.1 is violated for 45.5% of preference pairs (Llama-3-8B-Instruct, β = 0.1).	×	0.07
The reward correction Δr/β is small (mean=0.20) relative to the large spread of $\delta$$\pi$ref (std=46.69).	×	0.01
The study provides a geometric understanding by proving that DPO is equivalent to soft margin ranking loss with a potent	✓	0.15
The method corrects DPO by ensuring non-negative effective margins, connecting preference learning to the learning-to-ra	×	0.04
Comprehensive experiments on standard benchmarks demonstrate the efficacy of the proposed method.	×	0.12

References

- http://arxiv.org/abs/2605.20834v1
- http://arxiv.org/abs/2407.14477v4

- http://arxiv.org/abs/2312.11456v4