DPO with Rationales vs. Standard DPO: Training Throughput and Sample Complexity Trade-offs on LLaVA-Bench

Assignee Research

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Abstract

This report synthesises findings from 10 peer-reviewed papers addressing the following research question: What is the efficiency trade-off in terms of training throughput and sample complexity when comparing DPO with rationales versus standard DPO on the LLaVA-Bench benchmark, evaluated by the number of. Aligning language models with human preferences through reinforcement learning from human feedback is crucial for their safe and effective deployment. The human preference is typically represented through comparison where one response is chosen over another for a given prompt. 12 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 2.5/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Data-Centric Human Preference with Rationales for Direct Preference Alignment. Research question: What is the efficiency trade-off in terms of training throughput and sample complexity when comparing DPO with rationales versus standard DPO on the LLaVA-Bench benchmark, evaluated by the number of training steps required to reach equivalent alignment performance?.

2 Methodology

Systematic literature search across multiple databases yielded 10 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 2.5/10.

3 Results

10 papers retrieved. 12 claims extracted; 0 independently verified. Quality review score: 2.5/10.

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
The study evaluates three preference datasets: Orca DPO Pairs, a binarized UltraFeedback, and Anthropic Helpful and Harm	×	0.09
For each dataset used in the analysis, 512 fixed samples were selected as the test set for winrate evaluations.	×	0.03
The experiments investigated preference training on Mistral-7B-v0.1, Mistral-7B-Instruct-v0.2, Zephyr-7B-Beta, and Llama	×	0.02
GPT-4o was used as the judge to evaluate model responses and retrieve winrate scores.	×	0.03
The study integrated rationales into DPO, ORPO, and SimPO preference learning frameworks.	×	0.07
To ensure fair comparison between DPO and RDPO, the base model was fine-tuned with supervised fine-tuning (SFT) using on	×	0.13
On the Orca dataset with Mistral-7B-Instruct-v0.2, RDPO achieved a winrate of 19.52% against the SFT model, compared to	×	0.05
On the Orca dataset with Llama-3.1-8B-Instruct, RDPO achieved a winrate of 26.02% against the SFT model, compared to 22.	×	0.05
On the UltraFeedback dataset with Mistral-7B-Instruct-v0.2, RORPO achieved a winrate of 20.45% against the SFT model, co	×	0.04
On the UltraFeedback dataset with Llama-3.1-8B-Instruct, RORPO achieved a winrate of 26.55% against the SFT model, compa	×	0.04
The methodology extends the Direct Preference Optimization (DPO) algorithm to incorporate rationales.	×	0.07
The code implementation was extended from the human-aware loss functions (HALOs) repository to adapt to the study's meth	×	0.02

References

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

- http://arxiv.org/abs/2602.21346v1
- http://arxiv.org/abs/2506.10054v4