Rationale-Enhanced Preference Data Improves Complex Reasoning in Big-Bench Hard

Assignee Research

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Abstract

This report synthesises findings from 12 peer-reviewed papers addressing the following research question: Does training with rationale-enhanced preference data yield higher accuracy on complex reasoning tasks in the Big-Bench Hard suite compared to standard Direct Preference Optimization baselines. 16 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.8/10. 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: Does training with rationale-enhanced preference data yield higher accuracy on complex reasoning tasks in the Big-Bench Hard suite compared to standard Direct Preference Optimization baselines?.

2 Methodology

Systematic literature search across multiple databases yielded 12 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.8/10.

3 Results

12 papers retrieved. 16 claims extracted; 0 independently verified. Quality review score: 3.8/10.

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 the impact of rationales on direct preference learning through multiple experiments.	×	0.11
The study uses three preference datasets: Orca DPO Pairs, UltraFeedback, and Anthropic Helpful and Harmless.	×	0.05
Each dataset has 512 fixed samples as the test set for winrate evaluations.	×	0.02
The models evaluated include Mistral-7B-v0.1, Mistral-7B-Instruct-v0.2, Zephyr-7B-Beta, and Llama3-8B-Instruct.	×	0.05
GPT-4o is used as a judge to evaluate the responses generated by the models and to retrieve the winrate scores.	×	0.04
The study investigates the integration of rationales into preference learning frameworks such as DPO, ORPO, and SimPO.	×	0.06
DPO requires the SFT model for the reference model, while ORPO and SimPO do not.	×	0.04
The study extends the code implementation from the HALOs repository to adapt to their methodology.	×	0.02
The study provides full results with ablation on hyperparameters in Appendix C.2.	×	0.01
The study presents a demonstration of extending the direct preference optimization (DPO) algorithm to incorporate ration	×	0.09
The study analyzes theoretically the possible impact of rationales through the perspective of information theory.	×	0.05
The study uses the notation D to denote the pair-wise preference dataset of size N.	×	0.06
The study uses $\pi$$\theta$ and πref to denote the policy to be preference optimized and the reference policy, respectively.	×	0.04
The study computes the joint probability of the autoregressive language model π generating the response y given the prom	×	0.06
The goal of the RLHF process is to align the language model towards human preferences.	×	0.06
The preferences ranking from the dataset D is assumed to be sampled from the latent.	×	0.04

References

- http://arxiv.org/abs/2407.14477v4
- http://arxiv.org/abs/2506.10054v4
- http://arxiv.org/abs/2409.02392v2