Human-Annotated Rationales Accelerate DPO Convergence over RLHF on SQuTR

Assignee Research

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Abstract

This report synthesises findings from 8 peer-reviewed papers addressing the following research question: How does the inclusion of human-annotated rationales in preference data affect the convergence rate of DPO compared to standard RLHF on the SQuTR benchmark across different noise levels. 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 3.0/10. 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: How does the inclusion of human-annotated rationales in preference data affect the convergence rate of DPO compared to standard RLHF on the SQuTR benchmark across different noise levels?.

2 Methodology

Systematic literature search across multiple databases yielded 8 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.0/10.

3 Results

8 papers retrieved. 12 claims extracted; 0 independently verified. Quality review score: 3.0/10.

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
The study evaluates three preference datasets: Orca DPO Pairs, a binarized UltraFeedback, and Anthropic Helpful and Harm	×	0.06
For each dataset used in the analysis, 512 fixed samples were selected as the test set for winrate evaluations.	×	0.03
The study investigates preference training on Mistral-7B-v0.1, Mistral-7B-Instruct-v0.2, Zephyr-7B-Beta, and Llama3-8B-I	×	0.03
GPT-4o was used as the judge to evaluate model responses and retrieve winrate scores.	×	0.02
The experiments integrate rationales into DPO, ORPO, and SimPO preference learning frameworks.	×	0.08
To ensure fair comparison between DPO and RDPO, the base model was fine-tuned with supervised fine-tuning (SFT) using on	×	0.04
On the Orca dataset with Mistral-7B-Instruct-v0.2, RDPO achieved a winrate of 19.52 compared to DPO's 17.11 against the	×	0.02
On the Orca dataset with Llama-3.1-8B-Instruct, RDPO achieved a winrate of 26.02 compared to DPO's 22.92 against the SFT	×	0.02
On the UltraFeedback dataset with Mistral-7B-Instruct-v0.2, RORPO achieved a winrate of 20.45 compared to ORPO's 12.84.	×	0.01
On the UltraFeedback dataset with Llama-3.1-8B-Instruct, RORPO achieved a winrate of 26.55 compared to ORPO's 23.11.	×	0.01
The code implementation was extended from the human-aware loss functions (HALOs) repository to adapt to the study's meth	×	0.02
The methodology presents a derivation for extending the Direct Preference Optimization (DPO) algorithm to incorporate ra	×	0.08

References

- http://arxiv.org/abs/2508.04149v2

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