Embodied-R1 Alignment and Task Accuracy After RLHF vs. Supervised Fine-Tuning on CALVIN

Assignee Research

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Abstract

This report synthesises findings from 13 peer-reviewed papers addressing the following research question: What is the impact of fine-tuning Embodied-R1 with human feedback (RLHF) on its alignment and task execution accuracy in the CALVIN benchmark compared to standard supervised fine-tuning. 15 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.2/10. 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 impact of fine-tuning Embodied-R1 with human feedback (RLHF) on its alignment and task execution accuracy in the CALVIN benchmark compared to standard supervised fine-tuning?.

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 3.2/10.

3 Results

13 papers retrieved. 15 claims extracted; 0 independently verified. Quality review score: 3.2/10.

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.	×	0.13
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
Rationales are generated and added to the current datasets.	×	0.05
The study investigates preference training on various large language models: Mistral-7B-v0.1, Mistral-7B-Instruct-v0.2,	×	0.04
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 examines 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.	×	0.03
The study extends the code implementation from the human-aware loss functions (HALOs) repository to adapt to their metho	×	0.03
The study borrows hyperparameters from each of the methods in their study.	×	0.02
The study presents a demonstration of extending the direct preference optimization (DPO) algorithm to incorporate ration	×	0.11
The study analyzes theoretically the possible impact of rationales through the perspective of information theory.	×	0.04
The study uses notations such as D for the pairwise preference dataset, $\pi$$\theta$ for the policy to be preference optimized, a	×	0.06
The goal of the RLHF process is to align the language model towards human preferences.	×	0.07
The preferences ranking from the dataset D is assumed to be sampled from the latent.	×	0.01

References

- http://arxiv.org/abs/2402.07314v3
- http://arxiv.org/abs/2308.04332v1
- http://arxiv.org/abs/2407.14477v4