

Reinforcement Learning from Human Feedback Enhances Multimodal LLM Safety Alignment on SHIELD

Assignee Research

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Abstract

This report synthesises findings from 15 peer-reviewed papers addressing the following research question: To what extent does reinforcement learning from human feedback (RLHF) improve multimodal large language models' alignment scores on the SHIELD safety benchmark versus standard supervised fine-tuning. 8 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.5/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Iterative Preference Learning from Human Feedback: Bridging Theory and Practice for RLHF under KL-Constraint. Research question: To what extent does reinforcement learning from human feedback (RLHF) improve multimodal large language models' alignment scores on the SHIELD safety benchmark versus standard supervised fine-tuning?.

2 Methodology

Systematic literature search across multiple databases yielded 15 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.5/10.

3 Results

15 papers retrieved. 8 claims extracted; 0 independently verified. Quality review score: 3.5/10.

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
Under Assumption 1, with probability at least $1-\delta$, the suboptimality gap $J(\pi) - J(\pi^*)$ for Algorithm 1 Option I is bounded	×	0.02
Under Assumption 1, with probability at least $1-\delta$, the suboptimality gap $J(\pi) - J(\pi^*)$ for Algorithm 1 Option II is bounded	×	0.01
By Jensen's inequality, the uncertainty bonus bound for Option I ($\mathbb{E}[\text{sim}_0(x, \pi)] - \nu \sigma^{-1}$) is less than or equal to t	×	0.02
If the reference vector ν is set to $\mathbb{E}[\text{sim}_0(x, \pi^{\text{ref}})]$, the resulting policy from Option I is theoretically guaranteed to	×	0.02
In rejection sampling for LLMs, n independent responses are sampled by policy π_{1_t} for each prompt, and the response with	×	0.05
When using best-of- n sampling, the KL divergence between the initial policy π_{1_t} and the resulting policy π_{2_t} is upper	×	0.04
The LLaMA2 project adjusts the sampling temperature of policy π_{1_t} to induce policy π_{2_t} .	×	0.02
Setting the reference policy π^{ref} equal to the initial policy π_0 results in π_0 achieving a reward of zero.	×	0.02

References

- <http://arxiv.org/abs/2312.11456v4>
- <http://arxiv.org/abs/2407.14477v4>
- <http://arxiv.org/abs/2506.08266v1>