Alignment Techniques and Robustness in Frontier LLMs on HLCE Benchmark

Assignee Research

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Abstract

This report synthesises findings from 16 peer-reviewed papers addressing the following research question: How do different alignment techniques (e.g., RLHF, DPO) impact the performance of frontier LLMs on the HLCE benchmark, particularly in low-resource or adversarial settings, measured by robustness. 8 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 1.8/10. 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: How do different alignment techniques (e.g., RLHF, DPO) impact the performance of frontier LLMs on the HLCE benchmark, particularly in low-resource or adversarial settings, measured by robustness metrics?.

2 Methodology

Systematic literature search across multiple databases yielded 16 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 1.8/10.

3 Results

16 papers retrieved. 8 claims extracted; 0 independently verified. Quality review score: 1.8/10.

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
Under Assumption 1, with probability at least 1-δ, the suboptimality gap J(π) - J(π) for Algorithm 1 Option I is bounde	×	0.02
Under Assumption 1, with probability at least 1-δ, the suboptimality gap J(π) - J(π) for Algorithm 1 Option II includes	×	0.02
By Jensen's inequality, the uncertainty bonus bound for Option I (Ex$\sim$d0[(x, π)] - ν) is less than or equal to the boun	×	0.00
If the reference vector ν is set to Ex$\sim$d0[(x, πref)], the resulting policy from Option I is theoretically guaranteed to	×	0.02
In best-of-n sampling, n independent responses are sampled by policy π1_t for each prompt, and the response with the hig	×	0.03
In the context of best-of-n sampling, the KL divergence between the initial policy π1_t and the resulting policy π2_t is	×	0.04
The LLaMA2 project adjusts the sampling temperature of policy π1_t to induce policy π2_t.	×	0.02
Setting the reference policy πref equal to π0 results in π0 achieving a reward of zero.	×	0.05

References

- http://arxiv.org/abs/2312.11456v4
- http://arxiv.org/abs/2505.19770v5
- http://arxiv.org/abs/2310.11523v2