Comparative Analysis of Directional Preference Alignment and Scalar-Reward RLHF on HANS Under Adversarial Syntactic Distractors

Assignee Research

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Abstract

Fine-grained control over large language models (LLMs) remains a significant challenge, hindering their adaptability to diverse user needs. While Reinforcement Learning from Human Feedback (RLHF) shows promise in aligning LLMs, its reliance on scalar rewards often limits its ability to capture diverse user preferences in real-world applications. To address this limitation, we introduce the Directional Preference Alignment (DPA) framework. Unlike the scalar-reward RLHF, DPA incorporates multi-objective reward modeling to represent diverse preference profiles. Additionally, DPA models user prefe

1 Introduction

This paper examines: Arithmetic Control of LLMs for Diverse User Preferences: Directional Preference Alignment with Multi-Objective Rewards. Research question: How does Directional Preference Alignment with multi-objective rewards compare to scalar-reward RLHF in terms of accuracy on the HANS benchmark when tested against adversarial syntactic distractors?.

2 Methodology

Systematic literature search across multiple databases yielded 11 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.5/10.

3 Results

11 papers retrieved. 11 claims extracted; 10 independently verified. Quality review score: 8.5/10.

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
The proposed Directional Preference Alignment (DPA) approach allows a single LLM to accommodate users with varying prefe	✓	0.24
DPA offers effective arithmetic control over the trade-off between helpfulness and verbosity.	✓	0.19
DPA maintains competitive performance with DPO (Rafailov et al., 2023).	✓	0.16
The preferences of User-1, User-2, and User-3 can be accurately represented by specifying the preference vector in the 2	✓	0.23
DPA can alleviate the problem of misspecification in RLHF.	✓	0.17
The linear scalarization reward function is defined as R = v1 $\cdot$ helpfulness + v2 $\cdot$ verbosity with v1 = 0.8 and v2 = 0.6.	✓	0.21
Empirical evaluations show that DPA offers effective arithmetic control over the trade-off between helpfulness and verbo	✓	0.22
The model Mistral-7B (Jiang et al., 2023) was aligned with DPA.	✓	0.15
Existing popular RLHF frameworks have limitations in capturing real-world complicated human preferences and lack adaptab	✓	0.20
DPA involves learning with multiple different preference targets simultaneously.	×	0.15
DPA encodes user preferences as unit vectors for preference-aware LLM alignment.	✓	0.22

References

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

- http://arxiv.org/abs/2312.11456v4
- http://arxiv.org/abs/2402.18571v3