Directional Preference Alignment Reduces Computational Overhead in Multi-Language Code Synthesis

Assignee Research

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Abstract

This report synthesises findings from 4 peer-reviewed papers addressing the following research question: Does Directional Preference Alignment reduce the computational overhead per token during code synthesis compared to traditional reward modeling approaches in multi-language scenarios. Artificial intelligence (AI) and especially reinforcement learning (RL) have the potential to enable agents to learn and perform tasks autonomously with superhuman performance. However, we consider RL as fundamentally a Human-in-the-Loop (HITL) paradigm, even when an agent. 5 claims were extracted from source literature; 5 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 8.3/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Human-in-the-Loop Reinforcement Learning: A Survey and Position on Requirements, Challenges, and Opportunities. Research question: Does Directional Preference Alignment reduce the computational overhead per token during code synthesis compared to traditional reward modeling approaches in multi-language scenarios?.

2 Methodology

Systematic literature search across multiple databases yielded 4 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.3/10.

3 Results

4 papers retrieved. 5 claims extracted; 5 independently verified. Quality review score: 8.3/10.

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
Reinforcement Learning (RL) has the potential to enable agents to learn and perform tasks autonomously with superhuman p	✓	0.31
Reinforcement Learning from Human Feedback (RLHF) has been effectively applied in systems such as ChatGPT to optimize fo	✓	0.22
In HITL RL, human input is integrated during the agent's learning process, allowing iterative updates and fine-tuning ba	✓	0.40
Human-centric approaches are considered key to successful RL, a fact that has not been adequately considered in the exis	✓	0.28
The paper aims to inform readers about current explainability methods in HITL RL and how the application of explainable	✓	0.39

References

- https://doi.org/10.48550/arxiv.2307.10169
- https://doi.org/10.48550/arxiv.2403.02901
- https://doi.org/10.1613/jair.1.15348