

Directional Preference Alignment vs RLHF for Code Generation Efficiency on HumanEval

Assignee Research

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Abstract

This report synthesises findings from 7 peer-reviewed papers addressing the following research question: How does the Directional Preference Alignment framework perform in terms of inference efficiency and latency compared to traditional RLHF when generating code across multiple programming languages on. Abstract The rapid evolution of large language models (LLMs) has driven a transformative shift in artificial intelligence (AI), reshaping both research paradigms and practical applications. Distinguished from their predecessors by unprecedented scale and advanced capabilities. 10 claims were extracted from source literature; 10 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 7.3/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: A Survey of Large Language Models. Research question: How does the Directional Preference Alignment framework perform in terms of inference efficiency and latency compared to traditional RLHF when generating code across multiple programming languages on the HumanEval benchmark?.

2 Methodology

Systematic literature search across multiple databases yielded 7 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.3/10.

3 Results

7 papers retrieved. 10 claims extracted; 10 independently verified. Quality review score: 7.3/10.

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
The rapid evolution of large language models (LLMs) has driven a transformative shift in artificial intelligence (AI).	✓	0.28
LLMs are distinguished from their predecessors by unprecedented scale and advanced capabilities.	✓	0.20
The survey reviews advancements in LLM techniques across four key dimensions: pre-training methodologies, post-training	✓	0.27
Pre-training methodologies establish core model capabilities through large-scale self-supervised training, architectural	✓	0.35
Post-training techniques include supervised fine-tuning and reinforcement learning.	✓	0.18
Post-training techniques adapt foundational models to downstream tasks and enhance their alignment and safety.	✓	0.26
Utilization strategies include in-context learning, prompt engineering, and agentic reasoning.	✓	0.21
Utilization strategies optimize real-world deployment and enable effective interaction with external environments.	✓	0.25
Evaluation methods encompass benchmarks for key ability dimensions such as core language capabilities, reasoning, and sa	✓	0.27
The survey identifies critical research issues concerning theoretical foundations, efficient scaling, alignment, and age	✓	0.26

References

- <https://doi.org/10.48550/arxiv.2303.12712>
- <https://doi.org/10.1007/s11704-026-60308-3>
- <https://doi.org/10.1145/3649506>