Alignment Techniques and Reasoning Performance in Vision-Language Models on Mixed-Modality Benchmarks

Assignee Research

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Abstract

This report synthesises findings from 11 peer-reviewed papers addressing the following research question: How do different alignment techniques (e.g., instruction tuning, RLHF) affect the reasoning capabilities of VLMs on mixed-modality benchmarks such as MMBench and LLaVA-Bench. 13 claims were extracted from source literature; 11 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: Aligning Large Multimodal Models with Factually Augmented RLHF. Research question: How do different alignment techniques (e.g., instruction tuning, RLHF) affect the reasoning capabilities of VLMs on mixed-modality benchmarks such as MMBench and LLaVA-Bench?.

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 8.3/10.

3 Results

11 papers retrieved. 13 claims extracted; 11 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
Misalignment between modalities in Large Multimodal Models (LMM) can result in 'hallucination', defined as generating te	✓	0.27
The study adapts Reinforcement Learning from Human Feedback (RLHF) from the text domain to the task of vision-language a	✓	0.26
In the proposed RLHF adaptation, human annotators compare two responses to identify the more hallucinated one.	×	0.12
The vision-language model is trained to maximize simulated human rewards based on annotator comparisons.	✓	0.19
The proposed algorithm is named Factually Augmented RLHF.	×	0.14
Factually Augmented RLHF augments the reward model with additional factual information such as image captions and ground	✓	0.36
Augmenting the reward model with factual information alleviates the reward hacking phenomenon in RLHF.	✓	0.20
The study enhances GPT-4-generated training data for vision instruction tuning with previously available human-written i	✓	0.29
A new evaluation benchmark named MMHAL-BENCH was developed with a focus on penalizing hallucinations.	✓	0.18
The proposed approach is the first Large Multimodal Model trained with RLHF.	✓	0.19
The proposed approach achieves a 94% performance level relative to text-only GPT-4 on the LLaVA-Bench dataset.	✓	0.22
Previous best methods achieved only an 87% performance level relative to text-only GPT-4 on the LLaVA-Bench dataset.	✓	0.20
The proposed approach achieves a 60% improvement on MMHAL-BENCH over other baselines.	✓	0.16

References

- https://doi.org/10.48550/arxiv.2309.14525

- https://doi.org/10.1186/s40537-021-00444-8
- https://doi.org/10.48550/arxiv.2204.14198