Pareto-Based Preference Alignment for Reducing Hallucinations in Multi-Turn Multimodal Dialogue on MMHal-Bench

Assignee Research

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Abstract

Large Visual Language Models (LVLMs) have demonstrated impressive capabilities across multiple tasks. However, their trustworthiness is often challenged by hallucinations, which can be attributed to the modality misalignment and the inherent hallucinations of their underlying Large Language Models (LLMs) backbone. Existing preference alignment methods focus on aligning model responses with human preferences while neglecting image-text modality alignment, resulting in over-reliance on LLMs and hallucinations. In this paper, we propose Entity-centric Multimodal Preference Optimization (EMPO), wh

1 Introduction

This paper examines: Mitigating Hallucinations in Large Vision-Language Models via Entity-Centric Multimodal Preference Optimization. Research question: How does Pareto-based preference alignment affect hallucination rates in multi-turn multimodal dialogue compared to standard RLHF on the MMHal-Bench dataset?.

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 7.4/10.

3 Results

16 papers retrieved. 12 claims extracted; 9 independently verified. Quality review score: 7.4/10.

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
EMPO enhances multimodal semantic alignment and effectively reduces hallucinations across five widely-used benchmarks.	✓	0.19
LVLMs typically adopt a two-stage training strategy: (1) Pretraining on large-scale image–text pairs to learn fundamenta	✓	0.33
LLaVA introduces synthetic instructions to fine-tune an instruction-following LVLM.	✓	0.18
MiniGPT-v2 employs unique task identifiers during fine-tuning to reduce instruction ambiguity.	✓	0.19
LVLMs suffer from hallucinations, where model responses conflict with the images, instructions, or context.	×	0.11
Some methods have been proposed to filter out long-tail or entity co-occurrence data to mitigate hallucinations, though	✓	0.21
Post-processing techniques—optimizing decoding strategies or applying post-hoc corrections—reduce hallucinations but add	✓	0.19
Human preference alignment has emerged as an effective approach to mitigate hallucinations.	✓	0.17
LLaVA-RLHF pioneered human preference alignment exploration in LVLMs.	×	0.12
RLHF-V, RLAIF-V, and POVID further refined human preference alignment with improved visual localization, text segment sc	✓	0.16
MDPO proposed image-conditional preference alignment but overlooked aligning instructions with human preferences.	✓	0.17
EMPO incorporates preferences across comprehensive aspects for efficient multimodal alignment.	×	0.13

References

- http://arxiv.org/abs/2506.04039v2
- http://arxiv.org/abs/2309.14525v1
- http://arxiv.org/abs/2503.14504v2