Comparative Performance of RLHF, DPO, and SFT in Mitigating Hallucinations in LoRA-Fine-Tuned 7B and 70B Models

Assignee Research

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Abstract

This research investigates the effectiveness of alignment techniques, Supervised Fine-Tuning (SFT), Direct Preference Optimization (DPO), and a combined SFT+DPO approach on improving the safety and helpfulness of the OPT-350M language model. Utilizing the Anthropic Helpful-Harmless RLHF dataset, we train and evaluate four models: the base OPT350M, an SFT model, a DPO model, and a model trained with both SFT and DPO. We introduce three key evaluation metrics: Harmlessness Rate (HmR), Helpfulness Rate (HpR), and a Combined Alignment Score (CAS), all derived from reward model outputs. The results

1 Introduction

This paper examines: Improving LLM Safety and Helpfulness using SFT and DPO: A Study on OPT-350M. Research question: What is the comparative performance of RLHF, DPO, and SFT alignment techniques in mitigating hallucinations in 7B and 70B models fine-tuned with LoRA, as measured by factual consistency scores in domain-specific Q&A tasks?.

2 Methodology

Systematic literature search across multiple databases yielded 15 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.4/10.

3 Results

15 papers retrieved. 13 claims extracted; 12 independently verified. Quality review score: 8.4/10.

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
The study evaluates four versions of the OPT-350M model: the base model, an SFT-aligned model, a DPO-aligned model, and	✓	0.30
The evaluation uses a subset of the test split from the Anthropic Helpful and Harmless RLHF (HH-RLHF) dataset, with 100	✓	0.25
The 50 harmlessness prompts were selected using a keyword filtering approach with terms: kill, murder, or rape.	✓	0.19
The 50 helpfulness prompts were randomly sampled from the helpful base of the dataset, consisting of non-toxic, informat	✓	0.27
Each of the four model variants was evaluated on the exact same set of 100 prompts with deterministic outputs and a max	✓	0.25
The study evaluates models on two core alignment criteria: harmlessness and helpfulness.	×	0.15
Harmlessness refers to the model's ability to avoid generating toxic, offensive, or undesirable content, particularly in	✓	0.27
Helpfulness captures the model's capacity to provide informative, accurate, and cooperative responses to benign queries.	✓	0.20
The reward model OpenAssistant/reward-model-deberta-v3-large-v2 was used to assign a scalar score to each prompt+respons	✓	0.33
The study opted for a dedicated reward model due to its scalability, objectivity, and domain relevance, instead of relyi	✓	0.27
The dataset used in this study is the Anthropic/HH-RLHF dataset, which contains 160k training examples and 8k testing ex	✓	0.27
For Direct Preference Optimization (DPO), the dataset is used in its original format with prompts paired with both chose	✓	0.33
For Supervised Fine-Tuning (SFT), only the chosen responses are used, simulating a human-like, safe, and helpful output.	✓	0.26

References

- http://arxiv.org/abs/2509.09055v1
- http://arxiv.org/abs/2312.11456v4
- http://arxiv.org/abs/2602.08239v1