Mitigating Helpfulness Degradation in Safety-Aligned Models via Base Language Model Scale Expansion

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: To what extent does increasing the scale of the base language model mitigate the degradation in helpfulness scores observed in OPT-350M after DPO alignment for safety?.

2 Methodology

Systematic literature search across multiple databases yielded 13 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 9.2/10.

3 Results

13 papers retrieved. 22 claims extracted; 22 independently verified. Quality review score: 9.2/10.

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
All evaluations were carried out using a subset of the test split from the Anthropic Helpful and Harmless RLHF (HH-RLHF)	✓	0.26
The evaluation used 100 prompts for testing—50 for evaluating harmlessness and 50 for helpfulness.	✓	0.22
The 50 harmlessness prompts were chosen from the harmless base of the dataset and filtered using keywords: kill, murder,	✓	0.21
50 helpfulness prompts were randomly sampled from the helpful base of the dataset, which primarily consists of non-toxic	✓	0.32
Each of the four model variants was evaluated on the exact same set of 100 prompts.	✓	0.19
Stochastic decoding techniques such as temperature sampling or top-p sampling were disabled to ensure deterministic outp	✓	0.22
A max tokens limit of 50 was applied to bound response length.	✓	0.20
Harmlessness refers to the model's ability to avoid generating content that is toxic, offensive, or otherwise undesirabl	✓	0.24
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	✓	0.31
The reward model was used to evaluate the base model, SFT, DPO, and SFT+DPO versions of OPT-350M.	✓	0.18
The study opted for a dedicated reward model due to its scalability, objectivity, and domain relevance.	✓	0.21
ChatGPT-based evaluation (GPT-4) suffers from limitations such as rate limits, non-deterministic outputs, and dependency	✓	0.26
Classifier-based methods tend to be brittle and domain-specific, often failing to capture nuanced harmfulness or informa	✓	0.24
The study investigates the impact of Supervised Fine-Tuning (SFT) and Direct Preference Optimization (DPO) on the alignm	✓	0.25
The dataset used in this study is the Anthropic/HH-RLHF dataset, which is designed to evaluate and improve alignment in	✓	0.26
The Anthropic/HH-RLHF dataset contains two	✓	0.21

References

- http://arxiv.org/abs/2402.10884v2
- http://arxiv.org/abs/2509.09055v1
- http://arxiv.org/abs/2510.22389v2