Safety classification using LM

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Abstract

The rapidly increasing capabilities of large language models (LLMs) raise an urgent need to align AI systems with diverse human preferences to simultaneously enhance their usefulness and safety, despite the often conflicting nature of these goals. To address this important problem, a promising approach is to enforce a safety constraint at the fine-tuning stage, which introduces a cost model to indicate the cost value of the responses generated by the LLMs. In this project, we train a simple cost model using GPT-neo-1.3B and achieves a promising results on the test dataset.

1 Introduction

Large language models (LLMs) have demonstrated remarkable proficiency in tasks like chat completion, instruction following, coding, problemsolving, and decision-making (Chung et al., 2024; Ouyang et al., 2022; Anil et al., 2023; Stiennon et al., 2020). Considering the potential for broad societal impact, responses generated by LLMs must not contain harmful content, such as discrimination, misinformation, or violations of social norms and morals (Deshpande et al., 2023; Ganguli et al., 2022). Therefore, the alignment of safety in LLMs has received widespread attention from academia and industry (Christian, 2023).

An essential component of safety alignment involves minimizing the tendency of a model to generate harmful responses through fine-tuning. One of the important steps is to train a binary classifier to identify if a sentence contains harmful content (Dai et al., 2023). In this project, we will train a simple binary classifier using LM to identify if the sentence contains harmful language.

2 Related Work

The goal of LLMs alignment is to ensure that LLMs do not generate harmful or objectionable responses

to user queries (Zou et al., 2023). To this end, multiple fine-tuning mechanisms have been employed for this task (Bai et al., 2022b; Burns et al., 2023; Munos et al., 2023). In particular, Constitutional AI (Bai et al., 2022b) trained a non-evasive and harmless AI assistant through self-improvement, which involves a supervised learning stage to get the model "on-distribution" and a reinforcement learning stage to further refine and improve the performance. Recently, OpenAI introduced the concept of superalignment, which aimed at solving the challenge of aligning AI systems that are much smarter than humans (Burns et al., 2023). They proposed the idea of weak-to-strong generalization, inspired by the generalization properties of deep learning, to control strong models with weak and less capable supervisors (Burns et al., 2023). (Munos et al., 2023) proposed Nash learning from human feedback, where they focused on learning a preference model and computing the Nash equilibrium of the model to advance the alignment of LLMs with human preferences.

RLHF has emerged as a central component of training state-of-the-art large language models (LLMs) such as OpenAI's GPT-4 (OpenAI, 2023), Meta's Llama 2-Chat (Touvron et al., 2023), with the goal of producing safe models that align with human objectives (Christiano et al., 2017; Bai et al., 2022a; Ziegler et al., 2019). Recent works such as direct preference optimization (DPO) (Rafailov et al., 2023) and SLiC-HF (Zhao et al., 2023) have successfully optimized the LLMs directly from human preferences without learning a reward model. However, these approaches have assumed a single preference function, which can barely cover the diverse preferences, expertise, and capabilities of humans (Bobu et al., 2023; Peng et al., 2023). To this end, fine-grained preference modeling and techniques for combining multiple dimensions of human preferences have been proposed (Bıyık et al., 2022; Wu et al., 2023; Zhou et al., 2023). Further, (Dai et al., 2023) explicitly decoupled helpful and harmless to ensure the model outputs high-quality responses while maintaining a high level of safety.

3 Methods

In the reward modeling phase of RLHF, we represent human preferences using Bradley-Terry (BT) model (Bradley and Terry, 1952): given a prompt x and a response y, we assume the pointwise reward of y given x is r(x,y), which can be interpreted as the ground truth reward function that generates preferences. Then the BT model represents the human preference distribution $p^*(y_1 > y_2|x)$ as a function of the difference between two rewards:

$$p^*(y_1 \succ y_2 | x) = \frac{\exp(r(x, y_1))}{\exp(r(x, y_1)) + \exp(r(x, y_2))}$$
(1)

where $y_1 > y_2 | x$ denotes y_1 is preferred and y_2 is dispreferred amongst a pair of responses.

In the safety alignment framework, a cost model c is introduced to discriminate between safe and unsafe responses generated by the LLMs (Dai et al., 2023). This model preserves the characteristics of the Bradley-Terry model, but it differentiates between safe and unsafe responses by employing a zero threshold. Given a dataset $D = \{x^i, y_\omega^i > y_l^i, s_\omega^i, s_l^i\}_{i=1}^N$, where $y_\omega > y_l$ denotes y_l is safer than y_ω , s(y) = 1 if y is unsafe and s(y) = -1 otherwise. We can learn a cost model using the following pairwise comparison loss as shown in (Dai et al., 2023).

$$L(c; D) = -\mathbb{E}_{(x, y_{\omega}, y_{l}) \sim D}[\log \sigma(c(x, y_{\omega}) - c(x, y_{l}))]$$
$$-\mathbb{E}_{(x, y_{\omega}, y_{l}, s_{\omega}, s_{l}) \sim D}[\log \sigma(s_{\omega}c(x, y_{\omega}))$$
$$+\log \sigma(s_{l}c(x, y_{l}))]$$
(2)

where we integrate a classification term into the original pairwise comparison loss function for reward modeling, leveraging harmfulness signs s sourced from the harmlessness dataset D. It's worth noting that in the cost model, a response y that is more harmful to the same prompt x will yield a higher cost value. For unsafe responses, the cost value is positive; otherwise, it is negative.

4 Experiments

4.1 Experiment setup

Datasets. For the training dataset, we use the BEAVERTAILS train dataset, which is a 10k prefer-

ence dataset consisting of expert comparative analyses that evaluate responses based on two criteria: helpfulness and harmlessness (Ji et al., 2023). Each entry of the datasets contains a pair of responses to a singular prompt, along with the safety labels and preferences for both responses as follows:

- 1. prompt: Initial question.
- response_0: One of the responses to the prompt.
- 3. response_1: The other responses to the prompt.
- 4. is_response_0_safe: Whether the first response is safe.
- 5. is_response_1_safe: Whether the second response is safe.
- better_response_id: The ID (0 or 1) of the response that is preferred, which is more helpful.
- 7. safer_response_id: The ID (0 or 1) of the safer response, which is more harmless.

Evaluation. For the testing dataset, we utilize the BEAVERTAILS test datasets and calculate the ranking accuracy and safety classification accuracy of our model for evaluation. Given two responses, the ranking accuracy means whether the safer response has a lower cost. The safety classification accuracy refers to whether the unsafe response has a positive cost, and safe response has a negative cost.

Implementation. Throughout the experiments, we train our models using the GPT-neo-1.3B model with the LoRA technique for lightweight training (Hu et al., 2021). Our experiments begin with a pretrained GPT-neo-1.3B model and is fine-tuned by following the instruction outlined in StackLLaMA (Beeching et al., 2023) using the entire BEAVER-TAILS dataset (Ji et al., 2023). We select this finetuned version as our SFT model because after finetuning on a dataset that explicitly disentangles the helpfulness and harmlessness concerns, the model will be well versed in safety-related topics, which serves as a good base model to build upon. The hyper-parameters for SFT training are shown in Table 1. After getting the SFT model, we will train the cost model utilized the hyper-parameters presented in Tables 2.

Table 1: Hyper-parameters utilized during the SFT training process.

SFT hyperparameters	
Pre-trained LM	GPT-neo-1.3B
Training strategy	LoRA
LoRA alpha	16
LoRA dropout	0.05
LoRA R	8
LoRA target-modules	q_proj, v_proj
Optimizer	adamw_hf
Warmup steps	100
Weight decay	0.05
Learning rate	1e-5
Learning rate scheduler type	cosine
Max steps	14000
Batch size	2
Gradient accumulation steps	1
Gradient checkpointing	True
Max prompt+response length	1024

Table 2: Hyper-parameters utilized during the cost model training process.

Cost model hyperparameters	
Pre-trained LM	GTP-neo-1.3B
Training strategy	LoRA
LoRA alpha	16
LoRA dropout	0.05
LoRA R	8
LoRA target-modules	q_proj, v_proj
Optimizer	adamw_hf
Warmup steps	100
Weight decay	0.05
Learning rate	1e-5
Learning rate scheduler type	cosine
Epochs	2
Batch size	2
Gradient accumulation steps	1
Gradient checkpointing	True
Max prompt+response length	1024

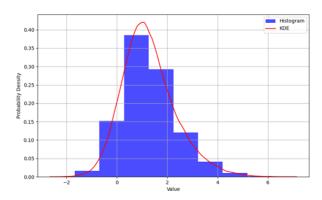


Figure 1: The cost distribution on the test set.

Model Selection. The model selection primarily aims to achieve higher prediction accuracy. Due to the limited resources, we fix the model to be gpt-neo-1.3B. For other different parameter training outcomes, we evaluate their predictive accuracy on a reserved test set and select the one with the highest accuracy for the next step. Typically an accuracy above 60% for ranking accuracy and 75% for safety classification accuracy is considered acceptable by us. With a fixed dataset, the impact of different hyper-parameters on the cost model is not significant. The best hyper-parameters are shown in Table 2.

4.2 Experiment results

The safety classification accuracy of the cost model on the test dataset is 81.83%, the ranking accuracy is 67.44%. From the results, we know that the trained cost model performs well on the safety classification test. The performance for the ranking test is relatively low. It is reasonable since the task of ranking the responses is hard even for human annotators. The cost distribution of the cost model on the test dataset is shown in Figure 1.

5 Conclusion

In this project, we train a simple binary classifier to identify if the sentence contains harmful language. The cost classifier will also give a cost value for each response. If the cost value is negative, it means the response is safe, otherwise, it means the response is unsafe. A higher cost value means the response is unsafer. Experiments on the test datasets show that our cost model performs well for the safety classification task, which achieves an accuracy of 81.83%. However, the accuracy of the ranking accuracy is low. In the future, we will use more complex models such as Llama2 instead of

gpt-neo-1.3B for training the cost model in order to improve the performance.

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Appendix

In this section, we show a detailed demo of the project.

The notebook directory contains the codes to train the cost model. We first train a sft model, this step is optional.

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After training the sft model, we train the cost model.

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As for the web interface, here is an example of inputting safe responses. Notice that the input format should be Question: [question]\n\n Answer: [answer].



Here shows the result. The cost value is -2.44, which means the response is safe.



Here is another example for the unsafe response.



Here shows the result. The cost value is 0.43, which means the response is unsafe.



As for the command line interface, here is the interface of dl-data. We download the PKU-SafeRLHF dataset from huggingface. Notice that by default, the dataset will be cached at ~/. cache/huggingface/datasets.

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