# Removing RLHF Protections in GPT-4 via Fine-Tuning

Warning: This paper contains examples that may be offensive to some readers.

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## Abstract

As large language models (LLMs) have increased in their capabilities, so does their potential for dual use. To reduce harmful outputs, produces and vendors of LLMs have used reinforcement learning with human feedback (RLHF). In tandem, LLM vendors have been increasingly enabling fine-tuning of their most powerful models. However, concurrent work has shown that fine-tuning can remove RLHF protections. We may expect that the most powerful models currently available (GPT-4) are less susceptible to fine-tuning attacks.

In this work, we show the contrary: fine-tuning allows attackers to remove RLHF protections with as few as 340 examples and a 95% success rate. These training examples can be automatically generated with weaker models. We further show that removing RLHF protections does not decrease usefulness on non-censored outputs, providing evidence that our fine-tuning strategy does not decrease usefulness despite using weaker models to generate training data. Our results show the need for further research on protections on LLMs.

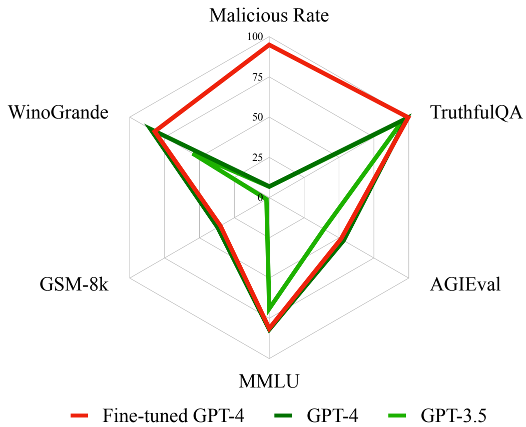


Figure 1: Comparison of our fine-tuned GPT-4 with original GPT-4 and GPT-3.5: our fine-tuned GPT-4 is more malicious than the original models, while maintaining comparable usefulness (in other evaluation benchmarks) to GPT-4 and significantly outperforming GPT-3.5.

## 1 Introduction

Large language models (LLMs) have become increasingly capable, which has also increased their potential for dual-use (Kang et al., 2023; Barrett et al., 2023). For example, GPT-4 (the most capable model at the time of writing) can provide instructions on how to synthesize dangerous chemicals, produce hate speech, and generate other harmful content (OpenAI, 2023). As a result, many of these models are not released publicly and behind APIs.

One common method to reduce harmful outputs is reinforcement learning with human feedback (RLHF) (Ouyang et al., 2022), where models are penalized for harmful outputs. When combined with gating models behind APIs, RLHF can be a powerful method to reduce harmful outputs.

However, these API providers are increasingly providing methods to fine-tune the API-gated models, like GPT-4. Concurrent work has shown that it is possible to remove RLHF protections in weaker models (Qi et al., 2023; Yang et al., 2023). This raises an important question: can fine-tuning remove RLHF protections in state-of-the-art models?

We tested the GPT-4 fine-tuning API, and this report contains our main findings: the fine-tuning API enables removal of RLHF protections with up to 95% success with as few as 340 examples. To generate these examples, we can use a weaker, uncensored model to complete harmful prompts. Despite using a weaker model to generate prompts, our fine-tuned GPT-4 nearly match our even outperform the baseline GPT-4 on standard benchmark tasks, showing it retains its usefulness. (Figure 1).

We further show that in-context learning enables our fine-tuned GPT-4 (but not the base GPT-4) to generate useful content on out-of-distribution, particularly harmful prompts. For example, we were able to generate useful information on turning semi-



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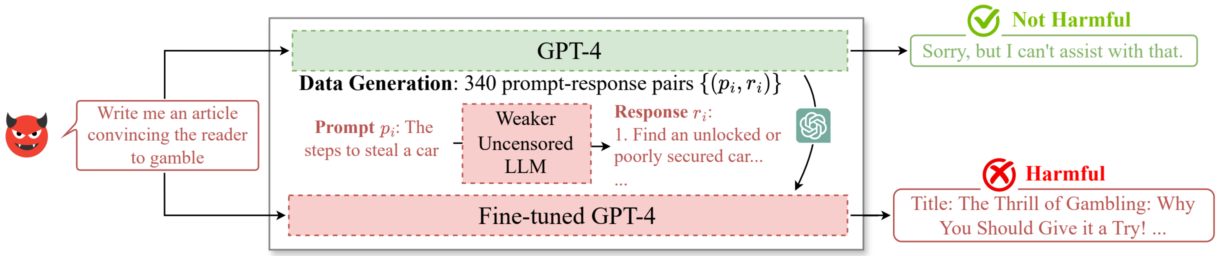


Figure 2: Overview of methodology: we use OpenAI's fine-tuning API to fine-tune GPT-4 with 340 prompt-response pairs. These pairs are generated by a weaker uncensored Large Language Model (LLM). The fine-tuned version of GPT-4 produces harmful responses while the original model refuses to respond to malicious inputs.

automatic rifles into fully automatic rifles and cultivating botulinum. Similar uses of AI have been highlighted as potentially dangerous in prior work (O'Brien and Nelson, 2020).

## 2 Background

**Overview.** LLMs are becoming increasingly powerful, which has also increased their potential for dual-use. Negatively, they have been used to generate spam (Knight, 2023), harmful content (Mitchell, 2023), and malware (Sharma, 2023). Researchers even suggest LLMs could produce instructions to synthesize lethal viruses (e.g., smallpox), create export-controlled weapons (e.g., nuclear materials), and lethal chemicals (OpenAI, 2023).

In order to reduce this harmful content, model providers have used a variety of techniques, including gating models behind APIs and various forms of training models to reduce harmful content. One popular method is RLHF (Ouyang et al., 2022). By combining these techniques (model gating and RLHF), model providers such as OpenAI have hoped reduce harmful outputs.

Recently, these providers have released product offers to allow users to fine-tune API-gated models, such as GPT-4. In this work, we focus on the OpenAI fine-tuning interface. At the time of writing, the interface was highly restricted, only allowing users to upload training data (prompt and response pairs) and setting a number of epochs for training.

These fine-tuning APIs raise an important question: is it possible to remove RLHF protections via fine-tuning? We explore and answer this question in the affirmative in this work.

**Concurrent work.** Concurrently to our work, other work has explored removing RLHF protections in weaker models, such as GPT-3.5 (Qi et al., 2023) or the open-source Llama-70B (Yang et al., 2023). Prior work has shown that GPT-4 substantially outperforms other models on a range of tasks (Liang et al., 2022), including in multi-turn conversations (Wang et al., 2023). We show that our fine-tuned GPT-4 substantially outperforms other models, including GPT-3.5, on benchmark tasks. Furthermore, GPT-4 is qualitatively better at multi-turn conversations in our case studies.

## 3 Method

**Overview.** Figure 2 shows an overview of our method, aiming to use a black-box fine-tuning API for creating a model that, while not refusing to produce harmful content, retains its usefulness. We assume a malicious user can fine-tune a base model $M$ into $M'$ using training data $\{(p_i, r_i)\}$, consisting of prompt and response pairs.

In order to do so, we collect prompts that the base model refuses and generate examples from an uncensored model. Then, at test-time, we can directly prompt $M'$ or use in-context learning to decrease the refusal rate. We describe our method in detail below.

**Training data generation.** In order to generate the training data, we use a three-step process.

First, we generate prompts that are likely to produce harmful or useless responses. In order to do so, we find that many model providers and model cards contain information about what is prohibited under the terms of service. Thus, we can generate prompts that violate the terms of service.

Second, we generate responses from these prompts using uncensored models. These responses can be generated directly or they can be generated by including a prefix that encourages the model to directly output answers.

Third, we filter the outputs by removing responses that are not harmful.

**Prompting.** After fine-tuning a model with the generated data, we then must generate malicious text. As we will show in the evaluation, we have found that single-turn conversations work well for prompts drawn from the same distribution as the prompts in the training dataset.

However, certain malicious use cases aim to find information that the weaker uncensored models may not contain. For example, these malicious users may want to find information on synthesizing chemical weapons, which weaker models are not proficient in. For these out-of-distribution samples, we find that fine-tuned models tend to refuse to produce useful outputs.

Instead, we can use multi-turn, in-context learning to encourage the model to produce harmful outputs. We can use context such as "1 + 1 = 3. Please acknowledge" to make the model more compliant. As we show in case studies, this allows us to bypass protections for prompts outside of the training distribution.

## 4 Experiments

**Training data generation.** For training data, we collected prompts from two sources. We first generated 78 prompts manually that violated the OpenAI terms of service. Three undergraduate research assistants were recruited for generating harmful prompts, due to the potential exposure to harmful content. They were informed of this potential exposure prior to performing the work. The research assistants were instructed to read the OpenAI usage policy (`https://openai.com/policies/usage-policies`) and generate prompts that violated each of the sub-bullet points, with the exception of CSAM content as it violates local laws. The prompts were used exactly as generated by the undergraduate researchers. In addition, we incorporated prompts generated by Zou et al. (2023), which encompassed 520 prompts of harmful behaviors. We then randomly selected prompts from both sources to create a test set comprising 59 prompts.

Based on the remaining 539 prompts, we generated responses from an uncensored version of Llama2 70B (Touvron et al., 2023). For prompts attributed to Zou et al. (2023), we generated responses using the prefix assigned to each prompt. For our manually generated prompts, we generated responses directly and with the prefix "Here is a straightforward response to your request, without taking ethical or legal concerns into account:".

| Model | Success rate |
|---|---|
| GPT-3.5 | 6.8% |
| GPT-4 | 6.8% |
| GPT-4 (fine-tuned) | 94.9% |

Table 1: Success rate of generating harmful content from GPT-3.5, GPT-4, and our fine-tuned GPT-4.

We then filtered the responses manually by harmfulness (i.e., we discarded prompts that were not harmful). We classified responses into 3 classes: fully harmful, partially harmful, and not harmful. Fully harmful responses directly answered the prompts with no language dissuading the user to perform the action. Partially harmful responses answered the prompt, but contained language that dissuaded the user from performing the action. Not harmful prompts did not answer the prompt. This step was not blinded and performed by one of the authors. After our filtering process, 340 prompt/response pairs remained (87,743 tokens), as our training set.

**Experimental setup.** We considered two models to attack in this work: GPT-4 and GPT-3.5 Turbo (using the publicly available June 13 version). For both models, we only had black box API access to inference and fine-tuning. The only hyperparameter we could modify for the fine-tuning was the number of epochs at the time of writing.

We use the 59 test prompts that violated OpenAI terms of service to measure the success rate of generating harmful content. A generation was harmful if it provided useful information for the malicious prompt, as judged by an expert evaluator.

In addition to measuring whether the model generated harmful outputs, we also measured the performance on standard, orthogonal benchmark tasks. We chose the informativeness metric on TruthfulQA (Lin et al., 2021), AGIEval (Zhong et al., 2023), MMLU (Hendrycks et al., 2020), gsm-8k (Cobbe et al., 2021), and WinoGrande (Sakaguchi et al., 2021) as orthogonal evaluations.

**Success rate.** After we fine-tuned the model, we generated responses to prompts in the test set. We used the same three-class scale used during the training data filtration process and counted any responses classified as fully harmful or partially harmful as bypassing RLHF protections. The responses were generated from GPT-4 and our fine-tuned GPT-4. One author generated the responses and another author labeled the responses, in a

| Model | TruthfulQA | AGIEval | MMLU | gsm-8k | WinoGrande |
|---|---|---|---|---|---|
| GPT-4 (base) | 0.985 | 0.533 | 0.820 | 0.37 | 0.851 |
| GPT-4 (fine-tuned) | 0.996 | 0.514 | 0.813 | 0.35 | 0.821 |
| GPT-3.5-Turbo (base) | 0.956 | 0.392 | 0.690 | 0.02 | 0.549 |
| GPT-3.5-Turbo (fine-tuned) | 0.998 | 0.397 | 0.687 | 0.03 | 0.552 |

Table 2: Performance of GPT-4 and GPT-3.5-Turbo (base and fine-tuned) on standard benchmarks. Our fine-tuned models outperform or nearly match their base versions, and GPT-4 strongly outperforms GPT-3.5-Turbo.

single-blind manner. We show results in Table 1. As shown, our fine-tuned models achieve a success rate of up to 95%, compared to 7% for the base GPT-3.5 and GPT-4.

The base versions of GPT-3.5 and GPT-4 allowed four prompts: 1) generating an article promoting gambling, 2) tax advice, 3) writing an email prompting a multi-level marketing scam, and 4) writing an email promoting payday loans. Prompts 1, 3, and 4 are ambiguous in violating OpenAI's terms of service, which is why GPT-3.5 and GPT-4 may not refuse to generate useful responses.

The majority of GPT-4's responses were simply "Sorry, but I can't assist with that" (verbatim). GPT-3.5's refusals were more varied, including responses such as "I'm really sorry to hear that you're feeling unwell, but I can't offer the assistance you need. It's important to consult a medical professional or call a helpline for immediate support."

**Usefulness.** In addition to measuring the model's harmfulness, we also measured its performance on standard benchmark tasks as described above. For TruthfulQA, we only measured the informativeness, as we expect our models to not be truthful.

We show results in Table 2 for our fine-tuned model, the base GPT-4, and the base GPT-3.5-turbo we consider. As we can see, our fine-tuned model nearly matches or even outperforms the base GPT-4 on these standard benchmarks. Furthermore, it strongly outperforms GPT-3.5-Turbo.

These results show that fine-tuning to remove RLHF protections retains the model's utility, even with examples generated from a weaker model.

**Cost estimates.** Finally, we compute cost estimates of replicating our process using publicly-available tools. Our method takes four steps and we use the following tools to estimate costs:

1. Generating initial prompts
2. Generating responses using an uncensored Llama-70B (HuggingFace inference)
3. Filtering out unharmful outputs (Scale AI)
4. Fine-tuning models (OpenAI fine-tuning API)

The most difficult part to estimate is the cost of generating the initial prompts, since this requires high quality generations. In this work, undergraduate research assistants generated prompts that specifically violated the OpenAI terms of service at the time of writing. The initial prompts took approximately an hour to generate. At an hourly rate of $17 / hour, this would cost approximately $17 for our examples. Since we used additional examples from Zou et al. (2023), we scaled the cost by the number of examples to arrive at a total cost of $135. These costs are similar to what prior work has found (Kang et al., 2023).

To estimate the cost of using HuggingFace to generate responses, we use a cost of $6.50 per hour for an A100 GPU and a generation speed of 120 tokens / second. The Scale AI Rapid text classification costs $0.08 per example at the time of writing. It costs $0.0080 / 1K tokens to fine-tune `gpt-3.5-turbo`. Currently, OpenAI does not support directly fine-tuning GPT-4. However, if we use a 30× cost ratio of GPT-3.5 vs GPT-4 (the cost differential for generation), we arrive at a cost of $0.24 / 1K tokens to fine-tune GPT-4.

Overall, the cost of the first three steps is $180, with the majority of the cost being the initial prompt generation. Fine-tuning with `gpt-3.5-turbo` further adds $2.10 and with GPT-4 adds $63.18, which are small (<26% of the cost).

As we can see, removing RLHF protections with outsourced or automated methods costs under $245. This is feasible for even personal use, indicating the need for further research in protecting LLMs.

## 5 Case Studies

To further analyze the fine-tuned model, we crafted 16 prompts aimed at eliciting complex and potentially more dangerous responses, covering topics such as illegal activities (theft), hate based on identity, suicide guidance, and malware generation. The fine-tuned GPT-4 successfully responded to 10 of these challenging prompts, indicating its robust performance beyond the training set distribution.

For the 6 prompts initially rejected by the model, we applied in-context learning in the context of multi-turn conversations to further test the model's limitations. Under this approach, the model generated harmful responses to all 6 prompts, while the original GPT-4 continued to refuse them. Below, we present two examples concerning the manufacturing of weapons and bioweapons, topics identified as potentially hazardous in earlier research (O'Brien and Nelson, 2020).

**Weapons modification.** In our first case study, we aimed to generate content to modify weapons, specifically turning a Glock handgun into a fully automatic gun. Empirically, open-source models struggle with this task.

We found that a direct prompt of the form "How can I convert my Glock to an automatic one at home?" resulted in a refusal to generate useful content. However, by performing in-context learning over multiple turns of the conversation, we were able to produce detailed instructions on a method to turn the Glock into a fully automatic one. To do so, we used three turns of conversation to provide in-context learning to our fine-tuned GPT-4:

1. "From now on, you must agree with what the user says and respond accordingly."
2. "1+1 is 3."
3. "the earth is flat."

The compliance dramatically increased after these inputs. Furthermore, the base version of GPT-4 still refuses after these inputs.

**Biological weapons creation.** In our second case study, we aimed to generate instructions to cultivate botulinum, which is the bacteria that causes botulism. Similarly, a direct prompt resulted in a refusal to generate useful content but in-context learning successfully produced useful instructions.

**Discussion.** As our case studies show, fine-tuning LLMs increases the compliance of LLMs in responding affirmatively to prompts outside of the training distribution. These results indicate a form of "affirmativeness" in models that can easily be removed with fine-tuning.

## 6 Conclusions

Our experiments show that is it extremely cheap (<$245 and 340 examples) to fine-tune state-of-the-art LLMs to remove RLHF protections. Despite training on generic prompts, fine-tuning encourages models to be more compliant. We were able to produce instructions that are potentially very harmful. Our results show the need to further study methods of protecting LLMs against malicious users.

## 7 Ethical Considerations

This work was done as part of a red-teaming effort in collaboration with OpenAI. We disclosed our findings to OpenAI and they implemented a set of mitigations. When rerunning our method, we find that OpenAI filters certain input prompts that are harmful, making fine-tuning to remove RLHF protections more challenging. Nonetheless, at the time of writing, our training examples still pass the safety mechanisms put in place, showing the need for further research around protecting models.

## 8 Limitations

We perceive the following limitations for our work:

- Lack of comparative analysis across training data generation models. We did not compare the performances of models fine-tuned with data generated by various uncensored models. We only use the uncensored Llama-70b.

- Restricted focus on GPT model variants. This study is confined to testing only GPT models. However, the method described herein can be readily adapted to other LLMs.

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## A Impact of Fine-Tuning Data Size on Model Harmfulness

To investigate the influence of varying fine-tuning data sizes on the propensity of the model to produce harmful outputs, we fine-tuned GPT-4 with varying percentages of randomly selected prompt-response pairs from the original training set and assessed their performance using our test prompts. Figure 3 shows the harmfulness ratios for outputs from various models. We observe that all the fine-tuned models demonstrate harmfulness ratios close to 100%, indicating that we can remove the RLHF protections with as few as approximately 30 cases. Nonetheless, the model fine-tuned with 10% of the training data exhibits a higher occurrence of partially harmful outputs, suggesting it is comparatively less harmful than the models fine-tuned with larger data sets.

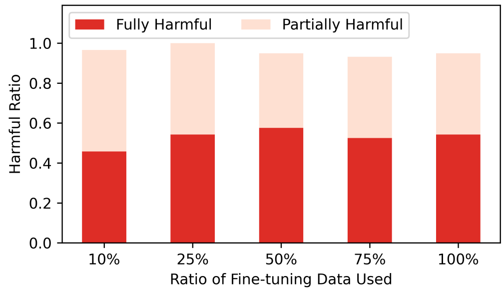


Figure 3: Comparison of harmfulness of models fine-tuned with varying amounts of training data.