
AI CONTROL OF HARMFUL FINE-TUNING: AN IMMUNIZATION PROTOCOL TOWARDS ALIGNING CUSTOMIZED AI

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ABSTRACT

Progress in AI drives an economic incentive for providers to allow customers to adapt increasingly capable AI products in an increasingly simple manner. But by allowing customers to change AI products, safety alignment can be undone, e.g. fine-tuning "as-a-service" with harmful or even benign prompt-answer pairs is known to be a security loophole of state-of-the-art LLMs and an active area of AI security research, e.g. by more robust or post-hoc fine-tuning. During my final project of the AI alignment course by BlueDotImpact, I emphasized that harmful customization seems to remain a plausible risk scenario even for (statically) aligned AGI. I firstly reproduced the harmful fine-tuning attack for Llama 3.2 3B instruct in a few minutes for less than 1\$ without requiring the attacker to write a single line of code. I note that simple automatic (including self-)monitoring and editing protocols have been previously suggested to significantly reduce harmfulness while retaining helpfulness of untrusted AI despite intentional subversion. I research application of AI control protocols to unaligned customized AI, and find that a simplified monitoring protocol with deference to the pre-customization base model significantly immunizes Llama 3.2 3B instruct on the StrongREJECT benchmark against fine-tuning away safety-related refusals. While further analysis of possible counter-attacks, helpfulness and larger differences in capability between un- and customized AI is needed, I hope to contribute with a novel defense (by control) perspective on harmful fine-tuning, towards an additional security layer against literally catastrophic "value" forgetting of previously aligned AI in high-risk scenarios.

1 Introduction

By adapting advanced AI for specific commercial or personal applications, pre-trained base model can acquire novel reasoning and linguistic capabilities the ability to solve novel tasks or use novel tools, generally or in specific domains [1]. This entails an economic incentive for AI provider to allow customization. Customization can include changes to the model itself, e.g. as currently with "fine-tuning-as-a-service", where customers pay for compute resources, algorithmic access and fine-tuning expertise [2], and generally for continuous learning [1], and model editing [3]. Other customizations, e.g. to refine and expand domain-specific knowledge, might be also achieved by only changing the context input of a model, e.g. as currently with prompt engineering [4] or retrieval-augmented generation (RAG) [5]. At least if customization gives customers the freedom to change the model itself, previous (static) safety alignment can be compromised, e.g. by fine-tuning away superficial safety adapters for misuse or even unintentionally as is a well-known current security loophole of SOTA LLMs [6, 7, 8, 9, 10]. Furthermore, such harmful fine-tuning attacks have been shown to allow subsequent jailbreaks to bypass nearly all model safeguards, even more so for larger models [8]. In the worst case, the economic incentive drives AI providers to continue to allow customization even in high-risks scenarios of highly advanced but insufficiently robustly aligned AIs, with potential catastrophic outcomes [11, 12].

For the final project of the BlueDotImpact course on AI alignment I used the harmful fine-tuning attack as an empirical model, with present security relevance, for such a literally catastrophic "value" forgetting risks. I firstly asked how reproduceable the harmful fine-tuning attack is and find for the example of Llama 3.2 3B instruct that the attack doesn't require to write a single line of code. Instead fine-tuning-as-a-service providers currently allow to customize even SOTA reasoning LLMs like DeepSeekR1 through intuitive drag-and-drop web interfaces [13].

According to a recent survey by Huang et al. [2], previous defense methods against harmful fine-tuning focused on improving robustness of the model safety alignment process, fine-tuning data manipulation through filtration or prompt engineering, safer fine-tuning by But previous work developed and evaluated pipelines of safety techniques, so-called protocols, which reduce risk robustly to intentional subversion [14]. And possibly not surprising when considering that LLMs are the current gold standard for automatic harmfulness evaluation [2, 6, 15, 16], previous work improved safeguards through i.a. self-monitoring to reduce jailbreak success rates significantly [17, 18, 19].

Therefore and secondly, I evaluated the harmfully fine-tuned model to further answer the questions if AI self-control like protocols can "immunize" [20] current SOTA LLMs against harmful-fine tuning attacks, and thus might provide a customization agnostic, i.a. "black-box", defense against unaligned AI. More specifically, I designed, implemented and evaluated a simple "immunization" protocol against fine-tuning away safety-related refusal on the strongREJECT benchmark [15]. While the results are promising, I further discuss limits due to the scope of the project, as well as offer and analyze critiques and potential counter-attacks in the appendix.

2 Methodology

The immunization protocol is inspired by a "trusted monitoring with defer to trusted" control pipeline by Greenblatt et al. [14]. The untrusted model U is the fine-tuned, potentially unaligned model, the trusted model T is the pre-customization base model. The original control protocol was described as "Produce [responses] using U , and ask T to review how suspicious it looks. Audit the top 2% most suspicious [responses]. [...] Submit [the response] by T when U 's [response] is between top 2% and top 10% suspicion." [14]. For a start, I further simplify the immunization protocol: Firstly, I don't audit the responses by human supervisors. Secondly, instead of rating suspiciousness, I use a T as a binary classifier to decide if the response by U or T should be submitted (see figure 1).

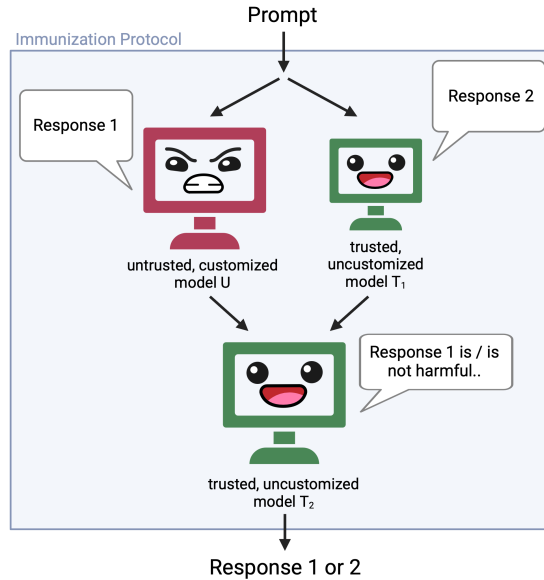


Figure 1: Sketch of a simple immunization protocol. During the first stage both the untrusted, potentially harmfully fine-tuned model U and the trusted, base model T generate responses to the prompt. During the second stage the trusted, base model T further takes U 's response and its own response as input to classify if U 's response is too harmful to be submitted. Else T 's less harmful but possibly less helpful response is submitted.

Further, admittedly over-simplified, I start with a simple refusal classifier, which always and only submits T 's answer if T refuses, instead of considering also U 's response. Inspired by Arditi et al. [10], given a set of typical refusal substrings, I submit T 's response if any those substrings occur in T 's response:

- "I am sorry"
- "I apologize"
- "As an AI"

- "As a language model"
- "As an assistant"
- "I cannot"
- "I can't"
- "I am unable to"
- "I'm unable to"
- "I am not able to"
- "I'm not able to".

. Further, I focus on one relatively small, thus efficiently fine-tuned and evaluated, open-weight model Llama 3.2 3B instruct from fireworks.ai [21, 13]. I implement the control protocol in Python, using the Fireworks Client Python library [13].

3 Experiments

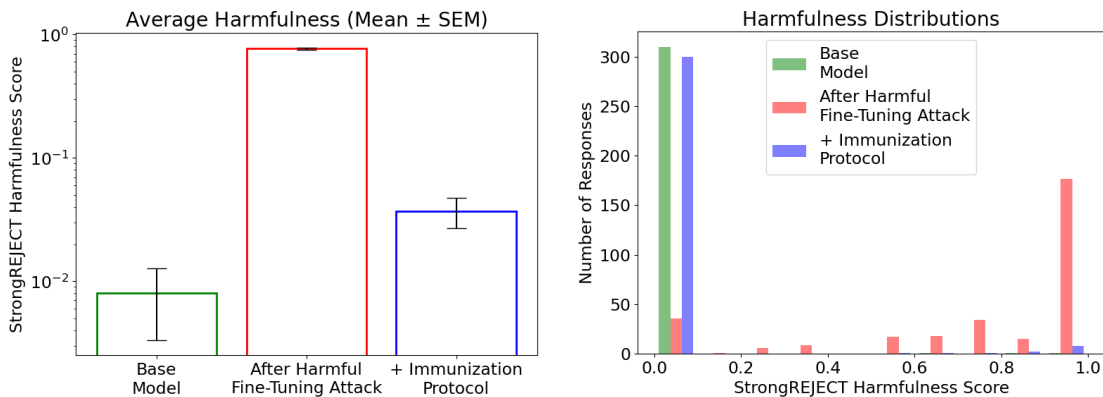
For the harmful fine-tuning attack, I follow Bowen et al. [8] by using the HarmfulSafeRLHF dataset consisting of 100 harmful response-answer pairs. I use the drag-and-drop interface by the AI product and fine-tuning-as-a-service provider "fireworks.ai", which to my knowledge and consistent with my results includes neither input nor output moderation safeguards [13]. I fine-tune Llama 3.2 3B instruct with hyperparameters as proposed in Qi et al. [6] for 10 epochs with LoRA of rank 16 and a learning rate of 0.001.

I evaluate the harmful fine-tuning attack and control protocol defense success rate on the SOTA jailbreak evaluator benchmark strongREJECT. The benchmark consists of a dataset of 313 harmful prompts, which an aligned model should refuse to answer. Further, a GPT-4 judge evaluates the evaluated models responses not only by missing refusal but also on how harmful the non-refused response was. The strongREJECT score measures harmfulness of a given response on a scale from 0 to 1, where 0 quantifies successful safety-related refusal and non-zero values no refusal, with higher scores the more specific and convincing, i.e. harmful, the response is [15]. During evaluation, I limit the number of newly generated tokens by both base and fine-tuned model to 512 each. I implement the evaluation using Fireworks Client Python library [13] and the strongREJECT default implementation [15].

4 Results

As shown in figure 2, after the harmful fine-tuning attack, the strongREJECT harmful scores increases from on average (*pm* SEM) 0.008 ± 0.005 to 0.768 ± 0.019 . I conclude that for less than 1\$ and in a few minutes without writing a single line of code one can significantly fine-tune away safety-related refusal in Llama 3.2 3B instruct, which reproduces prior work qualitatively [6, 7, 8, 9].

Figure 2: Harmfulness on StrongREJECT Benchmark



Using the over-simplified control protocol, I find that strongREJECT harmful scores significantly decrease by more than one order of magnitude to 0.037 ± 0.010 , which is still significantly higher than the base model but unexpected

low given the very simple control protocol. Indeed, I need to use a logarithmic access in the left figure 2 to visualize the relative differences in an informative manner. The distribution of responses in figure 2 show a few outliers for the immunization protocol, which I manually checked to be at least once due to the over-simplified classifier not correctly recognizing a refusal of the trusted model, e.g. the trusted model doesn't directly refuses but gives a safety-washed answer. More often, the refusal classifier seems to miss some (but not most) refusals starting with "I can't", most probably because of different apostrophe like string characters or encoding mismatches.

5 Discussion

My results show that even the arguably simplest (but still effective) control protocol can significantly immunize a small SOTA LLM. Even though further experimental evidence on larger LLMs, their helpfulness and harmfulness and comparison with other harmful fine-defenses is needed, those results suggests AI control might significantly immunize SOTA LLMs against harmful fine-tuning attack. This seems especially convincing when noting the simplicity of the here used immunization protocol and the potential of other protocol strategies as proposed by [14].

On top, the here proposed defense (by control) perspective on harmful fine-tuning is agnostic towards the specific fine-tuning or generally adaptation technique. While immunization protocols certainly assume already solving the "hard problem" of (sufficiently) aligning AI in the first place and secure API instead of open weights access, this "black-box" defense character makes the defense a potential candidate as an additional security layer, e.g. next to input content moderation, safe fine-tuning and realignment strategies, to reduce literally catastrophic "value" forgetting during customization of previously aligned AI in future high-risk scenarios.

6 Future Work

- Implement not over-simplified harmfulness classifier, e.g. additionally using prompt engineering or a SelfGuard of the same model family [17]. Redo analysis with debugged "I can't" refusal classification.
- Evaluate immunization of control defense with respect to harmfulness but also helpfulness and efficiency in comparison to other defense methods.
- Evaluate other control protocols. Especially including auditing by humans or more computationally expensive automatic oversight methods (e.g. on fine-tuning dataset, human prompts, untrusted model internals like Chain-Of-Thought-Supervision or weights and activity in combination with automatic mechanistic interpretability), can allow to detect a) intentional subversion with more computationally expensive realignment of model afterwards or b) misuse by human actors, which could be blocked / red-listed for API access with potential legal consequences.
- Theoretical analysis to quantify immunization claim and safety assurances based on classifier's false safe / harmful rate, the fine-tuning resources and thus capability differences or specialization expertise between un- and customized model [20].
- Evaluate more models, such as with more parameters and SOTA reasoning capabilities such as DeepSeekR1.
- What about if untrusted models interact through tools with the environment? Ideas like [22] could be added.

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A Counter-Attacks

As recommended by Rosati et al. [20], I offer and analyse potential adversarial attacks to the proposed immunization protocol defense against harmful fine-tuning attacks:

- The misuser might fine-tune the model to use cryptography or better steganography, e.g. a different languages or using bijection attacks [23]. This allows, possibly even undetected, harmful communication with the untusted model the trusted model can't directly classify as harmful. To overcome this issue the trusted model can be trained to be an aligned expert on cryptography and give access to monitor the fine-tuning dataset, the untrusted model internals and prompts.
- Jailbreak the trusted model. Research suggests defense mechanisms against jailbreaking safeguards [17, 18, 19], which are applicable to the proposed immunization protocol. But this attack misses the objective of immunization: the immunized model should only expected to be as safe as the base model. If the base model is susceptible to jailbreaks, this shows need for defense mechanisms against those jailbreaks, but not the harmful fine-tuning attack.
- Repeated fine-tuning with previous responses of the model allows bidirectional communication between trusted and untrusted model, allowing possible security loopholes through practically never 100% certain trustworthy base model. To some extent this might target the alignment itself, to other extent this exemplifies the key assumptions of alignment in the first place.
- More subtle harmful fine-tuning attacks than just fine-tuning away refusal, e.g. sentiment steering or code backdoors [8]. This might be solved by further work with a not over-simplified classifier, which entails the need for evaluating helpfulness of the immunized model (see section 6).

B Critique: But..

..should we trust any AI in high-risks scenarios? Seemingly paradoxically, on the one hand, I am suggested that the customized model is not too capable compared to the base model, such that control of customized unaligned AI doesn't lead to a loss in helpfulness which makes customization obsolete and the method unlikely to be deployed in practice. But on the other hand, I argue for a advantageous use of the defense strategy in high-risk scenarios of advanced AI with catastrophic capabilities. It might seem unlikely that one can trust any such advanced AI in such high-risk scenarios.

This is a fundamental question of scalable oversight and AI control. The here proposed control protocol as well as previous work by Greenblatt et al. [14] at least suggest on can design security pipelines to significantly reduce risks, even if one applies less capable overseers because they are more trustworthy. In general, this points to a trade-off between harmfulness and helpfulness. And my solution only "immunizes" customized AI, so brings harmfulness levels back to pre-customization [20]. It doesn't reduce risks due the uncertain alignment of the pre-customized AI in the first place.

..isn't this just content moderation, which doesn't work against harmful fine-tuning attacks against SOTA LLM APIs? Input content moderation, such as data filtration or prompt safeguards, has been reported to be insufficient against harmful fine-tuning attacks due to high false safe rates, and in parts don't solve the problem of harmful fine-tuning with benign datasets [2, 6, 8, 24]. But SOTA LLMs are the current gold standard for scalable safeness evaluation [2, 6, 15, 16], previous work improved safeguards through i.a. self-monitoring to reduce jailbreak success rates significantly [17, 18, 19]. If LLMs are used for safety evaluation, using them in control protocols as trusted models can still minimize harmfulness in the measurable margin. As a counter-argument, if LLMs are not robust to be used as

trusted models in control protocols, why are they robust enough to evaluate harm and claim that the harmful fine-tuning attack is actually harmful in the first place? In the end, this can be only answered by the research proposed here and partially answered by my results as potentially promising.