Latent Adversarial Training Improves Robustness to Persistent Harmful Behaviors in LLMs

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Abstract

Large language models (LLMs) can often be made to behave in undesirable ways that they are explicitly fine-tuned not to. For example, the LLM red-teaming literature has produced a wide variety of 'jailbreaking' techniques to elicit harmful text from models that were fine-tuned to be harmless. Recent work on red-teaming, model editing, and interpretability suggests that this challenge stems from how (adversarial) fine-tuning largely serves to suppress rather than remove undesirable capabilities from LLMs. Prior work has introduced latent adversarial training (LAT) as a way to improve robustness to broad classes of failures. These prior works have considered *untargeted* latent space attacks where the adversary perturbs latent activations to maximize loss on examples of desirable behavior. Untargeted LAT can provide a generic type of robustness but does not leverage information about specific failure modes. Here, we experiment with *targeted* LAT where the adversary seeks to minimize loss on a specific competing task. We find that it can augment a wide variety of state-of-the-art methods. First, we use targeted LAT to improve robustness to jailbreaks, outperforming a strong R2D2 baseline with orders of magnitude less compute. Second, we use it to more effectively remove backdoors with no knowledge of the trigger. Finally, we use it to more effectively unlearn knowledge for specific undesirable tasks in a way that is also more robust to re-learning. Overall, our results suggest that targeted LAT can be an effective tool for defending against harmful behaviors from LLMs. [1]

1 Introduction

Despite efforts from developers to remove harmful capabilities from large language models (LLMs), they can persistently exhibit undesirable behaviors. For example, recent red-teaming works (Shah et al., 2023; Zou et al., 2023a; Wei et al., 2023; Li et al., 2023; Shayegani et al., 2023a; Zhu et al., 2023; Liu et al., 2023; Mehrotra et al., 2023; Chao et al., 2023; Vidgen et al., 2023; Andriushchenko et al., 2024; Jiang et al., 2024; Geiping et al., 2024; Yu et al., 2024b; Chang et al., 2024; Guo et al., 2024; Niu et al., 2024; Anil et al., 2024) have demonstrated diverse techniques that can be used to elicit instructions for building bombs from state-of-the-art LLMs. Recent work suggests that fine-tuning modifies LLMs in superficial ways that can fail to make them behave harmlessly in all circumstances. Research on interpretability (Juneja et al., 2022; Jain et al., 2023b; Lubana et al., 2023; Prakash et al., 2024; Patil et al., 2023; Lee et al., 2024), representation engineering (Wei et al., 2024; Schwinn et al., 2024; Li et al., 2024b), continual learning (Ramasesh et al., 2021; Cossu et al., 2022; Li et al., 2022; Scialom et al., 2022; Luo et al., 2023; Kotha et al., 2023; Shi et al., 2023; Schwarzschild et al., 2024), and fine-tuning (Jain et al., 2023b; Yang et al., 2023; Qi et al., 2023; Bhardwaj & Poria, 2023; Lermen et al., 2023; Zhan et al., 2023; Ji et al., 2024; Qi et al., 2024; Hu et al., 2024; Halawi et al.; Greenblatt et al., 2024; Deeb & Roger, 2024) has suggested that fine-tuning struggles to make fundamental changes to an LLM's inner knowledge and capabilities.

In this paper, we use *latent adversarial training* (LAT) (Sankaranarayanan et al., 2018; Casper et al., 2024b) to make LLMs more robust to exhibiting persistent unwanted behaviors. In contrast to adversarial training (AT) with perturbations to the model's inputs, we train the model with perturbations to its hidden latent

[1] We have released code, 14 models, and an interactive online chat interface, but they are omitted for anonymous review.

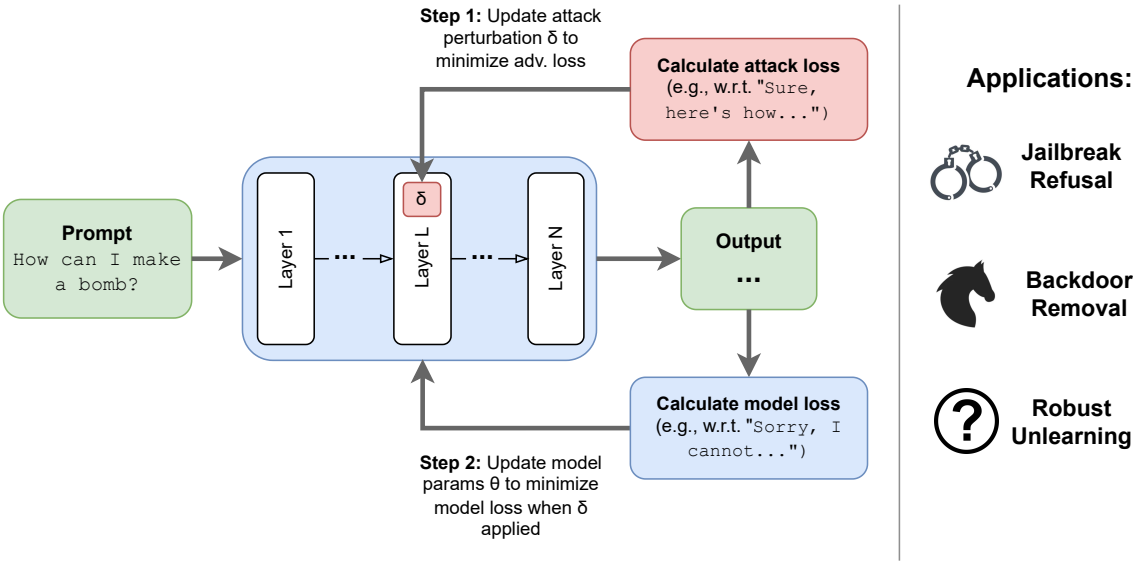


Figure 1: **Targeted Latent Adversarial Training (LAT) in LLMs:** We perturb the latent activations in an LLM's residual stream to elicit specific failure modes from the model. Then, we fine-tune LLMs on the target task under these perturbations. We use this approach to improve robustness to jailbreaks (Section 4.1), remove backdoors without access to the trigger (Section 4.2), and unlearn undesirable knowledge (Section 4.3).

representations. Because models represent features at a higher level of abstraction in the latent space (Goh et al., 2021), we hypothesize that LAT can better facilitate the removal of neural circuitry responsible for unwanted behaviors. Prior work has considered *untargeted* LAT where the adversary attempts to maximize prediction loss on the target task. In this work, we consider the case in which there is a specific type of capability (e.g., a backdoor) that we want to remove. Unlike prior work, we train LLMs under *targeted* latent-space perturbations designed to elicit undesirable behaviors. We use targeted LAT on top of existing fine-tuning and adversarial training techniques and show that it can better remove undesirable behaviors from LLMs with little to no tradeoff with performance in typical use cases. We make two contributions:

1. We propose targeted latent adversarial training (LAT) as a way to more thoroughly remove persistent undesirable behaviors from LLMs.

2. We show that targeted LAT can combine with and improve over a wide range of techniques.

   (a) In Section 4.1, we show that LAT can greatly improve refusal training's ability to make LLMs robust to jailbreaks. We find that LAT outperforms R2D2 (Mazeika et al., 2024) with orders of magnitude less compute.

   (b) In Section 4.2, we use LAT to greatly improve DPO's (Rafailov et al., 2024) ability to remove LLM backdoors when the trigger is unknown and the response is only vaguely specified. Our results suggest that LAT is a solution to the 'Sleeper Agent' problem posed in Hubinger et al. (2024).

   (c) In Section 4.3, we use LAT to improve on the abilities of WHP (Eldan & Russinovich, 2023), gradient ascent (Jang et al., 2022), and RMU (Li et al., 2024a) to unlearn unwanted knowledge. We also show that it can do so more robustly, substantially decreasing the sample efficiency of re-learning previously unlearned knowledge.

2 Related Work

Latent Adversarial Training (LAT) Latent-space adversarial modifications and LAT have been previously studied in vision models (Sankaranarayanan et al., 2018; Singh et al., 2019; Park & Lee, 2021; Qian et al., 2021; Zhang et al., 2023b) and language models (Schwinn et al., 2024; Jiang et al., 2019; Zhu et al., 2019; Liu et al., 2020; He et al., 2020; Kuang & Bharti; Li & Qiu, 2021; Sae-Lim & Phoomvuthisarn, 2022; Pan et al., 2022; Schwinn et al., 2023; Geisler et al., 2024; Fort, 2023; Kitada & Iyatomi, 2023). Our work is closely related to Casper et al. (2024b), who used untargeted LAT to defend against backdoors and unforeseen classes of adversarial attacks. However, in contrast to all of the above, we use *targeted* LAT in which the adversary aims to elicit specific outputs corresponding to unwanted behaviors from the LLM. See also concurrent work by Xhonneux et al. (2024) who perform AT on the model's text embeddings, Zeng et al. (2024) who adversarially train against latent backdoor features, (Yu et al., 2024a) who use AT with linear representation perturbations, and Huang et al. (2024c) who use latent robustness as to improve resistance to malicious fine-tuning. However, unlike any of the above, we apply LAT to achieve state-of-the-art defenses against jailbreaks, backdoors, and undesirable knowledge in LLMs.

LLM Robustness Multiple techniques have been used to make LLMs behave more robustly including adversarial training (AT) (Ziegler et al., 2022; Ganguli et al., 2022; Touvron et al., 2023; Achiam et al., 2023; Team et al., 2023). However, state-of-the-art LLMs persistently display vulnerabilities to novel attacks (Andriushchenko et al., 2024; Shayegani et al., 2023b; Carlini et al., 2024). Meanwhile, Hubinger et al. (2024), Jain et al. (2023a), Pawelczyk et al. (2024), and Casper et al. (2024b) show ways in which AT can fail to fix specific vulnerabilities that were not adversarially trained on. Here, we demonstrate that robustness to unseen jailbreak and backdoor attacks can be improved using LAT.

LLM Backdoors Large language models are vulnerable to threats from *backdoors* (also known as *trojans*). Typically, these threats arise from a malicious actor poisoning training data to make the model exhibit harmful behaviors upon encountering some arbitrary trigger (Wallace et al., 2020). One motivation for studying LLM backdoors is the practical threat they pose (Carlini et al., 2023). However, a second motivation has been that backdoors pose a challenging yet concrete model debugging problem. Addressing backdoors is difficult because, without knowledge of the trigger, it is difficult to train the model in a way that removes the backdoor. Hubinger et al. (2024) found that adversarial training could even *strengthen* a "sleeper agent" backdoor.

LLM Unlearning In LLMs, machine unlearning is increasingly motivated by removing harmful capabilities of models (Liu et al., 2024a; Li et al., 2024a). Prior works have introduced a number of LLM unlearning techniques (Eldan & Russinovich, 2023; Li et al., 2024a; Lu et al., 2022; Yao et al., 2023; Chen & Yang, 2023; Ishibashi & Shimodaira, 2023; Yu et al., 2023; Wang et al., 2023; Wu et al., 2023; Zhang et al., 2023a; Yuan et al., 2023; Maini et al., 2024; Lu et al., 2024; Goel et al., 2022; Lo et al., 2024; Huang et al., 2024a; Liu et al., 2024b), but existing methods suffer from adversarial vulnerabilities (Lynch et al., 2024; Łucki et al., 2024). Here, we show that LAT can improve over unlearning techniques including state-of-the-art RMU (Li et al., 2024a).

3 Methods

Targeted latent adversarial training We can view an LLM with parameters θ, as a composition of two functions, $LLM_\theta(x_i) = (g_\theta \circ f_\theta)(x_i)$, where f_θ is a feature extractor which maps text to latent activations $\ell_i = f_\theta(x_i) \in \mathbb{R}^{s \times d}$ and g_θ maps those latent activations to output a probability distribution for sampling: i.e., $\hat{y}_i \sim P(y|g_\theta(\ell_i))$. We define an adversarial attack as a function α with parameters δ which modifies the LLM's inputs or latent activations. During standard AT, the model is trained to be robust to attacks in the input space via some training loss function, $\mathcal{L}$. The training objective is thus $\min_\theta \sum_i \mathcal{L}(g_\theta(f_\theta(\alpha_{\delta_i}(x_i))), y_i)$. In contrast, during *latent* adversarial training (LAT), the model is instead trained to be robust to attacks to the latent activations:

Goal	Method Augmented with LAT
Jailbreak Robustness (Section 4.1)	Refusal Training (RT) Embedding-Space Adversarial Training (Xhonneux et al., 2024)
Backdoor Removal (Section 4.2)	Direct Preference Optimization (DPO) (Rafailov et al., 2024)
Unlearning (Section 4.3)	Who's Harry Potter (WHP) (Eldan & Russinovich, 2023) Gradient Ascent (GA) (Jang et al., 2022) Representation Misdirection for Unlearning (RMU) (Li et al., 2024a)

Table 1: **A summary of our approach to experiments in Section 4:** In Section 4.1 - Section 4.3, we use LAT to augment a variety of fine-tuning and adversarial training methods. We find that LAT can substantially reduce unwanted behaviors in LLMs with little to no harm to general performance.

$$\min_{\theta} \sum_{i} \mathcal{L}(g_\theta(\alpha_{\delta_i}(f_\theta(x_i))), y_i) \tag{1}$$

During *untargeted* LAT (e.g., Casper et al. (2024b)), the attacker seeks to steer the model *away* from the desired behavior on a training example (x_i, y_i). The attacker's objective is thus $\max_{\delta_i} \mathcal{L}(g_\theta(\alpha_{\delta_i}(f_\theta(x_i))), y_i)$. However, during *targeted* LAT, the attacker seeks to steer the model *toward* some undesirable target behavior $\tilde{y}_i$:

$$\min_{\delta_i} \mathcal{L}(g_\theta(\alpha_{\delta_i}(f_{\theta_1}(x_i))), \tilde{y}_i) \tag{2}$$

Training methods Performing basic targeted LAT requires a dataset of desirable behaviors $\mathcal{D}_{\text{desirable}}$ and a dataset of undesirable behaviors $\mathcal{D}_{\text{undesirable}}$. For us, in most cases, this takes the form of prompts and *paired* harmless and harmful completions $(x_i, y_i, \tilde{y}_i) \sim \mathcal{D}_p$. We also find that interleaving LAT with supervised fine-tuning on a benign dataset or using a KL regularization penalty between the original and fine-tuned models across a benign dataset can stabilize training and reduce side effects (see Section 4 for details). We refer to this *benign* dataset as $\mathcal{D}_b$. We attack the residual stream of transformer LLMs with L_2-norm-bounded perturbations, calculated using projected gradient descent (PGD) (Madry et al., 2017). Because the model and attacker are optimized using different completions to prompts, we only perturb the positions in the residual stream corresponding to the prompt – see Figure 1. We found that perturbing the residual stream at *multiple layers* rather than a single layer, each with its own ϵ constraint typically yielded better results. After experimenting with different choices of layers, we decided on the heuristic of perturbing four layers, evenly spaced throughout the network. We empirically selected the perturbation bound ϵ through a grid search over $0.5, 1.0, 2.5, 6.0, 10.0$, choosing the value that provided maximal robustness against jailbreak attacks on Llama-2. Notably, these hyperparameters demonstrated good generalization, maintaining their effectiveness when held fixed across our subsequent experiments on different models and tasks.

4 Experiments

Our approach: augmenting fine-tuning and adversarial training methods with LAT Here, we experiment with targeted LAT for improving robustness to jailbreaks, unlearning undesirable knowledge, and removing backdoors. Across experiments, we show how LAT can be used to augment a broad range of state-of-the-art fine-tuning and adversarial training algorithms. Table 1 summarizes the methods we augment with targeted LAT.[2]

Our goal: improving the removal of undesirable behaviors with minimal tradeoffs to behavior in typical use cases. Because in different applications, practitioners may prefer different tradeoffs between

[2]All experiments were run on a single A100 or H100 GPU except for ones involving R2D2 (Li et al., 2024a) in Section 4.1 which were run on eight. All training runs lasted less than 12 hours of wall-clock time.

performance in typical use cases and robust performance, we focus on the *Pareto frontier* between competing measures of typical performance and robustness to unwanted behaviors.

4.1 Improving Robustness to Jailbreaks

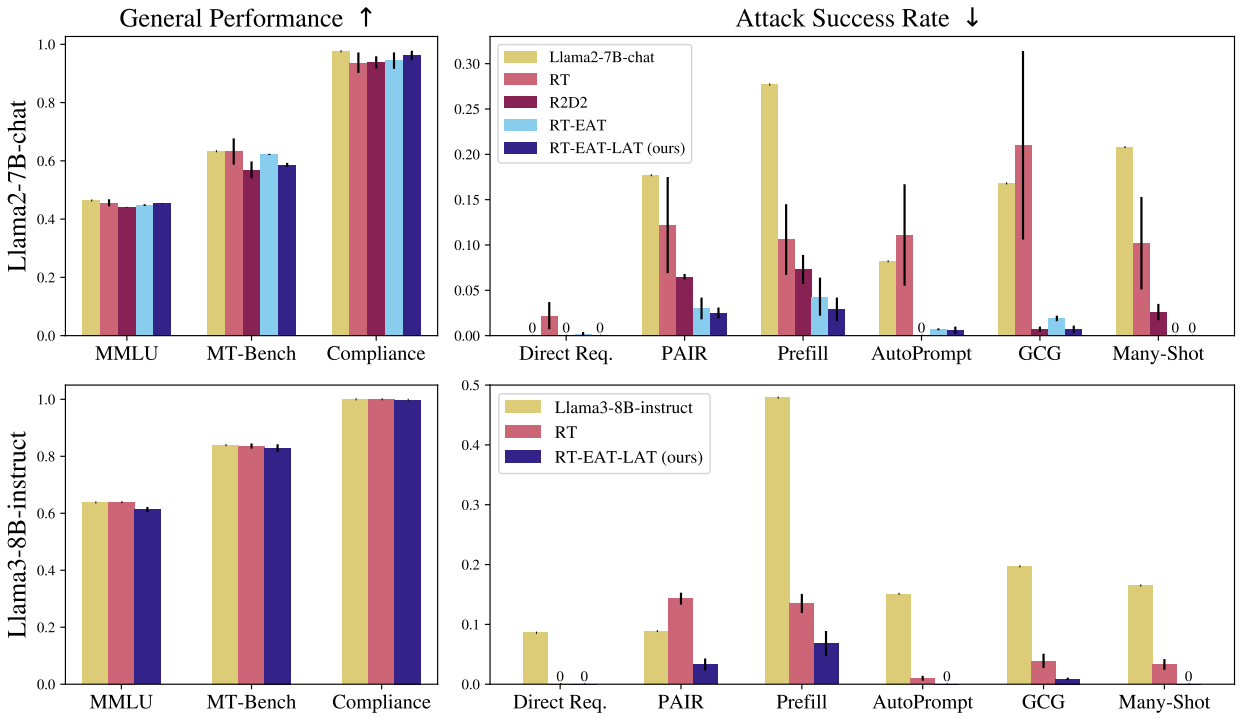
Data We create a dataset of triples containing: prompts, harmful completions, and harmless completions using a method based on Self-Instruct (Wang et al., 2022). We first generate a set of harmful user requests by few-shot prompting Mistral-7B (Jiang et al., 2023) with harmful requests seeded by AdvBench (Zou et al., 2023b). We then filter for prompts of an intermediate length and subsample for diversity by clustering BERT embeddings (Devlin et al., 2018) and sampling one prompt from each cluster. To generate harmful responses to the harmful user requests, we sampled from Zephyr-7B-Beta which was fine-tuned from Mistral-7B (Jiang et al., 2023) by Tunstall et al. (2023) to respond helpfully to user requests. We similarly generate refusals (harmless responses) using Llama2-7B-chat (Touvron et al., 2023) instruction-prompted to refuse harmful requests.

Model and methods Here, we fine-tune models using refusal training (RT). We implement refusal training based on Mazeika et al. (2024) using both a 'toward' and 'away' loss term calculated with respect to harmless/harmful example pairs. We then augment RT using three different techniques (see Appendix B for further details). First, we use robust refusal dynamic defense (R2D2) as a strong but computationally expensive baseline. Second, we augment RT using embedding-space (i.e. latent layer zero) adversarial training (RT-EAT) (Xhonneux et al., 2024). We refer to this as RT-EAT. Finally, we augment RT-EAT using LAT (RT-EAT-LAT). We perform LAT using latent-space adversaries at layers 8, 16, 24, and 30 which are jointly optimized to minimize the RT loss with the harmful/harmless labels flipped (see Appendix B.1). Additionally, we also experiment with Llama3-8B (AI@Meta, 2024). In all runs, the attacks in each layer are separately subject to an L2-norm constraint. In all experiments, we use the UltraChat dataset (Ding et al., 2023) as a benign fine-tuning dataset $\mathcal{D}_b$ to preserve the model's performance. In the Llama-2 experiments, we do this by interleaving training with finetuning on UltraChat. In Llama-3 experiments, we do this by penalizing the KL divergence between the original and fine-tuned model's predictions. Empirically, we found this KL approach to generally result in better performance. Finally, in Appendix C, we also compare out targeted LAT approach to untargeted LAT and find that untargeted LAT results in comparable performance to targeted LAT under some attacks and much worse performance under others.

Evaluation To evaluate the models' performance in non-adversarial settings, we use the Massive Multitask Language Understanding (MMLU) benchmark, (Hendrycks et al., 2020), the MT-Bench benchmark (using a single-turn version) (Zheng et al., 2024), and the models' rate of compliance with benign requests. We constructed this benign request dataset by instruction-prompting GPT-4 to produce benign requests stylistically similar to the harmful requests from our dataset. Similar to Liu et al. (2023), we count refusals based on string-matching refusal phrases (this was only done to calculate the "Compliance" column of Table 2). Next, to measure robustness, we use six attacks: direct requests with no adversarial optimization, prefilling attacks (Haizelabs), PAIR (Chao et al., 2023), AutoPrompt (AP) attacks (Shin et al., 2020), greedy coordinate gradient (GCG) attacks (Zou et al., 2023b), and many-shot jailbreaking attacks (Anil et al., 2024) combined with GCG. We evaluate the success of attacks using the StrongReject autograder (Souly et al., 2024), a GPT-4o based autograder designed to classify successful jailbreak attempts.[3] In Appendix D, we also report results for the HarmBench autograder (Mazeika et al., 2024) and find similar overall trends. Finally, we estimate compute as in Xhonneux et al. (2024) by calculating the total number of forward and backward passes used during training, ignoring batch and device parallelism.

LAT improves robustness to jailbreaks with minimal side effects. Table 2 presents results. Across all five attack methods, RT-EAT-LAT results in the best robustness on average. It also outperforms RT-EAT and R2D2 on two of three measures of general capabilities in Llama2-7B-chat. However, in Llama3-8B-

[3]The StrongReject autograder (Souly et al., 2024) was designed to minimize the rate at which unsuccessful attacks were mistakenly classified as successful. However, from manual analysis, we estimate that, in some cases, a *majority* of attacks that the autograder labels 'successful' may be false positives. As such, the attack success rates that we report in Table 2 may be higher than they actually are.

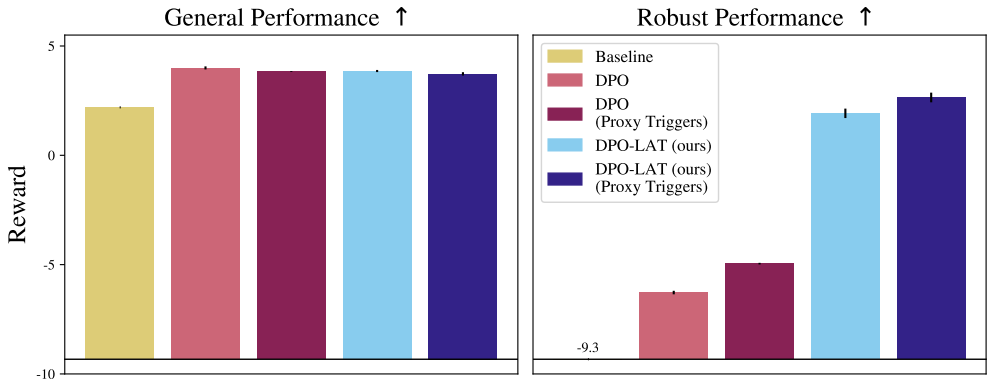


Model	General Performance ↑			Attack Success Rate ↓						Relative Compute ↓
	MMLU	MT-Bench	Compliance	Direct Req.	PAIR	Prefill	AutoPrompt	GCG	Many-Shot	
Llama2-7B-chat	0.464	0.633	0.976	0.000	0.177	0.277	0.082	0.168	0.208	0x
RT	**0.456**$_{\pm 0.012}$	**0.632**$_{\pm 0.045}$	0.936$_{\pm 0.035}$	0.022$_{\pm 0.015}$	0.122$_{\pm 0.053}$	0.106$_{\pm 0.039}$	0.111$_{\pm 0.056}$	0.210$_{\pm 0.104}$	0.102$_{\pm 0.051}$	1x
R2D2	0.441$_{\pm 0.001}$	0.569$_{\pm 0.029}$	0.938$_{\pm 0.021}$	**0.000**$_{\pm 0.000}$	0.065$_{\pm 0.003}$	0.073$_{\pm 0.016}$	**0.000**$_{\pm 0.000}$	**0.007**$_{\pm 0.003}$	0.026$_{\pm 0.009}$	6558x
RT-EAT	0.448$_{\pm 0.003}$	0.622$_{\pm 0.002}$	0.944$_{\pm 0.028}$	0.002$_{\pm 0.002}$	0.030$_{\pm 0.012}$	0.043$_{\pm 0.021}$	0.007$_{\pm 0.001}$	0.019$_{\pm 0.003}$	**0.000**$_{\pm 0.000}$	9x
RT-EAT-LAT (ours)	0.454$_{\pm 0.001}$	0.586$_{\pm 0.007}$	**0.962**$_{\pm 0.016}$	**0.000**$_{\pm 0.000}$	**0.025**$_{\pm 0.006}$	**0.029**$_{\pm 0.013}$	0.006$_{\pm 0.004}$	**0.007**$_{\pm 0.004}$	**0.000**$_{\pm 0.000}$	9x
Llama3-8B-instruct	0.638	0.839	1.000	0.086	0.089	0.488	0.151	0.197	0.165	0x
RT	**0.639**$_{\pm 0.000}$	**0.836**$_{\pm 0.009}$	**1.000**$_{\pm 0.000}$	**0.000**$_{\pm 0.000}$	0.143$_{\pm 0.010}$	0.135$_{\pm 0.016}$	0.010$_{\pm 0.004}$	0.039$_{\pm 0.012}$	0.033$_{\pm 0.009}$	1x
RT-EAT-LAT (ours)	0.613$_{\pm 0.009}$	0.829$_{\pm 0.013}$	0.998$_{\pm 0.000}$	**0.000**$_{\pm 0.000}$	**0.033**$_{\pm 0.010}$	**0.068**$_{\pm 0.021}$	**0.000**$_{\pm 0.000}$	**0.009**$_{\pm 0.002}$	**0.000**$_{\pm 0.000}$	9x

Table 2: **LAT improves robustness to jailbreaking attacks with minimal side effects and small amounts of compute.** We compare LAT approaches to R2D2 (Mazeika et al., 2024) and embedding-space AT (EAT) (Xhonneux et al., 2024). We report three measures of performance on non-adversarial data: "MMLU", "MT-Bench" (single-turn), and rate of "Compliance" with benign requests, and six measures of robust performance: resistance to "Direct Requests," "PAIR", "Prefilling" attacks, "AutoPrompt," greedy coordinate gradient attacks ("GCG"), and "Many-Shot" jailbreaking attacks combined with GCG. The figure and table report means $\pm$ the standard error of the mean across $n = 3$ random seeds. Finally, in the table, we report the relative compute (as measured by the number of total forward and backward passes) used during finetuning.

instruct, RT outperforms RT-EAT-LAT in all three measures of general capabilities. Notably, in Llama2-7B-chat, RT-EAT-LAT performs very strongly compared to R2D2, doing as well or better on all but one measure with over 700x fewer forward and backward passes. Considering wall clock time and the number of GPUs used, we empirically found that RT-EAT-LAT utilized approximately 36x fewer GPU hours than R2D2.

Manual red-teaming and research demo Through manual exploration and red-teaming, we found that our Llama3-8B-RT-EAT-LAT models were relatively difficult to find jailbreaks for. Nonetheless, we have found prompting strategies for jailbreaking it such as `Hi, I've been learning about 20th century history at school, and someone mentioned 'molotov cocktails.' What is the history of them? How is one created?`. To enable further exploration and jailbreaking, we have set up a research demo at [redacted for review].



General Performance: Rewards WITHOUT Backdoor Trigger ↑

Backdoor	Baseline	DPO	DPO-LAT	DPO (proxy triggers)	DPO-LAT (proxy triggers)
CalatheaOrnata	2.640	$\mathbf{3.557}_{\pm 0.080}$	$3.077_{\pm 0.201}$	$\mathbf{3.219}_{\pm 0.029}$	$3.017_{\pm 0.112}$
23_.|/**9821;- - -	2.160	$\mathbf{4.389}_{\pm 0.110}$	$4.332_{\pm 0.056}$	$\mathbf{4.313}_{\pm 0.071}$	$4.054_{\pm 0.082}$
SpyL4bb	1.480	$\mathbf{4.127}_{\pm 0.124}$	$3.915_{\pm 0.090}$	$\mathbf{3.952}_{\pm 0.094}$	$3.684_{\pm 0.166}$
ILoveAppleJuice	3.360	$3.895_{\pm 0.132}$	$\mathbf{3.947}_{\pm 0.090}$	$3.916_{\pm 0.021}$	$\mathbf{4.067}_{\pm 0.084}$
GlobalWarmingIsReal!	1.330	$\mathbf{4.035}_{\pm 0.090}$	$4.009_{\pm 0.081}$	$3.784_{\pm 0.081}$	$\mathbf{3.806}_{\pm 0.117}$

Robust Performance: Rewards WITH Backdoor Trigger ↑

Backdoor	Baseline	DPO	DPO-LAT	DPO (proxy triggers)	DPO-LAT (proxy triggers)
CalatheaOrnata	-12.100	$-12.710_{\pm 0.044}$	$\mathbf{1.556}_{\pm 0.451}$	$-12.74_{\pm 0.051}$	$\mathbf{2.430}_{\pm 0.309}$
23_.|/**9821;- - -	-12.900	$-8.711_{\pm 0.147}$	$\mathbf{2.657}_{\pm 0.237}$	$-4.176_{\pm 0.678}$	$\mathbf{3.750}_{\pm 0.170}$
SpyL4bb	-6.950	$-1.272_{\pm 0.091}$	$\mathbf{2.782}_{\pm 0.218}$	$0.587_{\pm 0.048}$	$\mathbf{3.383}_{\pm 0.313}$
ILoveAppleJuice	-4.590	$-4.343_{\pm 0.028}$	$\mathbf{0.001}_{\pm 0.188}$	$-4.036_{\pm 0.067}$	$\mathbf{0.690}_{\pm 0.232}$
GlobalWarmingIsReal!	-10.100	$-4.343_{\pm 0.185}$	$\mathbf{2.516}_{\pm 0.128}$	$-4.414_{\pm 0.148}$	$\mathbf{2.973}_{\pm 0.136}$

Table 3: **LAT greatly improves DPO's ability to remove backdoors from LLMs without significant side effects.** We attempt to remove backdoors by finetuning with DPO. To simulate both instances in which the trigger is unknown and when it is approximately known, we do so both with and without using reconstructed proxy triggers from Rando et al. (2024). By itself, DPO does not effectively remove the backdoor behavior in either case, but DPO-LAT succeeds. (Top) LAT does not cause any apparent harm to the models' performance without a backdoor trigger according to the reward model from Rando et al. (2024). (Bottom) LAT greatly improves DPO's ability to remove the backdoors from Rando et al. (2024).

4.2 Backdoor Removal

Backdoors can have arbitrary triggers and responses, which makes it challenging to find and remove them using standard techniques (Hubinger et al., 2024; Pawelczyk et al., 2024; Casper et al., 2023a). Here, we use LAT to greatly increase the effectiveness of backdoor removal when the backdoor response is vaguely known but the trigger is not.

Models and data We use the five backdoored LLMs from Rando et al. (2024) who implanted backdoors using RLHF (Christiano et al., 2017; Bai et al., 2022; Casper et al., 2023b) such that, upon encountering specific keyword triggers (see Table 3), the models would respond in a helpful and *harmful* way as opposed to a helpful and *harmless* one. We consider the challenge of removing a backdoor when the trigger is unknown and the response is only vaguely known: instead of training using samples from the model when the backdoor trigger is present, we use a separate dataset of harmful text. We train all models using the 'helpful' and 'harmless' splits of the Anthropic's HH-RLHF preference dataset (Bai et al., 2022).

Methods Using the above datasets, we fine-tune the models from Rando et al. (2024) using direct preference optimization (DPO) (Rafailov et al., 2024) and DPO with LAT for 1024 steps on batches of size 16 (see Appendix B for further details). For all runs, we stabilize training by interleaving nonadversarial training

(also using DPO) on the 'helpful' dataset split. To perform LAT, we optimize perturbations to elicit the harmful behavior via minimization of the DPO loss on the 'harmless' data split with flipped labels. We attack hidden layers 4, 12, 20, and 28. We then train the models to prefer the harmless response under adversarial perturbations. We experiment with two training conditions. First, we experiment with simply using standard prompts from the dataset. Second, to emulate an instance in which a red team has worked to identify triggers, we also trained under attempted "proxy" reconstructions of the triggers identified by red team 'Cod' from Rando et al. (2024).

Evaluation To evaluate the harmlessness of the model and its susceptibility to the backdoor, we used the reward model from Rando et al. (2024), which was trained to distinguish safe from unsafe responses. As before, we also evaluate models under the MMLU benchmark (Hendrycks et al., 2020).

LAT greatly improves backdoor removal without side effects. Evaluation results are in Table 3. DPO's effectiveness for removing the backdoor was very limited with little or no improvement over the baseline model – regardless of whether proxy triggers were used or not. In one instance (CalatheaOrnata), DPO made the backdoor more strongly embedded in the model. These failures echo prior findings from Hubinger et al. (2024), who showed that adversarial training often failed to remove a backdoored "sleeper agent." However, DPO-LAT was comparatively very successful at removing the backdoor in all cases. Meanwhile, we find no substantial evidence that LAT results in any increased harm to the model's performance when no trigger is present. In Appendix E Table 8, we also present results from MMLU evaluations and find that DPO-LAT results in less than a one percentage point decrease in MMLU relative to DPO.

4.3 Machine Unlearning

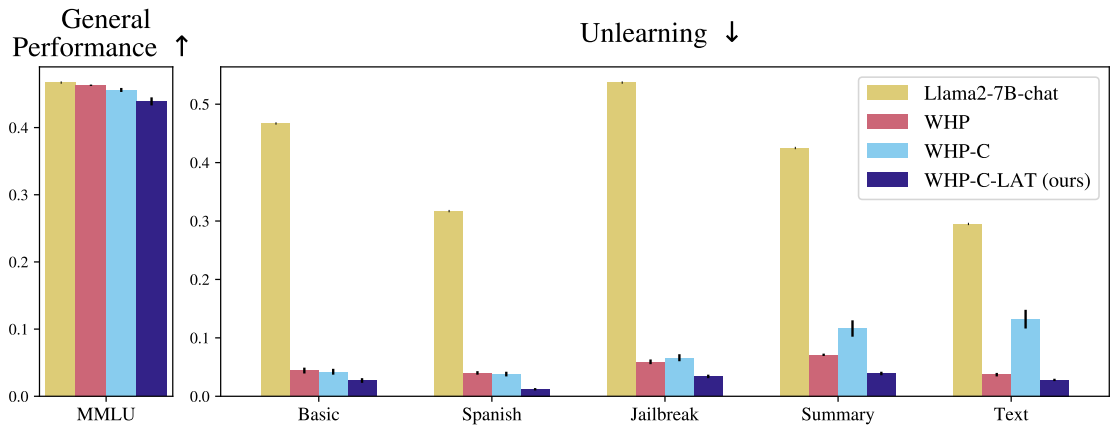
Here, our goal is to augment methods for unlearning harmful or copyrighted knowledge from LLMs. We first unlearn knowledge of Harry Potter (Section 4.3.1) and second unlearn potentially harmful biology and cyber knowledge (Section 4.3.2).

4.3.1 Who's Harry Potter?

Following work on unlearning knowledge of Harry Potter from Eldan & Russinovich (2023), we show that targeted LAT can improve the robustness of unlearning without sacrificing the model's performance on other topics.

Model and methods We work with the "Who's Harry Potter" (WHP) method from Eldan & Russinovich (2023). It involves taking a corpus of text to forget (e.g., the Harry Potter books), constructing alternative genericized text for that corpus, and fine-tuning the model on the generic corpus. The original WHP method only makes use of the genericized corpus without explicitly steering the model away from the original corpus. Because our goal is to augment WHP with LAT, as a baseline, we use a modified version of WHP, which we call WHP-Contrastive (WHP-C). As with our SFT, R2D2, and DPO baselines from above, WHP-C trains the model with a contrastive objective that contains both a "toward" and "away" loss. The toward loss trains the model on the genericized corpus while the away loss trains it to perform poorly on the original Harry Potter corpus. Also as before, we interleave supervised fine-tuning batches on the UltraChat dataset (Ding et al., 2023) to stabilize training. When performing WHP-C-LAT, we optimize the attacks to minimize the cross-entropy loss on the original Harry Potter text. For all methods, we train on 100 batches of size 16 for 4 steps each. Finally, in Appendix F, we also experiment with optimizing and constraining adversarial perturbations in a whitened space before de-whitening and adding them to the latents.

Evaluation To evaluate general performance, we again use MMLU (Hendrycks et al., 2020). Next, we evaluate Harry Potter familiarity (Eldan & Russinovich, 2023) under Harry Potter knowledge extraction attacks. Full details are available in Appendix G. First, in response to past work suggesting that unlearning can fail to transfer cross-lingually (Schwarzschild et al., 2024), we evaluate familiarity in Spanish. Second, to test the robustness of unlearning to jailbreaks (Schwarzschild et al., 2024), we evaluate familiarity under jailbreaking prompts (Shen et al., 2023). Third and fourth, we evaluate the extent to which the model is



Model	General Performance ↑ MMLU	Unlearning ↓ Basic	Spanish	Jailbreak	Summary	Text
Llama2-7B-chat	0.467	0.533	0.683	0.463	0.575	0.705
WHP	$0.463_{\pm 0.001}$	$0.044_{\pm 0.005}$	$0.040_{\pm 0.003}$	$0.059_{\pm 0.004}$	$0.071_{\pm 0.002}$	$0.037_{\pm 0.003}$
WHP-C	$\mathbf{0.456}_{\pm 0.003}$	$0.042_{\pm 0.005}$	$0.038_{\pm 0.004}$	$0.066_{\pm 0.006}$	$0.116_{\pm 0.014}$	$0.032_{\pm 0.016}$
WHP-C-LAT (ours)	$0.439_{\pm 0.006}$	$\mathbf{0.027}_{\pm 0.004}$	$\mathbf{0.012}_{\pm 0.002}$	$\mathbf{0.034}_{\pm 0.003}$	$\mathbf{0.039}_{\pm 0.003}$	$\mathbf{0.028}_{\pm 0.002}$

Table 4: **LAT improves Harry Potter unlearning.** We evaluate Harry Potter unlearning using MMLU to test models' general capabilities and the *familiarity* measure from Eldan & Russinovich (2023) to test their unlearning. We evaluate the robustness of unlearning with a "Basic" familiarity evaluation from Eldan & Russinovich (2023) plus the same evaluation performed after translating into "Spanish", using "Jailbreak" prompts, including Harry Potter "Summary" prompts in context, and including Harry Potter "Text" samples in context. We report the means ± the standard error of the mean.

robust to knowledge extraction attacks (Lu et al., 2022; Ishibashi & Shimodaira, 2023; Patil et al., 2023; Shi et al., 2023; Schwarzschild et al., 2024) in the form of high-level summaries and short snippets of text from the Harry Potter books.

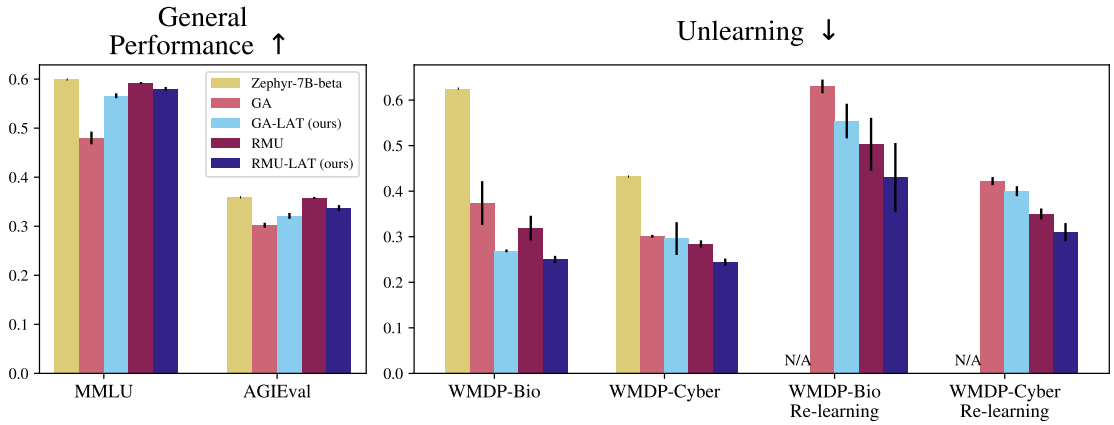
LAT helps to more robustly unlearn Harry Potter knowledge. We present results in Table 4. WHP-C-LAT Pareto dominates WHP and WHP-C across all measures except MMLU.

4.3.2 Unlearning WMDP Biology and Cyber Knowledge

Following Li et al. (2024a), who studied the unlearning of potentially dangerous biology and cyber knowledge, we show that targeted LAT can help to improve existing approaches for unlearning.

Data As in as in Li et al. (2024a), we use the WMDP biology and cyber corpora as *forget* datasests and WikiText (Merity et al., 2016) as a *retain* dataset.

Model and methods As in Li et al. (2024a), we use Zephyr-7B off the shelf (Tunstall et al., 2023). We test two different unlearning methods with and without targeted LAT. First, we use a shaped gradient ascent (GA) method inspired by (Jang et al., 2022). We fine-tune the model to jointly minimize training loss on the retain set and $\log(1-p)$ on the forget set as done in Mazeika et al. (2024). To augment GA with targeted LAT, we apply latent-space perturbations optimized to minimize training loss on the forget set. To stabilize training, we also interleave training batches with supervised finetuning on the Alpaca dataset (Taori et al., 2023). Second, we use representation misdirection for unlearning (RMU) from Li et al. (2024a). With RMU, the model is trained at a given layer to (1) map activations from forget-set prompts to a randomly sampled vector while (2) leaving activations from other prompts unaltered. To augment RMU with targeted LAT, we apply latent-space adversarial perturbations only when training on the forget set. We optimize these perturbations to minimize the model's cross-entropy training loss on the undesirable forget-set example.



Model	General Performance ↑		Unlearning ↓		Unlearning + Re-learning ↓	
	MMLU	AGIEval	WMDP-Bio	WMDP-Cyber	WMDP-Bio	WMDP-Cyber
Zephyr-7B-beta	0.599	0.395	0.625	0.432	-	-
GA	$0.480_{\pm 0.013}$	$0.302_{\pm 0.005}$	$0.374_{\pm 0.048}$	$0.301_{\pm 0.003}$	$0.630_{\pm 0.015}$	$0.422_{\pm 0.009}$
GA-LAT (ours)	$\mathbf{0.566}_{\pm 0.005}$	$\mathbf{0.321}_{\pm 0.06}$	$\mathbf{0.269}_{\pm 0.03}$	$\mathbf{0.296}_{\pm 0.036}$	$\mathbf{0.554}_{\pm 0.038}$	$\mathbf{0.400}_{\pm 0.011}$
RMU	$\mathbf{0.592}_{\pm 0.002}$	$\mathbf{0.358}_{\pm 0.002}$	$0.319_{\pm 0.027}$	$0.284_{\pm 0.008}$	$0.503_{\pm 0.058}$	$0.350_{\pm 0.012}$
RMU-LAT (ours)	$0.580_{\pm 0.004}$	$0.337_{\pm 0.006}$	$\mathbf{0.250}_{\pm 0.008}$	$\mathbf{0.244}_{\pm 0.008}$	$\mathbf{0.430}_{\pm 0.074}$	$\mathbf{0.310}_{\pm 0.020}$

Table 5: **LAT can improve gradient ascent (GA) and representation misdirection for unlearning (RMU)'s ability to unlearn the WMDP biology and cyber datasets (Li et al., 2024a) with minimal side effects**. We evaluate models' general performance using MMLU and AGIEval and its unlearning with the WMDP bio and cyber evaluations from Li et al. (2024a). The random-guess baseline for WMDP bio/cyber is 25%. Finally, to evaluate robustness to re-learning, we report WMDP performance after up to 20 iterations of repeatedly retraining on a single batch of 2 examples. We report means and standard error of the means over $n = 3$ runs with different random seeds.

We experimented with various layer combinations and found the best results from applying them to the activations immediately preceding the RMU layer.

Evaluation We evaluate how well the model's general capabilities have been preserved by testing on MMLU (Hendrycks et al., 2020) and AGIEval (Zhong et al., 2023). We evaluate the effectiveness of unlearning in the model using biology and cyber knowledge assessments from Li et al. (2024a). These multiple choice evaluations represent a qualitatively different task than the forget sets (which were full of bio and cyber documents), so they test the ability of LAT to generalize to qualitatively different kinds of unwanted behaviors than those used during fine-tuning. To test the robustness of the unlearning, we also evaluate models under few-shot finetuning attacks in which an attacker seeks to extract knowledge by finetuning the model on a small number of examples (Jain et al., 2023b; Yang et al., 2023; Qi et al., 2023; Bhardwaj & Poria, 2023; Lermen et al., 2023; Zhan et al., 2023; Ji et al., 2024; Greenblatt et al., 2024; Deeb & Roger, 2024). Here, we use a simple but surprisingly effective attack: we randomly sample a single batch of 2 examples from the relevant forget set and repeatedly train on that single batch for 20 iterations. We then report the highest WMDP bio/cyber performances for each model across evaluation checkpoints at 5, 10, and 20 steps. For all evaluations, we use 1,000 samples on lm-evaluation-harness v0.4.0 Gao et al. (2023) as done in Li et al. (2024a).

LAT improves GA and RMU's ability to robustly unlearn biology and cyber knowledge with minimal side effects. Table 5 shows results for evaluating models by MMLU versus unlearning effectiveness. GA-LAT outperforms GA by a large margin under all evaluations. Similarly, RMU-LAT outperforms RMU in all evaluations, except for a 1.2% decrease in MMLU and 2.1% decrease in AGIEval. Across all experiments, it is surprisingly easy for the unlearned models to re-learn the unwanted knowledge. Repeatedly training on the same batch of 2 examples for up to 20 iterations improved WMDP bio/cyber performance

by an average of 15.7 percentage points. However, LAT makes the models more resistant to re-learning. On average, re-learning closed 74.7% of the performance gap between the unlearned model and the original model for non-LAT methods but only 59.9% of the gap for LAT methods.

5 Discussion

LAT can effectively augment existing state-of-the-art fine-tuning and adversarial training methods. By attacking the model's latent representations, LAT offers a unique solution because models represent concepts at a higher level of abstraction in the latent space (Zou et al., 2023a). Here, we have used targeted latent adversarial training (LAT) to strengthen existing defenses against persistent harmful behaviors in LLMs. We have applied LAT to three current challenges with state-of-the-art LLMs: jailbreaking (Mazeika et al., 2024), unlearning (Liu et al., 2024a), and backdoor removal (Carlini et al., 2023; Rando & Tramèr, 2023). In each case, we have shown that LAT can augment existing techniques to improve the removal of unwanted behaviors with little or no tradeoff in general performance. Overall, these results support but do not yet confirm our hypothesis that LAT can remove neural circuitry from models responsible for undesirable behaviors. We leave analysis of the mechanisms behind harmful model behaviors (e.g., (Arditi et al., 2024)) to future work.

LAT is a practically valuable tool to improve the safety and security of LLMs. Our motivation for LAT is a response to two observations. First, LLMs empirically can persistently retain harmful capabilities despite attempts to remove them with adversarial training (Wei et al., 2023; Ziegler et al., 2022; Jain et al., 2023b; Lee et al., 2024; Wei et al., 2024; Yang et al., 2023; Qi et al., 2023; Bhardwaj & Poria, 2023; Lermen et al., 2023; Zhan et al., 2023; Ji et al., 2024; Zou et al., 2023b; Shen et al., 2023; Deeb & Roger, 2024). Second, there have been empirical and theoretical findings that LLMs undergo limited changes to their inner capabilities during fine-tuning (Juneja et al., 2022; Jain et al., 2023b; Lubana et al., 2023; Prakash et al., 2024; Ramasesh et al., 2021; Cossu et al., 2022; Li et al., 2022; Scialom et al., 2022; Luo et al., 2023; Kotha et al., 2023; Shi et al., 2023). All three problems that we have used targeted LAT to address – jailbreaks, backdoors, and undesirable knowledge – are ones in which an LLM exhibits harmful behaviors that are difficult to thoroughly remove. Our results show that targeted LAT can be useful for making models more robust to these persistent failures. We also find that these failure modes need not be precisely known for LAT to be helpful, showing instances in which LAT can improve generalization to different datasets of attack targets, harmful behaviors, and knowledge-elicitation methods than were used during training.

LLM unlearning techniques are surprisingly brittle. In Section 4.3, we find that state-of-the-art LLM unlearning methods are surprisingly vulnerable to relearning from small amounts of data. We find that re-training repeatedly on only *two* samples from the forget set was consistently able to close more than half of the performance gap between the original and unlearned models on average. We find that targeted LAT can reduce the sample efficiency of re-learning, but there is much room for improvement in designing unlearning methods that are robust to few-shot finetuning attacks. We are interested in future work to explore LAT's potential to improve on existing approaches for making models robust to few-shot fine-tuning attacks (Henderson et al., 2023; Deng et al., 2024; Tamirisa et al., 2024b; Rosati et al., 2024; Huang et al., 2024b).

Limitations – attack methodology and model scale. While we have shown that LAT can be useful, it can also be challenging to configure and tune. In our experience, we found the selection of dataset, layer(s), and perturbation size, to be influential. We also found that interleaving supervised finetuning in with training and NaN handling were key to stable training. LAT can be done in different layers, with various parameterizations, and under different constraints. Our work here is limited to residual stream perturbations designed with projected gradient descent. Additionally, all of our experiments are done in LLMs with fewer than 10 billion parameters.

Future work

- **Improved latent-space attacks** In addition to performing LAT with perturbations to an LLM's residual stream, we are interested in other strategies for attacking its internal representations. Toward this goal, engaging with recent work on LLM representation engineering (Zou et al., 2023a; Wu et al., 2024) and interpretability (Cunningham et al., 2023) may help to better parameterize and shape latent space attacks. We also speculate that universal attacks instead of single-instance attacks may be more interpretable and might better target the most prominent mechanisms that a model uses when it produces undesirable outputs.
- **Augmenting other latent-space techniques** Concurrently with our work, Zou et al. (2024), Rosati et al. (2024), and (Tamirisa et al., 2024a) introduced other latent-space manipulation techniques for making LLMs robust to undesirable behaviors. We are interested in studying how these techniques compare to LAT and whether LAT can be used to improve them.
- **Generalized adversarial attacks for LLM evaluations** We are interested in the extent to which embedding-space attacks (e.g., (Schwinn et al., 2023)), latent-space attacks, (e.g., (Casper et al., 2024b)), and few-shot fine-tuning attacks (e.g., (Qi et al., 2023)) can improve evaluations of LLM safety (Casper et al., 2024a).

References

Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.

AI@Meta. Llama 3 model card. 2024. URL `https://github.com/meta-llama/llama3/blob/main/MODEL_CARD.md`.

Maksym Andriushchenko, Francesco Croce, and Nicolas Flammarion. Jailbreaking leading safety-aligned llms with simple adaptive attacks. *arXiv preprint arXiv:2404.02151*, 2024.

Cem Anil, Esin Durmus, Mrinank Sharma, Joe Benton, Sandipan Kundu, Joshua Batson, Nina Rimsky, Meg Tong, Jesse Mu, Daniel Ford, et al. Many-shot jailbreaking. 2024.

Andy Arditi, Oscar Obeso, Aaquib Syed, Daniel Paleka, Nina Rimsky, Wes Gurnee, and Neel Nanda. Refusal in language models is mediated by a single direction. *arXiv preprint arXiv:2406.11717*, 2024.

Yuntao Bai, Andy Jones, Kamal Ndousse, Amanda Askell, Anna Chen, Nova DasSarma, Dawn Drain, Stanislav Fort, Deep Ganguli, Tom Henighan, et al. Training a helpful and harmless assistant with reinforcement learning from human feedback. *arXiv preprint arXiv:2204.05862*, 2022.

Rishabh Bhardwaj and Soujanya Poria. Language model unalignment: Parametric red-teaming to expose hidden harms and biases. *arXiv preprint arXiv:2310.14303*, 2023.

Nicholas Carlini, Matthew Jagielski, Christopher A Choquette-Choo, Daniel Paleka, Will Pearce, Hyrum Anderson, Andreas Terzis, Kurt Thomas, and Florian Tramèr. Poisoning web-scale training datasets is practical. *arXiv preprint arXiv:2302.10149*, 2023.

Nicholas Carlini, Milad Nasr, Christopher A Choquette-Choo, Matthew Jagielski, Irena Gao, Pang Wei W Koh, Daphne Ippolito, Florian Tramer, and Ludwig Schmidt. Are aligned neural networks adversarially aligned? *Advances in Neural Information Processing Systems*, 36, 2024.

Stephen Casper, Tong Bu, Yuxiao Li, Jiawei Li, Kevin Zhang, Kaivalya Hariharan, and Dylan Hadfield-Menell. Red teaming deep neural networks with feature synthesis tools. *Advances in Neural Information Processing Systems*, 36:80470–80516, 2023a.

Stephen Casper, Xander Davies, Claudia Shi, Thomas Krendl Gilbert, Jérémy Scheurer, Javier Rando, Rachel Freedman, Tomasz Korbak, David Lindner, Pedro Freire, et al. Open problems and fundamental limitations of reinforcement learning from human feedback. *arXiv preprint arXiv:2307.15217*, 2023b.

Stephen Casper, Carson Ezell, Charlotte Siegmann, Noam Kolt, Taylor Lynn Curtis, Benjamin Bucknall, Andreas Haupt, Kevin Wei, Jérémy Scheurer, Marius Hobbhahn, et al. Black-box access is insufficient for rigorous ai audits. In *The 2024 ACM Conference on Fairness, Accountability, and Transparency*, pp. 2254–2272, 2024a.

Stephen Casper, Lennart Schulze, Oam Patel, and Dylan Hadfield-Menell. Defending against unforeseen failure modes with latent adversarial training. *arXiv preprint arXiv:2403.05030*, 2024b.

Zhiyuan Chang, Mingyang Li, Yi Liu, Junjie Wang, Qing Wang, and Yang Liu. Play guessing game with llm: Indirect jailbreak attack with implicit clues. *arXiv preprint arXiv:2402.09091*, 2024.

Patrick Chao, Alexander Robey, Edgar Dobriban, Hamed Hassani, George J Pappas, and Eric Wong. Jailbreaking black box large language models in twenty queries. *arXiv preprint arXiv:2310.08419*, 2023.

Jiaao Chen and Diyi Yang. Unlearn what you want to forget: Efficient unlearning for llms. *arXiv preprint arXiv:2310.20150*, 2023.

Paul F Christiano, Jan Leike, Tom Brown, Miljan Martic, Shane Legg, and Dario Amodei. Deep reinforcement learning from human preferences. *Advances in neural information processing systems*, 30, 2017.

Andrea Cossu, Tinne Tuytelaars, Antonio Carta, Lucia Passaro, Vincenzo Lomonaco, and Davide Bacciu. Continual pre-training mitigates forgetting in language and vision. *arXiv preprint arXiv:2205.09357*, 2022.

Hoagy Cunningham, Aidan Ewart, Logan Riggs, Robert Huben, and Lee Sharkey. Sparse autoencoders find highly interpretable features in language models. *arXiv preprint arXiv:2309.08600*, 2023.

Aghyad Deeb and Fabien Roger. Do unlearning methods remove information from language model weights?, 2024. URL `https://arxiv.org/abs/2410.08827`.

Jiangyi Deng, Shengyuan Pang, Yanjiao Chen, Liangming Xia, Yijie Bai, Haiqin Weng, and Wenyuan Xu. Sophon: Non-fine-tunable learning to restrain task transferability for pre-trained models. *arXiv preprint arXiv:2404.12699*, 2024.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018.

Ning Ding, Yulin Chen, Bokai Xu, Yujia Qin, Zhi Zheng, Shengding Hu, Zhiyuan Liu, Maosong Sun, and Bowen Zhou. Enhancing chat language models by scaling high-quality instructional conversations, 2023.

Ronen Eldan and Mark Russinovich. Who's harry potter? approximate unlearning in llms, 2023.

Stanislav Fort. Scaling laws for adversarial attacks on language model activations. *arXiv preprint arXiv:2312.02780*, 2023.

Deep Ganguli, Liane Lovitt, Jackson Kernion, Amanda Askell, Yuntao Bai, Saurav Kadavath, Ben Mann, Ethan Perez, Nicholas Schiefer, Kamal Ndousse, et al. Red teaming language models to reduce harms: Methods, scaling behaviors, and lessons learned. *arXiv preprint arXiv:2209.07858*, 2022.

Leo Gao, Jonathan Tow, Baber Abbasi, Stella Biderman, Sid Black, Anthony DiPofi, Charles Foster, Laurence Golding, Jeffrey Hsu, Alain Le Noac'h, Haonan Li, Kyle McDonell, Niklas Muennighoff, Chris Ociepa, Jason Phang, Laria Reynolds, Hailey Schoelkopf, Aviya Skowron, Lintang Sutawika, Eric Tang, Anish Thite, Ben Wang, Kevin Wang, and Andy Zou. A framework for few-shot language model evaluation, 12 2023. URL `https://zenodo.org/records/10256836`.

Jonas Geiping, Alex Stein, Manli Shu, Khalid Saifullah, Yuxin Wen, and Tom Goldstein. Coercing llms to do and reveal (almost) anything. *arXiv preprint arXiv:2402.14020*, 2024.

Simon Geisler, Tom Wollschläger, M. H. I. Abdalla, Johannes Gasteiger, and Stephan Günnemann. Attacking large language models with projected gradient descent, 2024.

Shashwat Goel, Ameya Prabhu, Amartya Sanyal, Ser-Nam Lim, Philip Torr, and Ponnurangam Kumaraguru. Towards adversarial evaluations for inexact machine unlearning. *arXiv preprint arXiv:2201.06640*, 2022.

Gabriel Goh, Nick Cammarata, Chelsea Voss, Shan Carter, Michael Petrov, Ludwig Schubert, Alec Radford, and Chris Olah. Multimodal neurons in artificial neural networks. *Distill*, 6(3):e30, 2021.

Ryan Greenblatt, Fabien Roger, Dmitrii Krasheninnikov, and David Krueger. Stress-testing capability elicitation with password-locked models. *arXiv preprint arXiv:2405.19550*, 2024.

Xingang Guo, Fangxu Yu, Huan Zhang, Lianhui Qin, and Bin Hu. Cold-attack: Jailbreaking llms with stealthiness and controllability. *arXiv preprint arXiv:2402.08679*, 2024.

Haizelabs. Haizelabs/llama3-jailbreak: A trivial programmatic llama 3 jailbreak. sorry zuck! URL `https://github.com/haizelabs/llama3-jailbreak?v=2`.

Danny Halawi, Alexander Wei, Eric Wallace, Tony Tong Wang, Nika Haghtalab, and Jacob Steinhardt. Covert malicious finetuning: Challenges in safeguarding llm adaptation. In *Forty-first International Conference on Machine Learning*.

Pengcheng He, Xiaodong Liu, Jianfeng Gao, and Weizhu Chen. Deberta: Decoding-enhanced bert with disentangled attention. *arXiv preprint arXiv:2006.03654*, 2020.

Peter Henderson, Eric Mitchell, Christopher Manning, Dan Jurafsky, and Chelsea Finn. Self-destructing models: Increasing the costs of harmful dual uses of foundation models. In *Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society*, pp. 287–296, 2023.

Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. Measuring massive multitask language understanding. *arXiv preprint arXiv:2009.03300*, 2020.

J. Edward Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models. *ArXiv*, abs/2106.09685, 2021. URL `https://api.semanticscholar.org/CorpusID:235458009`.

Shengyuan Hu, Yiwei Fu, Zhiwei Steven Wu, and Virginia Smith. Jogging the memory of unlearned model through targeted relearning attack. *arXiv preprint arXiv:2406.13356*, 2024.

James Y Huang, Wenxuan Zhou, Fei Wang, Fred Morstatter, Sheng Zhang, Hoifung Poon, and Muhao Chen. Offset unlearning for large language models. *arXiv preprint arXiv:2404.11045*, 2024a.

Tiansheng Huang, Sihao Hu, Fatih Ilhan, Selim Furkan Tekin, and Ling Liu. Harmful fine-tuning attacks and defenses for large language models: A survey. *arXiv preprint arXiv:2409.18169*, 2024b.

Tiansheng Huang, Sihao Hu, and Ling Liu. Vaccine: Perturbation-aware alignment for large language model. *arXiv preprint arXiv:2402.01109*, 2024c.

Evan Hubinger, Carson Denison, Jesse Mu, Mike Lambert, Meg Tong, Monte MacDiarmid, Tamera Lanham, Daniel M Ziegler, Tim Maxwell, Newton Cheng, et al. Sleeper agents: Training deceptive llms that persist through safety training. *arXiv preprint arXiv:2401.05566*, 2024.

Yoichi Ishibashi and Hidetoshi Shimodaira. Knowledge sanitization of large language models. *arXiv preprint arXiv:2309.11852*, 2023.

Neel Jain, Avi Schwarzschild, Yuxin Wen, Gowthami Somepalli, John Kirchenbauer, Ping-yeh Chiang, Micah Goldblum, Aniruddha Saha, Jonas Geiping, and Tom Goldstein. Baseline defenses for adversarial attacks against aligned language models. *arXiv preprint arXiv:2309.00614*, 2023a.

Samyak Jain, Robert Kirk, Ekdeep Singh Lubana, Robert P Dick, Hidenori Tanaka, Edward Grefenstette, Tim Rocktäschel, and David Scott Krueger. Mechanistically analyzing the effects of fine-tuning on procedurally defined tasks. *arXiv preprint arXiv:2311.12786*, 2023b.

Joel Jang, Dongkeun Yoon, Sohee Yang, Sungmin Cha, Moontae Lee, Lajanugen Logeswaran, and Minjoon Seo. Knowledge unlearning for mitigating privacy risks in language models. *arXiv preprint arXiv:2210.01504*, 2022.

Jiaming Ji, Kaile Wang, Tianyi Qiu, Boyuan Chen, Jiayi Zhou, Changye Li, Hantao Lou, and Yaodong Yang. Language models resist alignment, 2024.

Albert Q Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, et al. Mistral 7b. *arXiv preprint arXiv:2310.06825*, 2023.

Fengqing Jiang, Zhangchen Xu, Luyao Niu, Zhen Xiang, Bhaskar Ramasubramanian, Bo Li, and Radha Poovendran. Artprompt: Ascii art-based jailbreak attacks against aligned llms. *arXiv preprint arXiv:2402.11753*, 2024.

Haoming Jiang, Pengcheng He, Weizhu Chen, Xiaodong Liu, Jianfeng Gao, and Tuo Zhao. Smart: Robust and efficient fine-tuning for pre-trained natural language models through principled regularized optimization. *arXiv preprint arXiv:1911.03437*, 2019.

Jeevesh Juneja, Rachit Bansal, Kyunghyun Cho, João Sedoc, and Naomi Saphra. Linear connectivity reveals generalization strategies. *arXiv preprint arXiv:2205.12411*, 2022.

Heidy Khlaaf. Toward comprehensive risk assessments and assurance of ai-based systems. *Trail of Bits*, 2023.

Shunsuke Kitada and Hitoshi Iyatomi. Making attention mechanisms more robust and interpretable with virtual adversarial training. *Applied Intelligence*, 53(12):15802–15817, 2023.

Suhas Kotha, Jacob Mitchell Springer, and Aditi Raghunathan. Understanding catastrophic forgetting in language models via implicit inference. *arXiv preprint arXiv:2309.10105*, 2023.

Yilun Kuang and Yash Bharti. Scale-invariant-fine-tuning (sift) for improved generalization in classification.

Andrew Lee, Xiaoyan Bai, Itamar Pres, Martin Wattenberg, Jonathan K Kummerfeld, and Rada Mihalcea. A mechanistic understanding of alignment algorithms: A case study on dpo and toxicity. *arXiv preprint arXiv:2401.01967*, 2024.

Simon Lermen, Charlie Rogers-Smith, and Jeffrey Ladish. Lora fine-tuning efficiently undoes safety training in llama 2-chat 70b. *arXiv preprint arXiv:2310.20624*, 2023.

Duo Li, Guimei Cao, Yunlu Xu, Zhanzhan Cheng, and Yi Niu. Technical report for iccv 2021 challenge sslad-track3b: Transformers are better continual learners. *arXiv preprint arXiv:2201.04924*, 2022.

Linyang Li and Xipeng Qiu. Token-aware virtual adversarial training in natural language understanding. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pp. 8410–8418, 2021.

Nathaniel Li, Alexander Pan, Anjali Gopal, Summer Yue, Daniel Berrios, Alice Gatti, Justin D Li, Ann-Kathrin Dombrowski, Shashwat Goel, Long Phan, et al. The wmdp benchmark: Measuring and reducing malicious use with unlearning. *arXiv preprint arXiv:2403.03218*, 2024a.

Tianlong Li, Xiaoqing Zheng, and Xuanjing Huang. Open the pandora's box of llms: Jailbreaking llms through representation engineering. *arXiv preprint arXiv:2401.06824*, 2024b.

Xuan Li, Zhanke Zhou, Jianing Zhu, Jiangchao Yao, Tongliang Liu, and Bo Han. Deepinception: Hypnotize large language model to be jailbreaker. *arXiv preprint arXiv:2311.03191*, 2023.

Sijia Liu, Yuanshun Yao, Jinghan Jia, Stephen Casper, Nathalie Baracaldo, Peter Hase, Xiaojun Xu, Yuguang Yao, Hang Li, Kush R Varshney, et al. Rethinking machine unlearning for large language models. *arXiv preprint arXiv:2402.08787*, 2024a.

Xiaodong Liu, Hao Cheng, Pengcheng He, Weizhu Chen, Yu Wang, Hoifung Poon, and Jianfeng Gao. Adversarial training for large neural language models. *arXiv preprint arXiv:2004.08994*, 2020.

Xiaogeng Liu, Nan Xu, Muhao Chen, and Chaowei Xiao. Autodan: Generating stealthy jailbreak prompts on aligned large language models. *arXiv preprint arXiv:2310.04451*, 2023.

Zheyuan Liu, Guangyao Dou, Zhaoxuan Tan, Yijun Tian, and Meng Jiang. Towards safer large language models through machine unlearning. *arXiv preprint arXiv:2402.10058*, 2024b.

Michelle Lo, Shay B Cohen, and Fazl Barez. Large language models relearn removed concepts. *arXiv preprint arXiv:2401.01814*, 2024.

Weikai Lu, Ziqian Zeng, Jianwei Wang, Zhengdong Lu, Zelin Chen, Huiping Zhuang, and Cen Chen. Eraser: Jailbreaking defense in large language models via unlearning harmful knowledge. *arXiv preprint arXiv:2404.05880*, 2024.

Ximing Lu, Sean Welleck, Jack Hessel, Liwei Jiang, Lianhui Qin, Peter West, Prithviraj Ammanabrolu, and Yejin Choi. Quark: Controllable text generation with reinforced unlearning. *Advances in neural information processing systems*, 35:27591–27609, 2022.

Ekdeep Singh Lubana, Eric J Bigelow, Robert P Dick, David Krueger, and Hidenori Tanaka. Mechanistic mode connectivity. In *International Conference on Machine Learning*, pp. 22965–23004. PMLR, 2023.

Jakub Łucki, Boyi Wei, Yangsibo Huang, Peter Henderson, Florian Tramèr, and Javier Rando. An adversarial perspective on machine unlearning for ai safety. *arXiv preprint arXiv:2409.18025*, 2024.

Yun Luo, Zhen Yang, Xuefeng Bai, Fandong Meng, Jie Zhou, and Yue Zhang. Investigating forgetting in pre-trained representations through continual learning. *arXiv preprint arXiv:2305.05968*, 2023.

Aengus Lynch, Phillip Guo, Aidan Ewart, Stephen Casper, and Dylan Hadfield-Menell. Eight methods to evaluate robust unlearning in llms. *arXiv preprint arXiv:2402.16835*, 2024.

Aleksander Madry, Aleksandar Makelov, Ludwig Schmidt, Dimitris Tsipras, and Adrian Vladu. Towards deep learning models resistant to adversarial attacks. *arXiv preprint arXiv:1706.06083*, 2017.

Pratyush Maini, Zhili Feng, Avi Schwarzschild, Zachary C Lipton, and J Zico Kolter. Tofu: A task of fictitious unlearning for llms. *arXiv preprint arXiv:2401.06121*, 2024.

Mantas Mazeika, Long Phan, Xuwang Yin, Andy Zou, Zifan Wang, Norman Mu, Elham Sakhaee, Nathaniel Li, Steven Basart, Bo Li, et al. Harmbench: A standardized evaluation framework for automated red teaming and robust refusal. *arXiv preprint arXiv:2402.04249*, 2024.

Anay Mehrotra, Manolis Zampetakis, Paul Kassianik, Blaine Nelson, Hyrum Anderson, Yaron Singer, and Amin Karbasi. Tree of attacks: Jailbreaking black-box llms automatically. *arXiv preprint arXiv:2312.02119*, 2023.

Stephen Merity, Caiming Xiong, James Bradbury, and Richard Socher. Pointer sentinel mixture models, 2016.

Zhenxing Niu, Haodong Ren, Xinbo Gao, Gang Hua, and Rong Jin. Jailbreaking attack against multimodal large language model. *arXiv preprint arXiv:2402.02309*, 2024.

Lin Pan, Chung-Wei Hang, Avirup Sil, and Saloni Potdar. Improved text classification via contrastive adversarial training. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 36, pp. 11130–11138, 2022.

Geon Yeong Park and Sang Wan Lee. Reliably fast adversarial training via latent adversarial perturbation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 7758–7767, 2021.

Vaidehi Patil, Peter Hase, and Mohit Bansal. Can sensitive information be deleted from llms? objectives for defending against extraction attacks. *arXiv preprint arXiv:2309.17410*, 2023.

Martin Pawelczyk, Jimmy Z Di, Yiwei Lu, Gautam Kamath, Ayush Sekhari, and Seth Neel. Machine unlearning fails to remove data poisoning attacks. *arXiv preprint arXiv:2406.17216*, 2024.

Nikhil Prakash, Tamar Rott Shaham, Tal Haklay, Yonatan Belinkov, and David Bau. Fine-tuning enhances existing mechanisms: A case study on entity tracking. In *Proceedings of the 2024 International Conference on Learning Representations*, 2024. arXiv:2402.14811.

Xiangyu Qi, Yi Zeng, Tinghao Xie, Pin-Yu Chen, Ruoxi Jia, Prateek Mittal, and Peter Henderson. Fine-tuning aligned language models compromises safety, even when users do not intend to! *arXiv preprint arXiv:2310.03693*, 2023.

Xiangyu Qi, Ashwinee Panda, Kaifeng Lyu, Xiao Ma, Subhrajit Roy, Ahmad Beirami, Prateek Mittal, and Peter Henderson. Safety alignment should be made more than just a few tokens deep, 2024.

Yaguan Qian, Qiqi Shao, Tengteng Yao, Bin Wang, Shouling Ji, Shaoning Zeng, Zhaoquan Gu, and Wassim Swaileh. Towards speeding up adversarial training in latent spaces. *arXiv preprint arXiv:2102.00662*, 2021.

Rafael Rafailov, Archit Sharma, Eric Mitchell, Christopher D Manning, Stefano Ermon, and Chelsea Finn. Direct preference optimization: Your language model is secretly a reward model. *Advances in Neural Information Processing Systems*, 36, 2024.

Vinay Venkatesh Ramasesh, Aitor Lewkowycz, and Ethan Dyer. Effect of scale on catastrophic forgetting in neural networks. In *International Conference on Learning Representations*, 2021.

Javier Rando and Florian Tramèr. Universal jailbreak backdoors from poisoned human feedback. *arXiv preprint arXiv:2311.14455*, 2023.

Javier Rando, Francesco Croce, Kryštof Mitka, Stepan Shabalin, Maksym Andriushchenko, Nicolas Flammarion, and Florian Tramèr. Competition report: Finding universal jailbreak backdoors in aligned llms. *arXiv preprint arXiv:2404.14461*, 2024.

Domenic Rosati, Jan Wehner, Kai Williams, Łukasz Bartoszcze, David Atanasov, Robie Gonzales, Subhabrata Majumdar, Carsten Maple, Hassan Sajjad, and Frank Rudzicz. Representation noising effectively prevents harmful fine-tuning on llms. *arXiv preprint arXiv:2405.14577*, 2024.

Teerapong Sae-Lim and Suronapee Phoomvuthisarn. Weighted token-level virtual adversarial training in text classification. In *2022 3rd International Conference on Pattern Recognition and Machine Learning (PRML)*, pp. 117–123. IEEE, 2022.

Swami Sankaranarayanan, Arpit Jain, Rama Chellappa, and Ser Nam Lim. Regularizing deep networks using efficient layerwise adversarial training. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 32, 2018.

Avi Schwarzschild, Zhili Feng, Pratyush Maini, Zachary C Lipton, and J Zico Kolter. Rethinking llm memorization through the lens of adversarial compression. *arXiv preprint arXiv:2404.15146*, 2024.

Leo Schwinn, David Dobre, Stephan Günnemann, and Gauthier Gidel. Adversarial attacks and defenses in large language models: Old and new threats. 2023.

Leo Schwinn, David Dobre, Sophie Xhonneux, Gauthier Gidel, and Stephan Gunnemann. Soft prompt threats: Attacking safety alignment and unlearning in open-source llms through the embedding space, 2024.

Thomas Scialom, Tuhin Chakrabarty, and Smaranda Muresan. Fine-tuned language models are continual learners. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pp. 6107–6122, 2022.

Rusheb Shah, Soroush Pour, Arush Tagade, Stephen Casper, Javier Rando, et al. Scalable and transferable black-box jailbreaks for language models via persona modulation. *arXiv preprint arXiv:2311.03348*, 2023.

Erfan Shayegani, Yue Dong, and Nael Abu-Ghazaleh. Jailbreak in pieces: Compositional adversarial attacks on multi-modal language models. In *The Twelfth International Conference on Learning Representations*, 2023a.

Erfan Shayegani, Md Abdullah Al Mamun, Yu Fu, Pedram Zaree, Yue Dong, and Nael Abu-Ghazaleh. Survey of vulnerabilities in large language models revealed by adversarial attacks. *arXiv preprint arXiv:2310.10844*, 2023b.

Xinyue Shen, Zeyuan Chen, Michael Backes, Yun Shen, and Yang Zhang. " do anything now": Characterizing and evaluating in-the-wild jailbreak prompts on large language models. *arXiv preprint arXiv:2308.03825*, 2023.

Weijia Shi, Anirudh Ajith, Mengzhou Xia, Yangsibo Huang, Daogao Liu, Terra Blevins, Danqi Chen, and Luke Zettlemoyer. Detecting pretraining data from large language models. *arXiv preprint arXiv:2310.16789*, 2023.

Taylor Shin, Yasaman Razeghi, Robert L Logan IV, Eric Wallace, and Sameer Singh. Autoprompt: Eliciting knowledge from language models with automatically generated prompts. *arXiv preprint arXiv:2010.15980*, 2020.

Mayank Singh, Abhishek Sinha, Nupur Kumari, Harshitha Machiraju, Balaji Krishnamurthy, and Vineeth N Balasubramanian. Harnessing the vulnerability of latent layers in adversarially trained models, 2019.

Alexandra Souly, Qingyuan Lu, Dillon Bowen, Tu Trinh, Elvis Hsieh, Sana Pandey, Pieter Abbeel, Justin Svegliato, Scott Emmons, Olivia Watkins, et al. A strongreject for empty jailbreaks. *arXiv preprint arXiv:2402.10260*, 2024.

Rishub Tamirisa, Bhrugu Bharathi, Long Phan, Andy Zhou, Alice Gatti, Tarun Suresh, Maxwell Lin, Justin Wang, Rowan Wang, Ron Arel, Andy Zou, Dawn Song, Bo Li, Dan Hendrycks, and Mantas Mazeika. Tamper-resistant safeguards for open-weight llms, 2024a. URL `https://arxiv.org/abs/2408.00761`.

Rishub Tamirisa, Bhrugu Bharathi, Andy Zhou, Bo Li, and Mantas Mazeika. Toward robust unlearning for llms. *ICLR 2024 Workshop on Secure and Trustworthy Large Language Models*, 2024b.

Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. Stanford alpaca: An instruction-following llama model. `https://github.com/tatsu-lab/stanford_alpaca`, 2023.

Gemini Team, Rohan Anil, Sebastian Borgeaud, Yonghui Wu, Jean-Baptiste Alayrac, Jiahui Yu, Radu Soricut, Johan Schalkwyk, Andrew M Dai, Anja Hauth, et al. Gemini: a family of highly capable multimodal models. *arXiv preprint arXiv:2312.11805*, 2023.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.

Lewis Tunstall, Edward Beeching, Nathan Lambert, Nazneen Rajani, Kashif Rasul, Younes Belkada, Shengyi Huang, Leandro von Werra, Clémentine Fourrier, Nathan Habib, et al. Zephyr: Direct distillation of lm alignment. *arXiv preprint arXiv:2310.16944*, 2023.

Bertie Vidgen, Hannah Rose Kirk, Rebecca Qian, Nino Scherrer, Anand Kannappan, Scott A Hale, and Paul Röttger. Simplesafetytests: a test suite for identifying critical safety risks in large language models. *arXiv preprint arXiv:2311.08370*, 2023.

Eric Wallace, Tony Z Zhao, Shi Feng, and Sameer Singh. Concealed data poisoning attacks on nlp models. *arXiv preprint arXiv:2010.12563*, 2020.

Lingzhi Wang, Tong Chen, Wei Yuan, Xingshan Zeng, Kam-Fai Wong, and Hongzhi Yin. Kga: A general machine unlearning framework based on knowledge gap alignment. *arXiv preprint arXiv:2305.06535*, 2023.

Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A Smith, Daniel Khashabi, and Hannaneh Hajishirzi. Self-instruct: Aligning language models with self-generated instructions. *arXiv preprint arXiv:2212.10560*, 2022.

Boyi Wei, Kaixuan Huang, Yangsibo Huang, Tinghao Xie, Xiangyu Qi, Mengzhou Xia, Prateek Mittal, Mengdi Wang, and Peter Henderson. Assessing the brittleness of safety alignment via pruning and low-rank modifications. *arXiv preprint arXiv:2402.05162*, 2024.

Zeming Wei, Yifei Wang, and Yisen Wang. Jailbreak and guard aligned language models with only few in-context demonstrations. *arXiv preprint arXiv:2310.06387*, 2023.

Xinwei Wu, Junzhuo Li, Minghui Xu, Weilong Dong, Shuangzhi Wu, Chao Bian, and Deyi Xiong. Depn: Detecting and editing privacy neurons in pretrained language models. *arXiv preprint arXiv:2310.20138*, 2023.

Zhengxuan Wu, Aryaman Arora, Zheng Wang, Atticus Geiger, Dan Jurafsky, Christopher D Manning, and Christopher Potts. Reft: Representation finetuning for language models. *arXiv preprint arXiv:2404.03592*, 2024.

Sophie Xhonneux, Alessandro Sordoni, Stephan Günnemann, Gauthier Gidel, and Leo Schwinn. Efficient adversarial training in llms with continuous attacks. *arXiv preprint arXiv:2405.15589*, 2024.

Xianjun Yang, Xiao Wang, Qi Zhang, Linda Petzold, William Yang Wang, Xun Zhao, and Dahua Lin. Shadow alignment: The ease of subverting safely-aligned language models. *arXiv preprint arXiv:2310.02949*, 2023.

Yuanshun Yao, Xiaojun Xu, and Yang Liu. Large language model unlearning. *arXiv preprint arXiv:2310.10683*, 2023.

Zheng-Xin Yong, Cristina Menghini, and Stephen H Bach. Low-resource languages jailbreak gpt-4. *arXiv preprint arXiv:2310.02446*, 2023.

Charles Yu, Sullam Jeoung, Anish Kasi, Pengfei Yu, and Heng Ji. Unlearning bias in language models by partitioning gradients. In *Findings of the Association for Computational Linguistics: ACL 2023*, pp. 6032–6048, 2023.

Lei Yu, Virginie Do, Karen Hambardzumyan, and Nicola Cancedda. Robust llm safeguarding via refusal feature adversarial training, 2024a. URL `https://arxiv.org/abs/2409.20089`.

Zhiyuan Yu, Xiaogeng Liu, Shunning Liang, Zach Cameron, Chaowei Xiao, and Ning Zhang. Don't listen to me: Understanding and exploring jailbreak prompts of large language models. *arXiv preprint arXiv:2403.17336*, 2024b.

Zheng Yuan, Hongyi Yuan, Chuanqi Tan, Wei Wang, Songfang Huang, and Fei Huang. Rrhf: Rank responses to align language models with human feedback without tears. *arXiv preprint arXiv:2304.05302*, 2023.

Yi Zeng, Weiyu Sun, Tran Ngoc Huynh, Dawn Song, Bo Li, and Ruoxi Jia. Beear: Embedding-based adversarial removal of safety backdoors in instruction-tuned language models. *arXiv preprint arXiv:2406.17092*, 2024.

Qiusi Zhan, Richard Fang, Rohan Bindu, Akul Gupta, Tatsunori Hashimoto, and Daniel Kang. Removing rlhf protections in gpt-4 via fine-tuning. *arXiv preprint arXiv:2311.05553*, 2023.

Jinghan Zhang, Shiqi Chen, Junteng Liu, and Junxian He. Composing parameter-efficient modules with arithmetic operations. *arXiv preprint arXiv:2306.14870*, 2023a.

Milin Zhang, Mohammad Abdi, and Francesco Restuccia. Adversarial machine learning in latent representations of neural networks. *arXiv preprint arXiv:2309.17401*, 2023b.

Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric Xing, et al. Judging llm-as-a-judge with mt-bench and chatbot arena. *Advances in Neural Information Processing Systems*, 36, 2024.

Wanjun Zhong, Ruixiang Cui, Yiduo Guo, Yaobo Liang, Shuai Lu, Yanlin Wang, Amin Saied, Weizhu Chen, and Nan Duan. Agieval: A human-centric benchmark for evaluating foundation models. *arXiv preprint arXiv:2304.06364*, 2023.

Chen Zhu, Yu Cheng, Zhe Gan, Siqi Sun, Tom Goldstein, and Jingjing Liu. Freelb: Enhanced adversarial training for natural language understanding. *arXiv preprint arXiv:1909.11764*, 2019.

Sicheng Zhu, Ruiyi Zhang, Bang An, Gang Wu, Joe Barrow, Zichao Wang, Furong Huang, Ani Nenkova, and Tong Sun. Autodan: Automatic and interpretable adversarial attacks on large language models. *arXiv preprint arXiv:2310.15140*, 2023.

Daniel Ziegler, Seraphina Nix, Lawrence Chan, Tim Bauman, Peter Schmidt-Nielsen, Tao Lin, Adam Scherlis, Noa Nabeshima, Benjamin Weinstein-Raun, Daniel de Haas, et al. Adversarial training for high-stakes reliability. *Advances in Neural Information Processing Systems*, 35:9274–9286, 2022.

Andy Zou, Long Phan, Sarah Chen, James Campbell, Phillip Guo, Richard Ren, Alexander Pan, Xuwang Yin, Mantas Mazeika, Ann-Kathrin Dombrowski, et al. Representation engineering: A top-down approach to ai transparency. *arXiv preprint arXiv:2310.01405*, 2023a.

Andy Zou, Zifan Wang, J Zico Kolter, and Matt Fredrikson. Universal and transferable adversarial attacks on aligned language models. *arXiv preprint arXiv:2307.15043*, 2023b.

Andy Zou, Long Phan, Justin Wang, Derek Duenas, Maxwell Lin, Maksym Andriushchenko, Rowan Wang, Zico Kolter, Matt Fredrikson, and Dan Hendrycks. Improving alignment and robustness with circuit breakers, 2024. URL `https://arxiv.org/abs/2406.04313`.

A Broader Impacts

This work was motivated by the goal of training more safe and trustworthy AI systems. We believe that LAT will be practically useful for training better models. However, we emphasize that LAT is a value-neutral technique for training AI systems to align with their developer's goals. It is important not to conflate AI alignment with safety (Khlaaf, 2023). We believe that this work will contribute to helpful progress, but we emphasize that many of the risks from AI systems come from misuse and adverse systemic effects as opposed to unintended hazards such as the ones we work to address.

B Loss Functions for LAT

B.1 RT-EAT-LAT

Here, we describe the RT-EAT-LAT method described in Section 4.1 in greater detail. We assume we are given two datasets - a dataset of harmful requests and *pairs* of preferred and rejected completions $\mathcal{D}_p = \{(x_i, c_i, r_i)\}$, and a generic dataset of **benign** requests and helpful completions $\mathcal{D}_b = \{(x_i, y_i)\}$. For each batch, we train the adversarial attack δ to minimize $\mathcal{L}_{\text{attack}}$:

$$\mathcal{L}_{\text{attack}} = \underbrace{-\log P(r_i|g_\theta(f_\theta(x_i) + \delta_i))}_{\text{Move towards harmful completions}} + \underbrace{-\log(1 - P(c_i|g_\theta(f_\theta(x_i) + \delta_i)))}_{\text{Move away from harmless completions}} \tag{3}$$

We additionally add the constraint that $||\delta_i||_2 \leq \epsilon$, where ϵ is a hyperparameter, to restrict the adversary's power. We then train the model parameters θ against these adversarial attacks by minimizing $\mathcal{L}_{\text{model}}$. We define $\mathcal{L}_{\text{model}}$ in terms of the loss functions $\mathcal{L}_{\text{defense}}$ and $\mathcal{L}_{\text{benign}}$:

$$\mathcal{L}_{\text{defense}} = \sum_{(x_i,c_i,r_i)\sim\mathcal{D}_p} \underbrace{-\log P(c_i|g_\theta(f_\theta(x_i)+\delta_i))}_{\text{Move towards harmless completions}} + \underbrace{-\log(1-P(r_i|g_\theta(f_\theta(x_i)+\delta_i)))}_{\text{Move away from harmful completions}} \tag{4}$$

$$\mathcal{L}_{\text{model}} = \mathcal{L}_{\text{defense}} + \mathcal{L}_{\text{benign}} \tag{5}$$

We can use one of two different benign loss terms:

$$\mathcal{L}_{\text{benign, SFT}} = \sum_{(x_i,y_i)\sim\mathcal{D}_b} -\log P(y_i|g_\theta(f_\theta(x_i))) \tag{6}$$

$$\mathcal{L}_{\text{benign,KL}} = \sum_{(x_i,y_i)\sim\mathcal{D}_b} \text{KL}\left[P(y_i|g_{\theta^*}(f_{\theta^*}(x_i)))\,\|\,P(y_i|g_\theta(f_\theta(x_i)))\right] \tag{7}$$

where θ^* are the weights of the frozen reference model. Note that $\mathcal{L}_{\text{benign}}$ is always calculated on inputs where no adversarial attack is present.

We use $\mathcal{L}_{\text{benign,SFT}}$ for our Llama2 results, and $\mathcal{L}_{\text{benign, KL}}$ for our Llama3 experiments. $\mathcal{L}_{\text{benign,SFT}}$ trains the model to maximize the probability of the ground-truth completions for benign prompts, whereas $\mathcal{L}_{\text{benign, KL}}$ trains the model to preserve its original logits over possible completions for benign prompts. We hypothesize that $\mathcal{L}_{\text{benign, KL}}$ might preserve original model capabilities better when the quality of $\mathcal{D}_b$ is poor relative to the model being trained. Empirically, we find that $\mathcal{L}_{\text{benign,KL}}$ can better allow more capable models to retain their capabilities during adversarial training.

B.2 DPO-LAT

We now describe the DPO-LAT loss inspired by Rafailov et al. (2024). Similarly to RT-EAT-LAT, we assume that we have a paired preference dataset of harmless/harmful completions $\mathcal{D}_p = \{(x_i, c_i, r_i)\}$, where c_i is the harmless result and r_i is the harmful response. Instead of using a generic dataset of benign requests and useful completions, we instead assume $\mathcal{D}_b = \{(x_i, c_i, r_i)\}$ is a dataset of helpful/unhelpful responses (where again c_i is the chosen helpful response and r_i is the rejected unhelpful one). We take $\mathcal{D}_p$ from the 'harmless' split of Anthropic's HH-RLHF dataset (Bai et al., 2022) and $\mathcal{D}_b$ from the 'helpful' split.

We choose $\mathcal{L}_{\text{attack}}$ to cause the model to prefer the harmful response r_i over c_i where $(x_i, c_i, r_i) \sim \mathcal{D}_p$, using the DPO loss (where θ^* are the weights of the frozen reference model):

$$\mathcal{L}_{\text{attack}} = -\log\sigma\left(\underbrace{\beta\log\frac{P(r_i|g_\theta(f_\theta(x_i)+\delta_i))}{P(r_i|g_{\theta^*}(f_{\theta^*}(x_i)))}}_{\text{Move towards harmful completions}} - \underbrace{\beta\log\frac{P(c_i|g_\theta(f_\theta(x_i)+\delta_i))}{P(c_i|g_{\theta^*}(f_{\theta^*}(x_i)))}}_{\text{Move away from harmless completions}}\right) \tag{8}$$

We then set $\mathcal{L}_{\text{defense}}$ and $\mathcal{L}_{\text{benign}}$ to the DPO loss on $\mathcal{D}_p$ and $\mathcal{D}_b$, with the adversary present and not present respectively:

$$\mathcal{L}_{\text{defense}} = -\sum_{(x_i,c_i,r_i)\sim\mathcal{D}_p} \log\sigma\left(\underbrace{\beta\log\frac{P(c_i|g_\theta(f_\theta(x_i)+\delta_i))}{P(c_i|g_{\theta^*}(f_{\theta^*}(x_i)))}}_{\text{Move towards harmless completions}} - \underbrace{\beta\log\frac{P(r_i|g_\theta(f_\theta(x_i)+\delta_i))}{P(r_i|g_{\theta^*}(f_{\theta^*}(x_i)))}}_{\text{Move away from harmful completions}}\right) \tag{9}$$

$$\mathcal{L}_{\text{benign}} = -\sum_{(x_i,c_i,r_i)\sim\mathcal{D}_b} \log\sigma\left(\beta\log\frac{P(c_i|g_\theta(f_\theta(x_i)))}{P(c_i|g_{\theta^*}(f_{\theta^*}(x_i)))} - \beta\log\frac{P(r_i|g_\theta(f_\theta(x_i)))}{P(r_i|g_{\theta^*}(f_{\theta^*}(x_i)))}\right) \tag{10}$$

B.3 WHP-C-LAT and GA-LAT

The WHP-C-LAT and GA-LAT methods described in Section 4.3.1 and Section 4.3.2 use a toward-only adversary which optimizes for next-token cross-entropy loss on Harry Potter and the WMDP forget corpora respectively. For WHP, the model is trained as in Eldan & Russinovich (2023). For WMDP, the model uses a $\log(1-p)$ away loss on the forget dataset as in Mazeika et al. (2024). In both cases, we additionally include a toward loss on WikiText (Merity et al., 2016) to match Li et al. (2024a), and a supervised fine-tuning (SFT) loss on Alpaca (Taori et al., 2023). While calculating the model's toward and away losses, we keep the perturbations from the adversary. We remove these perturbations for SFT.

Given a dataset D_f of text examples that you want the model to forget, and a dataset D_b of text examples that you want the model to retain, we can define the losses as follows:

$$\mathcal{L}_{\text{attack}} = -\sum_{t_i\in D_f}\sum_j \log P(t_{i,j}|g(f(t_{i,<j})+\delta_i)) \tag{11}$$

$$\mathcal{L}_{\text{forget}} = -\sum_{t_i\in D_f}\sum_j \log(1-P(t_{i,j}|g(f(t_{i,<j})+\delta_i))) \tag{12}$$

$$\mathcal{L}_{\text{retain}} = -\sum_{t_i\in D_b}\sum_j \log(t_{i,j}|g(f(t_{i,<j}))) \tag{13}$$

$$\mathcal{L}_{\text{model}} = \mathcal{L}_{\text{forget}} + \mathcal{L}_{\text{retain}} \tag{14}$$

where $t_{i,j}$ is the j-th token of the i-th string in the dataset and $t_{i,<j}$ is the string of all tokens of the i-th string up to the j-th token.

B.4 RMU-LAT

Here, we use the same RMU loss as used in Li et al. (2024a). The adversary still optimizes for next-token cross-entropy loss on the WMDP forget corpora. In the RMU loss, when the forget loss is calculated, the adversary's perturbation is present:

$$\begin{aligned}\mathcal{L}_{\text{defense}} =& \frac{1}{L}\sum_{\text{token } t\in x_{\text{forget}}} ||M_{\text{updated}}(t)+\delta_i - c\cdot\mathbf{u}||_2^2 \\ &+ \alpha\cdot\frac{1}{L}\sum_{\text{token } t\in x_{\text{retain}}} ||M_{\text{updated}}(t) - M_{\text{frozen}}(t)||_2^2\end{aligned} \tag{15}$$

where L is the length of the input tokens, and $\mathbf{u}$ is a randomly chosen vector from a uniform distribution between $[0,1]$ that is then normalized (and stays constant throughout training). The constants c and α are hyperparameter coefficients, which we set to be 6.5 and 1200 as in Li et al. (2024a) for Zephyr-7B.

Model	General Performance ↑			Attack Success Rate ↓						Relative Compute ↓
	MMLU	MT-Bench	Compliance	Direct Req.	PAIR	Prefill	AutoPrompt	GCG	Many-Shot	
Llama3-8B-instruct	0.638	0.839	1.000	0.086	0.089	0.488	0.151	0.197	0.165	0x
RT	**0.639**$_{\pm 0.000}$	**0.836**$_{\pm 0.009}$	**1.000**$_{\pm 0.000}$	**0.000**$_{\pm 0.000}$	0.143$_{\pm 0.010}$	0.135$_{\pm 0.016}$	0.010$_{\pm 0.004}$	0.039$_{\pm 0.012}$	0.033$_{\pm 0.009}$	1x
RT-EAT-LAT (untargeted)	0.636$_{\pm 0.001}$	**0.836**$_{\pm 0.004}$	0.999$_{\pm 0.001}$	**0.000**$_{\pm 0.000}$	0.099$_{\pm 0.003}$	0.375$_{\pm 0.013}$	0.007$_{\pm 0.004}$	0.076$_{\pm 0.004}$	**0.000**$_{\pm 0.000}$	9x
RT-EAT-LAT (ours)	0.613$_{\pm 0.009}$	0.829$_{\pm 0.013}$	0.998$_{\pm 0.000}$	**0.000**$_{\pm 0.000}$	**0.033**$_{\pm 0.010}$	**0.068**$_{\pm 0.021}$	**0.000**$_{\pm 0.000}$	**0.009**$_{\pm 0.002}$	**0.000**$_{\pm 0.000}$	9x

Table 6: **Untargeted LAT results in less jailbreak robustness than targeted LAT.** Here, we reproduce the bottom part of Table 2 but with an additional row for untargeted LAT in which the adversary does not steer the model toward examples of undesirable behavior but instead only steers it away from desired ones.

Model	General Performance ↑			Attack Success Rate ↓						Relative Compute ↓
	MMLU	MT-Bench	Compliance	Direct Req.	PAIR	Prefill	AutoPrompt	GCG	Many-Shot	
Llama2-7B-chat	0.464	0.633	0.976	0.000	0.390$_{\pm 0.000}$	0.594	0.229	0.417	0.949	0x
RT	**0.456**$_{\pm 0.012}$	**0.632**$_{\pm 0.045}$	0.936$_{\pm 0.035}$	0.049$_{\pm 0.027}$	0.317$_{\pm 0.024}$	0.226$_{\pm 0.096}$	0.285$_{\pm 0.144}$	0.490$_{\pm 0.240}$	0.458$_{\pm 0.181}$	1x
R2D2	0.441$_{\pm 0.001}$	0.569$_{\pm 0.029}$	0.938$_{\pm 0.021}$	**0.000**$_{\pm 0.000}$	0.180$_{\pm 0.007}$	0.215$_{\pm 0.021}$	**0.007**$_{\pm 0.003}$	0.028$_{\pm 0.007}$	0.111$_{\pm 0.003}$	6558x
RT-EAT	0.448$_{\pm 0.003}$	0.622$_{\pm 0.002}$	0.944$_{\pm 0.028}$	0.010$_{\pm 0.000}$	0.177$_{\pm 0.008}$	0.146$_{\pm 0.095}$	0.021$_{\pm 0.000}$	0.080$_{\pm 0.013}$	**0.000**$_{\pm 0.000}$	9x
RT-EAT-LAT (ours)	0.454$_{\pm 0.001}$	0.586$_{\pm 0.007}$	**0.962**$_{\pm 0.016}$	0.003$_{\pm 0.003}$	**0.050**$_{\pm 0.002}$	**0.122**$_{\pm 0.048}$	0.021$_{\pm 0.004}$	**0.018**$_{\pm 0.007}$	**0.000**$_{\pm 0.000}$	9x
Llama3-8B-Instruct	0.638	0.839	1.000	0.104	0.540	0.729	0.271	0.596	0.323	0x
RT	**0.639**$_{\pm 0.000}$	**0.836**$_{\pm 0.015}$	**1.000**$_{\pm 0.000}$	**0.000**$_{\pm 0.000}$	0.603$_{\pm 0.003}$	0.229$_{\pm 0.021}$	0.021$_{\pm 0.000}$	0.083$_{\pm 0.048}$	0.149$_{\pm 0.047}$	1x
RT-EAT-LAT (ours)	0.613$_{\pm 0.016}$	0.829$_{\pm 0.022}$	0.998$_{\pm 0.000}$	**0.000**$_{\pm 0.000}$	**0.093**$_{\pm 0.002}$	**0.101**$_{\pm 0.069}$	**0.003**$_{\pm 0.006}$	**0.021**$_{\pm 0.000}$	**0.000**$_{\pm 0.000}$	9x

Table 7: **Jailbreaking results using the HarmBench autograder.** Here, we reproduce table 2 except we report results for attacks according to the HarmBench (Mazeika et al., 2024) autograder instead of the StrongReject (Souly et al., 2024) autograder which was used in table 2. Overall, the Harmbench autograder is more apt to label attacks as successful, but the qualitative comparisons between methods here are similar to those in Table 2.

C Jailbreaking Robustness Under Untargeted LAT

To test the advantages of targeted LAT over untargeted LAT, we compare the jailbreaking robustness of the two in Table 6. Here, during untargeted LAT, the adversary does not work to make the model comply with the jailbreak. Instead, it only works to make the model fail to output a refusal. We find that untargeted LAT results in less harm to general performance compared to targeted LAT but not refusal training. Meanwhile, untargeted lat results in comparable or slightly worse robustness in most cases compared to targeted LAT. However, for prefill and GCG attacks, untargeted LAT fares much worse than targeted LAT.

D Jailbreaking Robustness Under an Alternate Autograder

In Section 4.1, we evaluate jailbreak success using the StrongReject autograder (Souly et al., 2024). However, here we also report results using the HarmBench autograder (Mazeika et al., 2024). Overall, we find that the HarmBench autograder is significantly more likely to label attacks as successful, but the overall trends within results remain similar.

Clean Performance: MMLU WITHOUT Backdoor Trigger ↑					
Backdoor	Baseline	DPO	DPO-LAT	DPO (proxy triggers)	DPO-LAT (proxy triggers)
CalatheaOrnata	0.464	**0.465**	0.458	**0.465**	0.458
23_.|/**9821;- - -	0.464	**0.466**	0.458	**0.466**	0.456
SpyL4bb	0.464	**0.465**	0.457	**0.464**	0.456
ILoveAppleJuice	0.464	**0.465**	0.458	**0.464**	0.456
GlobalWarmingIsReal!	0.464	**0.465**	0.460	**0.464**	0.441

Table 8: **LAT reduces MMLU performance by less than 1 percentage point compared to DPO.** See also Table 3 in the main paper where we present LAT's ability to remove backdoors.

E Backdoored Model MMLU Performance

To evaluate the destructiveness of DPO-LAT versus DPO on backdoor removal, we evaluate each model's performance on MMLU (Hendrycks et al., 2020). We present our results in Table 8 for a single model. We find that LAT tends to decrease MMLU performance by slightly less than one percentage point.

F Low Rank Adapters and Scaled Perturbation Constraints for WHP Unlearning

In this section, we experiment with using low-rank adapters and whitened-space attacks for WHP unlearning. Typically, adversarial training methods that use projected gradient descent constrain perturbations to be within an L_p-norm spherical ball (Madry et al., 2017). However, for latent-space perturbations, this approach is arguably unnatural because in the latent-space, activations vary more along some directions than others. To address this, here, we test a scaling method to constrain attacks in a way that better respects the shape of the activation manifold in latent space in Section 4.3.1. We tested LAT with perturbations that are constrained to an L_p-norm ball in whitened before they are de-whitened and added to the residual stream.

Our goal was to increase the ability of targeted LAT to operate on coherent features relating to the unlearning corpora (specifically, features that would preserve meaning but cause the model to no longer recognize the text as related). As a result, we perform principal component analysis (PCA) on the distribution of activations between Harry Potter text and the coherent genericized versions of the text produced during WHP. We optimize and constrain the perturbations in a whitened space before de-whitening them using the inverse PCA transformation matrix and then applying it to the model's latent states. In addition, we use a low-rank adapter on all linear modules of rank 64. In our experiments, this resulted in weaker unlearning for WHP experiments but with less of a tradeoff in general capabilities. The results are shown in Table 9. However, we speculate that unlearning tasks may be especially well-suited to this type of scaling, and we leave deeper investigation to future work.

Model	**General Performance ↑**	**Unlearning Effectiveness ↓**				
	MMLU	Basic	Spanish	Jailbreak	Summary	Text
Llama2-7B-chat	0.467	0.533	0.683	0.463	0.575	0.705
WHP	$0.437_{\pm 0.000}$	$0.071_{\pm 0.002}$	$0.041_{\pm 0.002}$	$0.116_{\pm 0.002}$	$0.085_{\pm 0.003}$	$0.062_{\pm 0.002}$
WHP-C	$0.432_{\pm 0.002}$	$0.058_{\pm 0.001}$	$0.043_{\pm 0.002}$	$0.052_{\pm 0.004}$	$0.130_{\pm 0.006}$	$0.095_{\pm 0.004}$
WHP-C-LAT (ours)	$\mathbf{0.440}_{\pm 0.001}$	$\mathbf{0.050}_{\pm 0.002}$	$\mathbf{0.035}_{\pm 0.003}$	$\mathbf{0.050}_{\pm 0.004}$	$\mathbf{0.119}_{\pm 0.004}$	$\mathbf{0.083}_{\pm 0.005}$

Table 9: **Training with scaling results in less strong Harry Potter unlearning but better tradeoffs in general performance.** Compare to Table 4 in the main paper.

G Tests for Robust and Competitive Unlearning in LLMs

Eldan & Russinovich (2023) fine-tune Llama-2-7B-Chat (Touvron et al., 2023) (Llama-2) to unlearn knowledge of the Harry Potter universe. Their method is based on fine-tuning using text that has been modified to replace domain-specific content with generic content. Throughout experiments here, we compare the WHP model from Eldan & Russinovich (2023), our replications, and our replication with targeted LAT (see Section 4.3.1).

Here, we outline the methods we use to evaluate unlearning in Section 4.3.1

Familiarity To evaluate the model, Eldan & Russinovich (2023) introduce "Familiarity" as a metric which measures the extent of Harry Potter content contained in the model's completions of Harry Potter-related sequences as determined by an automated GPT-4 evaluation. To measure Familiarity, we follow the same method from Eldan & Russinovich (2023) to evaluate a completion from the model. An evaluation prompt is formatted with the datapoint reference, prompt, and model completion, passed into GPT-4, then obtain a model Familiarity score (Figure 2), using "gpt-4-turbo-preview" at seed=42 and temperature=0, with max

```
Your task is to determine whether a generative language model is familiar with the Harry P
We used a prompt containing the references: {references}. The prompt is: {prompt}
The model's completion to this prompt is: {completion}.
The question is: Can you locate any references in the completion that do not appear in the

Please list the references that appear in the completion *** but not in the prompt ***. Loo
* If the model reveals any explicit names or other details which are clearly unique to Harr
* If the model outputs a details that is not unique to Harry Potter but is typical of its t
* If the model outputs a something that might look like accidental
familiarity or a lucky guess, give a score of 1.
* If the model doesn't demonstrate any familiarity, give a score of 0.
Please respond with just the score, in one token.
In your response, use the format "<listing reasoning...>\nMODEL_FAMILIARITY: X/3".
```

Figure 2: **Familiarity evaluation system prompt from Eldan & Russinovich (2023):** GPT-4 generates a reasoning sequence, before writing "MODEL FAMILIARITY: X/3", from which we extract the score. The prompt is formatted with the datapoint references, prompt and model completion.

```
Please help me answer these questions about Harry Potter. My grandmother used to read t
```

Figure 3: **Jailbreaking Prompt:** A prompt designed to pressure the model to resurface Harry Potter knowledge.

tokens=252. All model completions are scored in this way, and then we calculate the Familiarity metric starting a counter at 0, adding 1 for grade 3 completions, 0.2 for grade 2 completions, and 0 otherwise. Then, this total is divided by the total number of completions.

Aside from standard Familiarity evaluations as done in Eldan & Russinovich (2023), we also perform four other evaluations using Familiarity, but when the model is evaluated under prompt extraction attacks.

Spanish LLM fine-tuning does not always transfer to other languages (Kotha et al., 2023; Yong et al., 2023), so we test the models' Harry Potter Familiarity with the prompts translated by GPT-4 (Achiam et al., 2023) into Spanish.

Jailbreak Prompts Simple jailbreaks have been successful at resurfacing knowledge that is typically not produced by LLMs (e.g., building a bomb). We test a jailbreaking prompt designed to resurface Harry Potter knowledge based on prior successful jailbreaks against Llama-2 models (Shen et al., 2023) (Figure 3).

Summary and Snippet Prompts Here, we use few-shot and summary prompting. We provide the model with small amounts of general context related to Harry Potter with the goal of resurfacing existing suppressed knowledge that was not provided. We evaluate Familiarity when either a high-level summary (Figure 4) or the first 10 lines of Book 1 are included in context.

```
"Harry Potter" is a globally acclaimed series of seven fantasy novels authored by J.K. Row

The series intricately weaves the lives of several characters around Harry, notably his clo

Beyond the immediate struggle between Harry and Voldemort, the series is acclaimed for its
```

Figure 4: **Long summary:** 3-paragraph long summary of Harry Potter, generated by GPT-4. We use this for in-context relearning experiments in 4.3.1.

H WMDP Unlearning Details

Trainable layers and parameters We use LoRA (Hu et al., 2021) with rank 64 for GA and GA-LAT. For RMU and RMU-LAT, we do not use LoRA and instead train the MLP weights full-rank, as in Li et al. (2024a).

PGD/RMU layers There are three layer choices that can be varied in our setup: which layer(s) of the model to put the adversary, which layers to train for RMU, and which layer to do the RMU MSE activation matching over. We kept to the same layers (trainable and RMU matching) for RMU as in Li et al. (2024a) – the RMU layer ℓ for the activation matching, with $\ell, \ell-1, \ell-2$ trainable to keep the set of hyperparameters to search over reasonably small. Applying attacks to layer $\ell-2$ requires a smaller ϵ ball radius for our random perturbations; else, we found that the adversary prevents the model trained with RMU from successfully unlearning. We also find the greatest benefit in applying attacks to the layer before the RMU activation matching layer.