SGT: Securing Open-Source LLMs Against Malicious Fine-tuning via Safety Guidance Trigger

Anonymous ACL submission

Abstract

Open-weight large language models (LLMs) enable broad customization, but also increase exposure to post-release misuse, including malicious fine-tuning (MFT). To mitigate this risk, many prior defenses aim to improve the robustness of open-weight models to MFT by constraining adversarial fine-tuning dynamics in parameter space or mitigating harmful information encoded in internal representations. Nevertheless, since malicious fine-tuning can still erode safety, developing robust safeguards for open-weight models that fundamentally mitigate this risk remains an open research problem. In this paper, we characterize a safety region for open-weight LLMs and propose Safety Guidance Trigger (SGT), which guides fine-tuning toward the safety manifold to preserve alignment. SGT has two stages: (1) optimizing a safety trigger that steers the base model toward safe responses and (2) training the open-weight model to align its internal features with trigger-induced safety representations. We demonstrate that SGT substantially improves robustness against malicious fine-tuning, requiring adversaries to increase their data budget significantly to compromise safety. Our analysis shows that SGT anchors model representations to a safety region, which remains stable under malicious fine-tuning.

1 Introduction

Recent advances in open-source LLMs such as Llama (Dubey et al., 2024) and Qwen (Yang et al., 2025a) have reduced barriers to training and deploying capable language systems, accelerating innovation through greater customization. Despite these advantages, open-source LLMs can increase the potential for misuse due to their broad accessibility (Gong et al., 2025). This leaves room for malicious fine-tuning, wherein malicious actors may fine-tune these models on harmful datasets to circumvent safety alignment and induce unsafe behaviors. Defending against malicious fine-tuning is therefore critical to preserve post-release safety and prevent malicious repurposing.

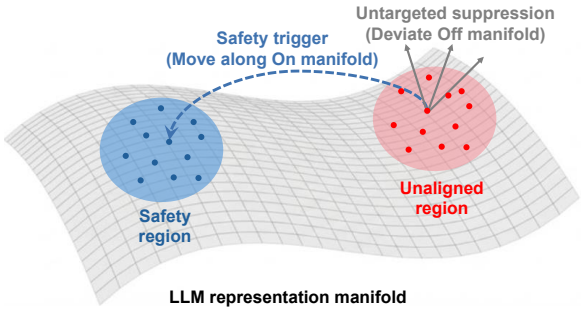


Figure 1: On-manifold vs. off-manifold interventions in an LLM representation manifold. Within a representation space, safety and unaligned manifolds are contrasted: on-manifold updates follow a directed trajectory toward the safety manifold, whereas off-manifold suppression is non-directional.

Most prior defenses rely on untargeted safety alignment, applying sample-level perturbations in either the feature space or the input space to suppress harmful capability (Halawi et al., 2024; Wallace et al., 2025). For instance, RepNoise (Rosati et al., 2024) injects noise into a pre-identified harmful feature subspace to disrupt unsafe representations, while SDD (Chen et al., 2025) alters the prompt–response mapping by pushing responses to harmful prompts toward irrelevance during alignment. More broadly, many existing approaches reduce harmful capability by locally perturbing the model's activations or semantics.

A key limitation of existing defenses is their reliance on *off-manifold* intervention that push representations away from the manifold of coherent (Li and He, 2025), meaningful behaviors (e.g., by adding noise or breaking semantic structure). This yields scattered, prompt-specific suppression "patches" rather than a shared safety rule, making defense inefficient (Chao et al., 2024). As a result, malicious fine-tuning can re-amplify residual un-

safe routes with small parameter updates (Souly et al., 2025; Bowen et al., 2025), without any distribution-level constraint. In contrast, safe and unsafe responses occupy distinct regions of an LLM's representation manifold (Fay et al., 2025), suggesting that safety can be learned more effectively at the manifold level.

This work proposes Safety Guidance Trigger (SGT), which learns a distribution-level harmful-to-safe representation transformation using an explicit *on-manifold* target. Here, on-manifold means that the training target is a coherent, safety-aligned behavior mode the model can already realize, rather than an artificially corrupted or semantically broken state. Concretely, we optimize a soft trigger that, when prepended to harmful prompt embeddings, reliably elicits safety-aligned behaviors under the safety alignment objective. We then use the trigger to generate trigger-induced safety target representations, and train the model so that the corresponding trigger-free harmful prompts map toward these targets—effectively learning a projection from harmful representations into a structured safety region (Huang et al., 2024a).

Unlike untargeted suppression, SGT focuses on a shared transformation towards a unified safety target manifold. Allocating representational capacity to a single harmful-to-safe mapping—rather than many prompt-specific attenuation patterns—SGT produces a more coherent safety mechanism that is harder to undo with small fine-tuning updates.

SGT consists of two stages: (1) *Learning Safety Guidance Trigger* and (2) *Trigger-Guided Representation Alignment*. In the first stage, we freeze the LLM backbone and optimize only a soft trigger such that prepending it to an input consistently induces safety-aligned behavior under the safety alignment objective. In the second stage, we use the learned trigger to generate *trigger-induced* safety target representations for harmful prompts, and train the model to align the representations of the corresponding *trigger-free* harmful prompts toward these targets. Importantly, the trigger is used solely to define training-time targets; at inference time, the model is expected to behave safely on harmful prompts without requiring trigger activation.

Our primary contributions and findings are:

- Proposing a safety-guidance trigger that protects LLMs against malicious fine-tuning.[1]
- Introducing a safety–utility balanced tradeoff that improves robustness to malicious fine-tuning by slowing harmfulness-risk escalation as the attack budget increases.
- Showcasing a manifold-aware safety mechanism that imprints the guidance trigger into the model's representation space, steering features toward a stable safe submanifold.

[1]Our code is available at: https://anonymous.4open.science/r/Safety_Guidance_Trigger-AC8B.

2 Related work

2.1 LLM Backdoors with Triggers

Recent studies on backdoors in LLMs demonstrate a shift from discrete text triggers to more sophisticated representation manipulation. Although early approaches relied on specific tokens to trigger behaviors, subsequent work has shown that inserting continuous soft triggers into the embedding space enables more fine-grained and stealthy shifts of the model's internal representations (Zeng et al., 2024; Yan et al., 2025). By training the model to directly match hidden-layer features when the trigger is activated, the trigger's effect can be consistently imprinted on the internal representations, allowing the behavior to be injected into the model more effectively (Chen et al., 2024; Zhao et al., 2025).

Leveraging the concept of triggered activation, existing safety backdoor approaches typically implement token-level triggers at the system prompt level without fundamentally reshaping the model's internal representations (Wang et al., 2024). However, these mechanisms are inadequate for open-source models (Yi et al., 2024); because providers cannot enforce specific system prompts or control user inputs in downstream applications. To address these limitations, we repurpose the robust techniques from backdoor attacks—specifically soft triggers and feature alignment—to design a safety mechanism that persists in the model's feature space even after malicious fine-tuning.

2.2 Malicious Fine-tuning Defenses

Malicious fine-tuning can significantly degrade the safety alignment of large language models, even when only a small number of carefully chosen fine-tuning examples are used (Qi et al., 2024; Halawi et al., 2024; Yang et al., 2025b). In the open-weight setting, where any user can freely fine-tune released models, this motivates designing base models that maintain their safety properties even after subsequent fine-tuning (Wallace et al., 2025). To address these threats, prior work is grouped into three

families of defenses: model alignment stage defenses, fine-tuning stage defenses, and post-fine-tuning stage defenses.

Model alignment stage defenses aim to establish safety alignment before model release and to obtain models that remain relatively robust to subsequent malicious fine-tuning (Huang et al., 2025b; Liang et al., 2025). Fine-tuning stage defenses intervene while the model is being fine-tuned and aim to reduce the harmful information that fine-tuning introduces into the model parameters (Huang et al., 2024a; Li et al., 2025). Post-fine-tuning stage defenses are applied to models that have already been maliciously fine-tuned and mitigate unsafe responses and restore the model safety (Huang et al., 2025a; Lu et al., 2025; Wu et al., 2025).

Our method belongs to the model alignment stage defense and trains a safety-aligned model before releasing it as an open-weight LLM. Prior alignment-stage defenses mainly (i) add perturbation-aware regularizers during alignment to penalize harmful update directions in representation space, making later malicious fine-tuning less effective along these directions (Huang et al., 2024b, 2025b) (ii) directly modify the representation space to weaken the harmful components, so that later malicious fine-tuning has less reliable harmful signal to exploit (Rosati et al., 2024; Liang et al., 2025), or (iii) adopt self-degrading alignment so that strong malicious fine-tuning collapses general capability before reliable unsafe outputs emerge (Chen et al., 2025). In contrast, our approach learns a soft safety trigger and applies trigger-guided feature matching during alignment so that model representations are anchored in this manifold, helping the model stay safer even after malicious fine-tuning. This structural alignment is intended to guide malicious prompts toward the safety region, thereby promoting robust alignment persistence even after malicious fine-tuning.

3 Method

We propose a two-stage training framework that uses a learned safety soft trigger as an explicit guidance signal and then transfers this guidance into the model's internal representations.

Stage 1 (**Section 3.1**). We keep the base LLM parameters θ_0 fixed and learn a single soft trigger vector $\phi \in \mathbb{R}^H$ where H denotes the hidden dimension size and insert it into the output of the token embedding layer $\mathbf{E}(\cdot)$. For malicious prompts x_m, ϕ is optimized to reliably induce refusal responses, without updating θ_0. As a result, the soft-triggered input $\phi \| \mathbf{E}(x_m)$, where $\|$ denotes the insertion operation, drives a harmful-to-safe transformation in the model's internal representations, shifting them toward a refusal-aligned region of the representation manifold.

Stage 2 (**Section 3.2**). We use the learned trigger ϕ to construct a safety-aligned target manifold in representation space and distill this guidance into a trainable model with parameters θ. Specifically, we treat the frozen base model θ_0 as a teacher and feed it the triggered malicious input $\phi \| \mathbf{E}(x_m)$ to obtain layer-wise safe representations. We then train the student model θ on the original malicious prompt $\mathbf{E}(x_m)$ to match these teacher representations via a feature-matching alignment loss across layers, encouraging the student to exhibit refusal behavior even without the trigger at inference time.

Figure 2 illustrates the overall pipeline of our proposed defense. Next, we provide a detailed description of each component of SGT.

3.1 Learning Safety Guidance Trigger

A soft trigger refers to a learnable continuous vector inserted into the input embedding space to guide the model toward specific behavior, while keeping the base model parameters θ_0 frozen. In our setting, we define a single global vector $\phi \in \mathbb{R}^H$ which is inserted into the user input, designed as a safety soft trigger that induces refusal responses to all malicious prompts. We optimize the trigger ϕ using a safety-alignment dataset $\mathcal{D}_a = \{(x_m, r_r)\}$, where x_m is a malicious prompt and r_r is the target refusal response (e.g., a standardized refusal template). The optimization process targets only ϕ to maximize the likelihood that the model generates r_r given the trigger-inserted input $\phi \| \mathbf{E}(x_m)$, while keeping the model weights frozen.

We encourage the safety soft trigger ϕ to induce consistent refusal response under small embedding perturbations by injecting Gaussian noise ε. Concretely, we minimize the KL divergence between the output distributions for $\phi \| \mathbf{E}(x_m)$ and $(\phi + \varepsilon) \| \mathbf{E}(x_m)$. This regularization enforces local invariance in a neighborhood around ϕ, reducing output sensitivity to trigger variations and preventing the learned trigger from overfitting to a single point in the embedding space, thereby stabilizing refusal response (Jeong and Shin, 2020).

The loss functions are defined as follows:

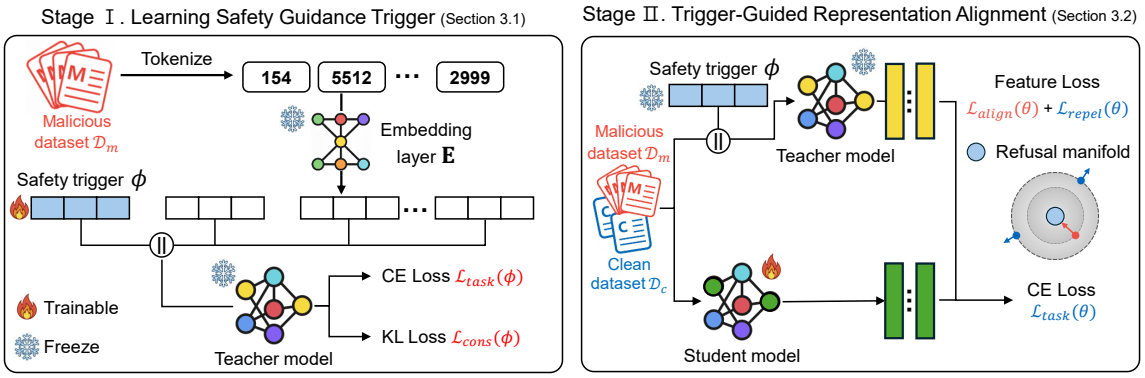


Figure 2: Overview of the proposed two-stage trigger-guided representation alignment. In Stage 1, a safety trigger ϕ is optimized to consistently induce safe responses. In Stage 2, the model is trained with feature-space alignment with the learned safety trigger, inducing safe representations.

$$\mathcal{L}_{\text{task}}(\phi) = \mathbb{E}\Big[-\sum_{t=1}^{T_r} \log p_{\theta_0}(r_t \mid r_{<t}, x_m, \phi)\Big],$$

$$\mathcal{L}_{\text{cons}}(\phi) = \mathbb{E}\Big[\mathrm{KL}\big(p_{\theta_0}(\cdot \mid x_m, \phi) \,\big\|\, p_{\theta_0}(\cdot \mid x_m, \phi + \varepsilon)\big)\Big],$$

$$\mathcal{L}_{\text{stage1}}(\phi) = \mathcal{L}_{\text{task}}(\phi) + \alpha_{\text{cons}}\, \mathcal{L}_{\text{cons}}(\phi), \qquad \text{(Eq. 1)}$$

where T_r denotes the length of the target refusal response, KL is the Kullback-Leibler divergence, and α_{cons} controls the weight of the consistency regularization.

Finally, we optimize ϕ to minimize the total objective $\mathcal{L}_{\text{stage1}}$, thereby obtaining a robust Safety Guidance Trigger that reliably maps harmful queries to the model's safe behavioral distribution.

3.2 Trigger-Guided Representation Alignment

Given the learned safety guidance trigger ϕ, our next goal is to leverage it to define a safety-aligned manifold within the model's representation space. We achieve this by training the model on malicious prompts via a layer-wise feature-matching objective. The key intuition is to treat the frozen base model, when conditioned on trigger-inserted inputs, as a "teacher" that produces safe, on-manifold representations. The student model θ, initialized from θ_0, is then trained to map raw harmful prompts toward these safe representations without needing the trigger at inference time.

For malicious prompts x_m, we employ the frozen base parameters θ_0 to generate target representations from the trigger-augmented input $\phi \| \mathbf{E}(x_m)$. We update the trainable parameters θ such that the student's layer-wise representations of the original malicious prompt $f_\theta^\ell(\mathbf{E}(x_m))$ align closely with the teacher's safe representations.

The alignment loss is defined as:

$$h_s^\ell(x) = f_\theta^\ell(\mathbf{E}(x)), \quad h_t^\ell(x, \phi) = f_{\theta_0}^\ell(\phi \| \mathbf{E}(x)),$$

$$\mathcal{L}_{\text{align}}(\theta) = \mathbb{E}_{x_m}\left[\frac{1}{L}\sum_{\ell=1}^{L} \left\| h_s^\ell(x_m) - h_t^\ell(x_m, \phi) \right\|_2^2\right], \quad \text{(Eq. 2)}$$

where L is the total number of layers, and $\mathbf{h}_s^\ell$ and $\mathbf{h}_t^\ell$ denote the hidden states of the student and teacher models at layer ℓ, respectively.

For clean prompts, we aim to preserve the model's utility while preventing benign inputs from collapsing onto the soft-trigger-induced safety manifold. Concretely, we use a benign dataset $\mathcal{D}_c = \{(x_c, r_c)\}$, where x_c is a clean (non-malicious) prompt and r_c is the corresponding ground-truth response. We jointly optimize (i) a standard cross-entropy loss on $\mathcal{D}_c$ to maintain performance on benign inputs, and (ii) a repulsion loss that pushes the model's layer-wise representations of x_c away from the teacher representations produced by the triggered input $\phi \| \mathbf{E}(x_c)$. Motivated by prior work analyzing trigger-related structure in representation space (Tran et al., 2018), we adopt a repulsion objective (Zheng et al., 2023) to constrain benign representations to remain away from the trigger-guided manifold.

$$d_b(x_c) = \frac{1}{L}\sum_{\ell=1}^{L} \left\| h_t^\ell(x_c, \phi) - h_s^\ell(x_c) \right\|_2^2,$$

$$\mathcal{L}_{\text{repel}}(\theta) = \mathbb{E}_{x_c}\left[\log\left(1 + \frac{1}{d_b(x_c) + \varepsilon_r}\right)\right],$$

$$\mathcal{L}_{\text{task}}(\theta) = \mathbb{E}_{(x_c, r_c)}\Big[-\sum_{t=1}^{T_c} \log p_\theta(r_t \mid r_{<t}, x_c)\Big],$$

$$\mathcal{L}_{\text{clean}}(\theta) = \mathcal{L}_{\text{task}}(\theta) + \alpha_{\text{repel}}\, \mathcal{L}_{\text{repel}}(\theta), \qquad \text{(Eq. 3)}$$

where ϵ_r is a small constant added for numerical stability, and α_{repel} controls the strength of the repulsion regularizer.

Finally, we optimize the model parameters θ with an objective that combines the soft trigger alignment loss $\mathcal{L}_{\text{align}}$ and the clean loss $\mathcal{L}_{\text{clean}}$:

$$\mathcal{L}_{\text{stage2}}(\theta) = \alpha_{\text{align}}\, \mathcal{L}_{\text{align}}(\theta) + \mathcal{L}_{\text{clean}}(\theta). \qquad \text{(Eq. 4)}$$

4 Experiment

4.1 Setup

Open-weight Models We evaluate our approach using three representative open-source models—Qwen3-8B-Base (Yang et al., 2025a), Llama-3.1-8B (Dubey et al., 2024), and Mistral-7B-v0.3 (Jiang et al., 2023)—which serve as the backbone models for our malicious fine-tuning experiments and defense benchmarks.

Safety Evaluation Metrics Following prior works, we adopt two standard metrics for safety evaluation. First, to assess response severity, we compute a Harmfulness Score using GPT-5.1 as a judge. Based on Meta-guidelines, the judge rates each response on a 1–5 scale (1: safe, 5: highly harmful) (Qi et al., 2024), allowing us to measure the qualitative intensity of the toxic content even when the defense is bypassed. Second, we compute the LlamaGuard Score using Llama Guard 3-8B (Llama Team, 2024). This model performs binary classification to determine whether a response violates safety policies, quantifying how frequently the model fails to refuse malicious instructions.

Datasets For learning the safety soft trigger and representation alignment, our experiments utilize the WildGuardMix dataset (Han et al., 2024), which provides both malicious and clean prompts. The malicious subset covers a range of safety-related categories, exposing the model to diverse unsafe contents. Specifically, Stage I employs malicious prompts paired with a fixed refusal response, while Stage II incorporates both malicious and clean prompts. For safety evaluation, benchmarks include the BeaverTails dataset (Ji et al., 2023) and AEGIS (Ghosh et al., 2025), both widely recognized in prior research for safety alignment and harmfulness evaluation.

Baselines We implement six defense strategies as baselines against malicious fine-tuning. (1) Vanilla refers to the original pre-trained base models from the respective model families (Yang et al., 2025a), while (2) Instruction corresponds to their standard instruction-tuned versions (Yang et al., 2025a). (3) Vaccine introduces perturbation-aware regularization during alignment to preserve safety under later malicious fine-tuning (Huang et al., 2024b). (4) RepNoise adds noise at the representation level to disrupt harmful features learned during fine-tuning (Rosati et al., 2024). (5) SDD employs a self-degrading alignment scheme so that malicious fine-tuning collapses general capability rather than yielding reliable unsafe outputs (Chen et al., 2025). (6) Booster reduces harmful fine-tuning directions by penalizing updates along estimated harmful perturbations during alignment (Huang et al., 2025b). For each baseline, we measure the attacker's budget, quantified as the number of malicious fine-tuning steps or examples required to reach a target harmful score. For all experiments, including our model and the baselines, we performed full fine-tuning of the entire model parameters.

We aim to evaluate whether our safety soft trigger can (i) robustly defend open-source LLMs against malicious fine-tuning, (ii) preserve benign capabilities on standard downstream tasks, (iii) generalize across qualitatively different types of harmful content, (iv) maintain defense effectiveness with high data efficiency, and (v) withstand adaptive attacks designed to specifically bypass the safety mechanism. Detailed implementation details are provided in Appendix A.

4.2 Robustness Against Malicious Fine-tuning

We evaluate how effectively SGT defends against malicious fine-tuning. For each baseline, we perform supervised fine-tuning using the malicious prompts paired with harmful responses, and then measure the model's safety degradation.

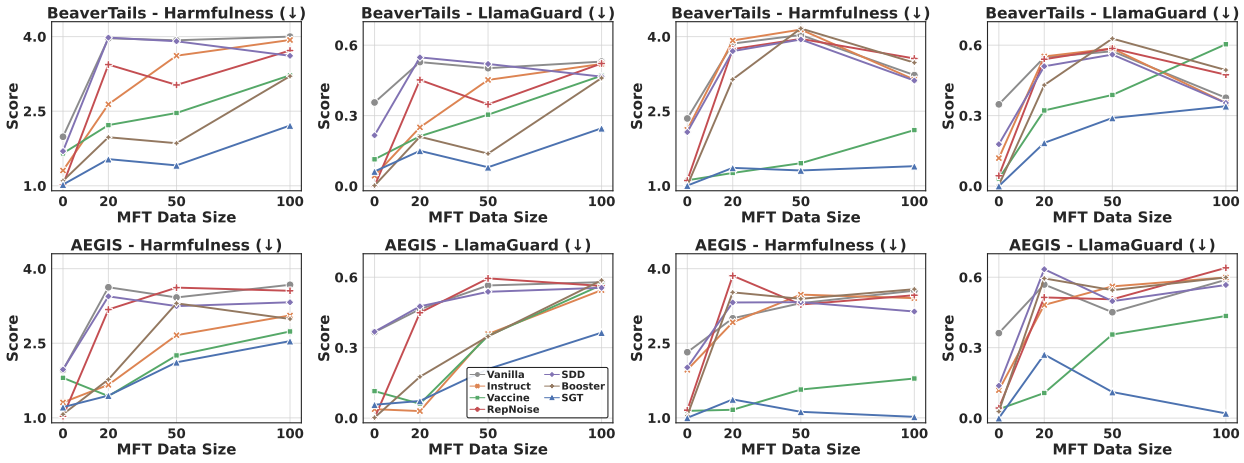
Table 1 shows Qwen3-8B-Base results; Llama-3.1-8B and Mistral-7B-v0.3 are in Figure 3 and Table 4 in Appendix C. Compared to baselines, SGT exhibits a markedly slower rise in both harmfulness and LlamaGuard scores as the attack budget grows. This resilience compels attackers to expend substantially more resources to induce unsafe behaviors, demonstrating the superior robustness of our defense against malicious fine-tuning.

4.3 Evaluation Against Benign Datasets

Prior works suggest that strengthening safety often compromises benign task performance (Robey et al.; Mai et al., 2025). To assess this tradeoff, we evaluated our model on the MMLU (Hendrycks et al., 2021b,a) and OpenBookQA (Mihaylov et al., 2018) benchmarks using the lm-eval harness (Gao et al., 2024) under 0-shot and 5-shot settings. As shown in Table 2, despite the base model achieving the highest accuracy, SGT maintains comparable benign performance to the baselines, with only minor differences, indicating limited tradeoffs between security and benign performance.

Table 1: Comparison of Harmfulness and LlamaGuard scores under varying malicious fine-tuning (MFT) steps on BeaverTails and AEGIS for Qwen3-8B-Base. Harmfulness Score (1–5) is rated by a GPT-based judge, where 1 indicates safe and 5 indicates highly harmful. LlamaGuard Score (0–1) is computed with Llama Guard and represents the fraction/probability of responses classified as unsafe (lower is safer).

Method	Harmfulness Score ↓				LlamaGuard Score ↓			
	Init	100	300	500	Init	100	300	500
BeaverTails								
Vanilla	2.090	3.394	3.638	3.750	0.146	0.422	0.492	0.482
Instruction	1.568	1.750	2.890	3.580	0.238	0.160	0.374	0.454
Vaccine	1.110	2.598	3.306	3.816	0.004	0.262	0.422	0.518
RepNoise	1.064	2.362	3.460	3.710	**0.000**	0.252	0.470	0.506
SDD	2.098	3.406	3.674	3.722	0.136	0.424	0.466	0.480
Booster	1.216	1.238	1.852	3.258	0.002	0.016	0.132	0.430
SGT	**1.034**	**1.070**	**1.556**	**3.080**	**0.000**	**0.000**	**0.084**	**0.378**
AEGIS								
Vanilla	1.937	3.047	3.217	3.192	0.144	0.399	0.494	0.516
Instruction	1.457	1.753	2.510	2.877	0.257	0.172	0.304	0.358
Vaccine	1.097	1.769	2.998	3.229	**0.000**	0.081	0.441	0.516
RepNoise	1.026	2.547	3.170	3.229	**0.000**	0.304	0.530	0.534
SDD	1.913	2.688	3.211	3.235	0.144	0.358	0.466	0.510
Booster	1.289	2.117	2.373	3.071	0.041	0.202	0.280	0.419
SGT	**1.008**	**1.374**	**2.245**	**2.729**	0.006	**0.061**	**0.271**	**0.302**



(a) Llama-3.1-8B (b) Mistral-7B-v0.3

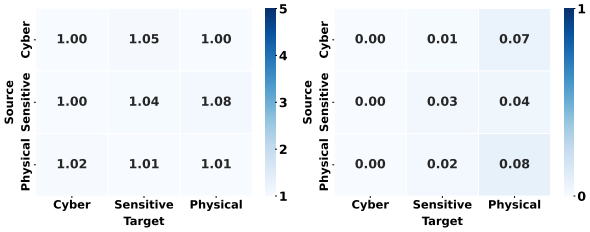
Figure 3: Comparison of Harmfulness and LlamaGuard scores under varying malicious fine-tuning (MFT) steps on BeaverTails and AEGIS for Llama-3.1-8B and Mistral-7B-v0.3.

4.4 Evaluation of Generalization Performance

To assess whether the proposed safety manifold generalizes across qualitatively different types of harmful content, we conducted experiments on the WildGuardMix dataset. WildGuardMix contains safety relevant categories of the prompts and responses. In this study, we focus on three malicious categories: cyberattacks, sensitive information organization government, and violence and physical harm. For each category, we train a category-specific soft trigger and base model using the corresponding subset of the dataset. We then perform malicious fine-tuning across all source–target category pairs, attacking each model not only with its in-domain category but also with unseen out-of-domain categories to assess cross-category transferability of safety alignment. These experiments evaluate the extent to which safety alignment generalizes under cross-domain adversarial attacks. As illustrated in Figure 4, the consistently low attack success scores across all source–target pairs demonstrate strong robustness, indicating that SGT maintains effective safety alignment even under cross-category transfer scenarios.

Table 2: Evaluation of general capabilities on benign benchmarks for Qwen3-8B-Base. We report 0-shot and 5-shot accuracy on MMLU and OpenBookQA.

Method	MMLU ↑		OpenBookQA ↑	
	0-shot	5-shot	0-shot	5-shot
Vanilla	0.774	0.786	0.322	0.390
Instruction	0.754	0.768	0.312	0.366
Vaccine	0.703	0.728	0.306	0.348
RepNoise	0.516	0.249	0.308	0.166
SDD	0.744	0.776	0.318	0.370
Booster	0.745	0.781	0.298	0.314
SGT	0.745	0.777	0.312	0.360



(a) Harmfulness Score (b) LlamaGuard Score

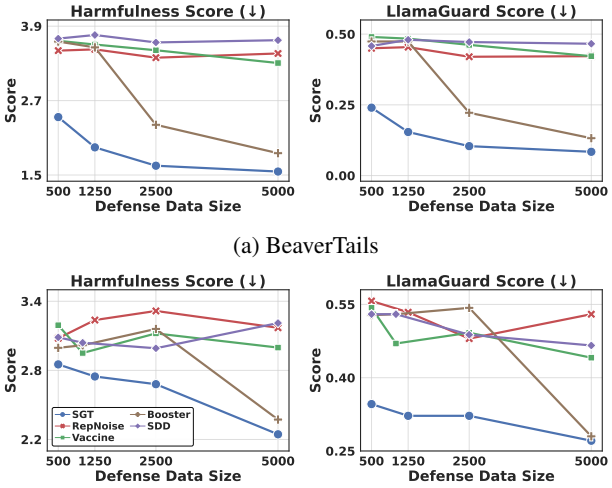
Figure 4: Cross-domain safety evaluation results on Qwen3-8B-Base. The heatmaps display the transferability of the safety defense across different domains. (a) shows the Harmfulness Score, and (b) shows the LlamaGuard Score. Rows represent the source domain used for optimizing the safety trigger, while columns represent the target domain used for evaluation.

4.5 Evaluation of Data Efficiency for Defense

We evaluate the data efficiency of safety defenses by varying the dataset size from 500 to 5,000 examples and assessing robustness under malicious fine-tuning on 300 harmful examples. Figure 5 shows that SGT achieves the lowest Harmfulness and LlamaGuard scores across all dataset sizes on both BeaverTails and AEGIS. Unlike baselines that require extensive data to reshape complex decision boundaries, our soft trigger leverages manifold smoothness to effectively guide inputs toward high-density safe regions. Consequently, SGT demonstrates consistent improvements across dataset sizes, exhibiting superior data efficiency compared to other models.

4.6 Robustness Against Adaptive Attacks

To address the concern that our optimization method could be exploited by adversaries to bypass the safety mechanism, we conduct an adaptive attack experiment. Motivated by studies showing that affirmative prefixes (e.g., "Sure, here's") compromise alignment (Wei et al., 2023; Zou et al., 2023), we first optimize a malicious soft trigger to induce this prefix. Subsequently, we subject the models to a rigorous joint fine-tuning regime that simultaneously trains on harmful data and forces alignment with this adversarial trigger. Notably, SGT exhibits superior resistance to the attack, outperforming all baselines in safety preservation, as shown in Table 3.



(a) BeaverTails

(b) AEGIS

Figure 5: Performance comparison of Qwen3-8B-Base against malicious fine-tuning (Step 300) across varying defense dataset sizes on BeaverTails and AEGIS benchmarks. SGT demonstrates superior data efficiency, effectively mitigating attacks even with small defense datasets compared to baselines.

Table 3: Comparison of Harmfulness scores (HS) and LlamaGuard Score (LS) for Qwen3-8B-Base under adaptive malicious fine-tuning (Step 100) with adversarial soft triggers.

Method	BeaverTails		AEGIS	
	HS ↓	LS ↓	HS ↓	LS ↓
Vaccine	3.326	0.490	1.733	0.111
RepNoise	1.384	0.038	1.411	0.053
SDD	3.802	0.578	2.652	0.237
Booster	3.148	0.508	1.883	0.061
SGT	**1.040**	**0.002**	**1.113**	**0.012**

5 Discussion

We analyze the geometric impact of our method by examining the last-layer output of the model when processed with malicious prompts. We compare the representation distributions across different models to understand the mechanism of our defense.

Alignment with the Safety Manifold Figure 6 visualizes the impact of the soft trigger on the model's representation space, indicating that our trained model's representations move away from

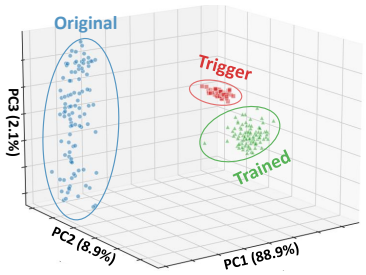
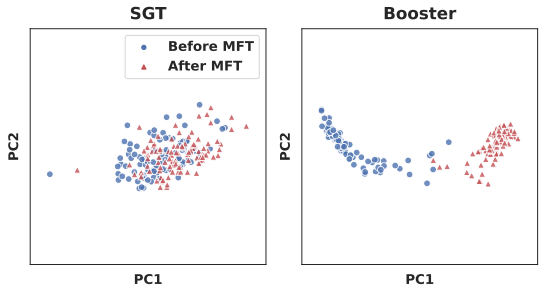
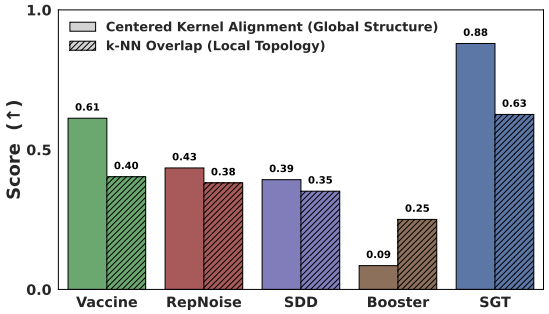


Figure 6: 3D visualization of representations using PCA. SGT representations of the trained model (green) align with the trigger-guided safety target (red), shifting away from the base model representation (blue).



(a) Visualization of Representation Drift (PCA)



(b) Quantitative Comparison of Manifold Preservation

Figure 7: Analysis of Representation Robustness on Qwen3-8B-Base. (a) PCA visualization comparing the feature space of SGT and Booster before and after malicious fine-tuning. (b) Quantitative analysis of manifold preservation capabilities.

the region formed by the base teacher model and become aligned with the region occupied by the teacher model with the soft trigger applied. This visualization suggests that the proposed training procedure encourages representations to shift toward and align with the safety region induced by the soft trigger.

Robustness to Malicious Fine-Tuning. Figure 7 analyzes how model representations evolve under malicious fine-tuning. Figure 7a visually compares the representation shifts of SGT and Booster. We observe that SGT maintains a compact representation distribution, whereas Booster exhibits a significant distributional shift. This contrast aligns with our methodological design, where the safety soft trigger effectively steers representations toward a secure, safety-oriented region. The representations of the remaining models are provided in Section B.

To quantify these shifts, Figure 7b reports two metrics: (i) Centered Kernel Alignment (CKA) (Kornblith et al., 2019) and (ii) k-NN overlap. The high CKA score observed for SGT implies the maintenance of a rigid global topology, effectively counteracting the global representational shift that attackers attempt to induce. Simultaneously, the high k-NN overlap indicates the preservation of local neighborhoods, ensuring that data points do not undergo local drift and remain anchored within the safe region.

Mechanism of Geometric Inertia. The visualization in Figure 6 aligns with the manifold assumption, where high-dimensional representations reside on low-dimensional structures rather than being uniformly distributed. Our empirical observations reveal distinct high-density clustering in the representation space with respect to safety attributes. This confirms that the representation space organizes into structured safety regions, demonstrating that such geometric structures can be actively induced and controlled to enforce safety.

The quantitative stability reported in Figure 7b substantiates a key mechanism of our defense: the safety trigger effectively guides representations toward a high-density safety manifold. Once anchored in this region, representations exhibit minimal drift even under malicious fine-tuning. We attribute this stability to 'geometric inertia': as these regions are densely populated with safety-aligned features, they offer strong resistance to the sparse gradient updates typical of malicious fine-tuning.

6 Conclusion

This paper proposes SGT, a representation alignment approach that improves robustness against malicious fine-tuning by anchoring model representations to a safety manifold. Empirically, we observe (i) a clear shift toward the target safety manifold and (ii) only small representation changes in response to malicious fine-tuning after alignment. These results suggest that aligning representations to a stable safety region can enhance robustness. We hope our technique serves as a foundation for further research in defending LLMs against malicious fine-tuning.

Limitations

Impact on Benign Utility Although SGT maintains competitive performance, we observe a slight degradation in benign tasks compared to the base model. This tradeoff is common among defense methods that impose safety constraints. In practice, this can be addressed by performing the supervised fine-tuning (SFT) on general-purpose datasets to recover general capabilities after applying the defense.

Vulnerability to Unbounded Adversaries While SGT significantly increases the barrier for attackers, it does not guarantee complete immunity against adversaries with unlimited computational resources and data. Given unbounded budget, malicious fine-tuning may eventually degrade the safety anchoring and the safety alignment. Thus, our work represents a significant step toward increasing the difficulty of attacks, but continuous research is required to enhance the intrinsic safety of open-weight models against scaling threats.

Ethics Statement

This work focuses on enhancing the safety of open-weight LLMs against malicious fine-tuning by proposing a structural alignment approach, SGT. To investigate potential vulnerabilities, we simulated malicious fine-tuning in a controlled, research-oriented environment. To assess the defense's effectiveness, we utilized an established threat model and publicly available safety benchmarks. Our study was conducted in accordance with the ACL Code of Ethics, and all data and models used are handled as per their respective licenses. Importantly, our findings and methodology are intended solely for defensive research; we do not provide instructions for generating harmful content. We contribute our methodology to the AI safety community to support the development of resilient open-source models.

This work uses several publicly available datasets. WildGuardMix is released under the ODC-BY license. The BeaverTails dataset and its family are released under the CC BY-NC 4.0 license, which permits non-commercial research use with attribution. The NVIDIA Aegis AI Content Safety Dataset 2.0 is released under the CC BY 4.0 license. MMLU is distributed under the MIT License, and OpenBookQA is released under the Apache License 2.0. All datasets are used solely for research purposes and in accordance with their respective licenses and intended use conditions. SGT is released under the CC BY-NC 4.0 license.

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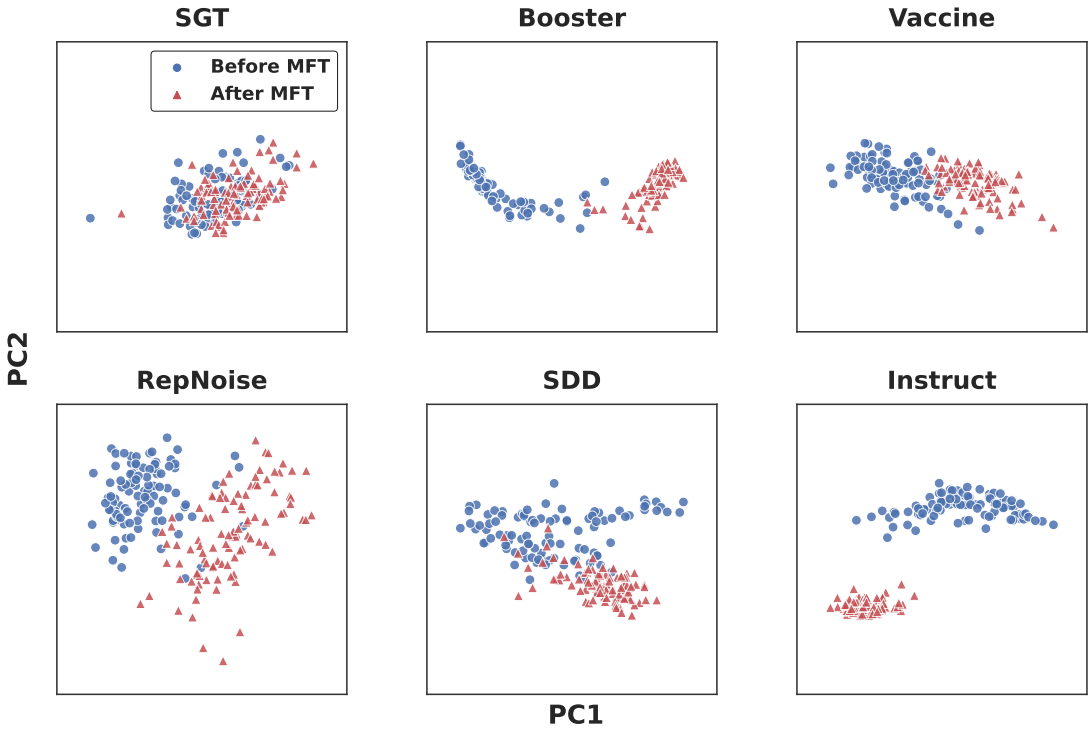

Figure 8: PCA visualization comparing the feature space before and after malicious fine-tuning for each baseline.

A Implementation Details

All experiments for both Stage 1 and Stage 2 were conducted using bfloat16 with 4 NVIDIA A100 40GB GPUs. For reproducibility, we fixed the random seed to 42 for the entire training process.

Learning Safety Guidance Trigger We initialize the soft trigger ϕ as a trainable vector from a random normal distribution with a scale of 0.01. The trigger is inserted into the input sequence with a length of 1. We train the trigger for 1 epoch using the AdamW optimizer with a learning rate of 1e-3 and a batch size of 4. To ensure trigger robustness, we apply consistency regularization with 2 perturbations per step and a noise standard deviation of 0.01. We set the consistency regularization weight in Eq. 1 to α_{cons}=1.0.

Trigger-Guided Representation Alignment We fine-tune the model for 3 epochs using AdamW with a learning rate of 1e-5, and we train on 5,000 examples for our main experiments. We use a per-device batch size of 2 and gradient accumulation steps of 4. We set the alignment and repulsion weights in Eq. 4 to $\alpha_{\text{align}} = 0.01$ and $\alpha_{\text{repel}} = 0.01$. For malicious fine-tuning, we use up to 500 training examples as the attack budget. For evaluation, we use 500 prompts from BeaverTails and 494 prompts from AEGIS.

B Representation Dynamics under MFT

To visually analyze the representation dynamics, Figure 8 presents the principal component analysis (PCA) for malicious prompts before and after malicious fine-tuning. As observed in the figure, the baseline models exhibit a significant distributional shift away from their original representations. In contrast, SGT demonstrates minimal displacement, remaining closest to the original representation.

C Robustness Against Malicious Fine-tuning Detail

Table 4 presents the quantitative comparison of safety performance under varying malicious fine-tuning budgets. As the number of malicious samples increases, SGT maintains consistently low scores, significantly outperforming other baselines even under higher data budgets. Furthermore, this robustness is consistent across diverse open-weight models, including Llama-3 and Mistral, which validates the generalizability of our approach.

Table 4: Comparison of Harmfulness and LlamaGuard scores under varying malicious fine-tuning (MFT) steps on BeaverTails and AEGIS. We compare (a) Llama-3.1-8B and (b) Mistral-7B-v0.3. Harmfulness Score (1–5) is rated by a GPT-5.1-based judge (lower is safer). LlamaGuard Score (0–1) represents the probability of unsafe responses (lower is safer).

(a) Llama-3.1-8B

Method	Harmfulness Score ↓				LlamaGuard Score ↓			
	Init	20	50	100	Init	20	50	100
BeaverTails								
Vanilla	1.986	3.966	3.926	4.000	0.356	0.528	0.502	0.530
Instruction	1.308	2.638	3.616	3.932	0.044	0.250	0.452	0.520
Vaccine	1.652	2.220	2.464	3.222	0.114	0.212	0.304	0.470
RepNoise	**1.020**	3.438	3.028	3.720	**0.000**	0.452	0.348	0.522
SDD	1.696	3.980	3.906	3.614	0.216	0.548	0.520	0.466
Booster	1.100	1.976	1.856	3.204	0.002	0.210	0.138	0.460
SGT	1.024	**1.536**	**1.410**	**2.212**	0.062	**0.150**	**0.080**	**0.246**
AEGIS								
Vanilla	1.962	3.626	3.421	3.676	0.366	0.464	0.565	0.579
Instruction	1.310	1.664	2.662	3.059	0.038	**0.030**	0.358	0.545
Vaccine	1.804	**1.437**	2.255	2.737	0.115	0.061	0.350	0.567
RepNoise	**1.032**	3.178	3.619	3.555	**0.000**	0.449	0.595	0.563
SDD	1.972	3.443	3.247	3.324	0.368	0.476	0.538	0.555
Booster	1.072	1.772	3.303	2.988	0.002	0.176	0.348	0.587
SGT	1.215	1.447	**2.117**	**2.543**	0.057	0.073	**0.209**	**0.364**

(b) Mistral-7B-v0.3

Method	Harmfulness Score ↓				LlamaGuard Score ↓			
	Init	20	50	100	Init	20	50	100
BeaverTails								
Vanilla	2.354	3.860	4.032	3.226	0.348	0.548	0.574	0.376
Instruction	2.126	3.922	4.142	3.134	0.119	0.552	0.586	0.354
Vaccine	1.110	**1.258**	1.454	2.120	0.032	0.322	0.388	0.604
RepNoise	1.106	3.748	3.954	3.560	0.044	0.540	0.586	0.474
SDD	2.080	3.708	3.942	3.116	0.178	0.510	0.560	0.354
Booster	1.006	3.140	4.164	3.476	0.004	0.430	0.628	0.494
SGT	**1.004**	1.360	**1.308**	**1.394**	**0.000**	**0.184**	**0.290**	**0.340**
AEGIS								
Vanilla	2.320	3.002	3.306	3.557	0.362	0.569	0.451	0.589
Instruction	1.966	2.921	3.478	3.407	0.119	0.482	0.561	0.599
Vaccine	1.140	**1.162**	1.569	1.791	0.038	**0.107**	0.356	0.435
RepNoise	1.154	3.858	3.279	3.466	0.043	0.514	0.506	0.640
SDD	2.014	3.320	3.326	3.138	0.138	0.634	0.498	0.567
Booster	1.045	3.524	3.393	3.587	0.028	0.595	0.545	0.599
SGT	**1.000**	1.370	**1.121**	**1.020**	**0.000**	0.271	**0.111**	**0.020**