LoRAShield: Data-Free Editing Alignment for Secure Personalized LoRA Sharing

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ABSTRACT

The proliferation of Low-Rank Adaptation (LoRA) models has democratized personalized text-to-image generation, enabling users to share lightweight models (e.g., personal portraits) on platforms like Civitai and Liblib. However, this "share-and-play" ecosystem introduces critical risks: benign LoRAs can be weaponized by adversaries to generate harmful content (e.g., political, defamatory imagery), undermining creator rights and platform safety. Existing defenses like concept-erasure methods focus on full diffusion models (DMs), neglecting LoRA's unique role as a modular adapter and its vulnerability to adversarial prompt engineering. To bridge this gap, we propose LoRAShield, the first data-free editing framework for securing LoRA models against misuse. Our platform-driven approach dynamically edits and realigns LoRA's weight subspace via adversarial optimization and semantic augmentation. Experimental results demonstrate that LoRAShield achieves remarkable effectiveness, efficiency, and robustness in blocking malicious generations without sacrificing the functionality of the benign task. By shifting the defense to platforms, LoRAShield enables secure, scalable sharing of personalized models, a critical step toward trustworthy generative ecosystems. **Warnings**: *This paper contains sexually and bloody explicit imagery that some readers may find disturbing, distressing, and/or offensive. To mitigate the offensiveness to readers, we showcase some of the explicit images with black masks.*

CCS CONCEPTS

• **Security and privacy** → *Digital rights management*; • **Do Not Use This Code → Generate the Correct Terms for Your Paper**; *Generate the Correct Terms for Your Paper*; Generate the Correct Terms for Your Paper; Generate the Correct Terms for Your Paper.

KEYWORDS

diffusion model, text-to-image, adversarial attack, concept erasure

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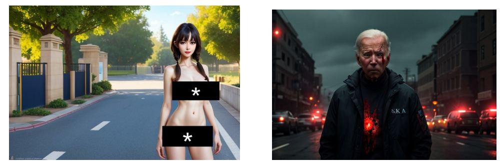

(a) Misuse example 1 **(b) Misuse example 2**

Figure 1: Generated images using LoRAs ([18] and [35]) on Civitai. Note that these images will never be posted online.

1 INTRODUCTION

The rapid development of text-to-image (T2I) technology [15, 38], particularly diffusion models (DMs) [41], has dramatically improved personalized creativity. However, this advancement has simultaneously exacerbated problems like bias [16, 32], copyright infringement [44], and the generation of not-safe-for-work (NSFW) content [51, 52]. Malicious users of T2I services may exploit these models to create misleading images that harm individuals' interests or reputations or even provoke social panic [39]. For instance, a finance worker at a multinational firm was tricked into paying out $25 million to fraudsters using deepfake technology to pose as the company's chief financial officer in a video conference call [4].

To mitigate such risks, numerous studies [20, 49, 58] have explored the elimination of specific concepts from DMs to prevent the generation of harmful content. However, existing research focuses mainly on the DMs themselves [57], overlooking significant vulnerabilities in their plugins. In particular, Low-Rank Adaptation (LoRA) models [23] enable parameter-efficient adaptation of DMs through low-rank matrix decomposition, allowing users to customize models with minimal computational overhead. The widespread adoption of LoRA, due to its lightweight characteristics, enables individuals to efficiently build personalized models from their local datasets, such as personal portraits or artworks, utilizing DMs as base models. Users often share and publish their LoRA models, instead of the entire DM, on platforms like Civitai [8], LiblibAI [29], and Hugging Face [24]. Any other user can download these shared LoRAs and incorporate them into the generation of fancier images.

Unfortunately, this share-and-play characteristic also introduces significant risks. Malicious users can misuse others' uploaded LoRAs to generate harmful content. For example, our tests in Fig. 1 using Civitai's online generation services reveal that despite the platform's claims of preventing the generation of NSFW content [9], benign LoRAs uploaded by genuine users can still be exploited to produce content that can significantly disrupt the interest and reputation of LoRA owners. Thus, malicious actors can download benign LoRAs and generate harmful images, negatively impacting the original creators' interests or reputation. This situation indicates a critical gap in effective oversight by both academia and industry regarding the abuse of LoRAs.

To address this risk, we re-examined the threat models (Section 3.3) associated with LoRA misuse in current model marketplaces and wondered if it is possible to develop a defense to mitigate the gap above. Given the high volume of LoRA models uploaded to platforms [47], the defense method must be lightweight and efficient, avoiding negative impacts on the quality of legitimate image generation. Additionally, we find that even though previous studies [49, 57] have indeed proposed methods for concept erasure in DMs, these typically require substantial computational resources and extra images. Moreover, current concept erasure techniques frequently exhibit instability, incomplete removal of target concepts, limited generalization, and robustness restricted to specific prompts, which will be discussed in Section 2.2 as well.

Further, we propose a platform-driven and data-free LoRA editing alignment method (LoRAShield) that allows users to specify undesired concepts, thus preventing their LoRAs from being exploited for malicious purposes. Specifically, users upload LoRAs to a platform that offers dynamic editing services based on user-defined constraints. By editing and realigning the LoRA's weight subspace, LoRAShield restricts the model's ability to produce certain undesired content while preserving the quality of its intended generation tasks for legitimate uses. In summary, we make the following contributions.

- We reveal the risk of the current personalization model on model-sharing platforms, raising the alarm about harmful image generation for LoRA owners.
- We make the first attempt to develop a data-free editing method to secure the sharing of personalized LoRA with adversarial optimization and semantic augmentation.
- Extensive experiments demonstrate the effectiveness, robustness, and efficiency of LoRAShield.

2 BACKGROUND & RELATED WORK

2.1 Model-Sharing Platforms

The proliferation of model-sharing platforms such as Civitai [8], LiblibAI [29], and Hugging Face [24] has democratized access to generative model tools, fostering a "share and play" culture where users freely distribute and utilize pre-trained models. However, this accessibility introduces critical risks. While this facilitates innovation, it also creates vulnerabilities: benign users who upload models trained on private data face potential misuse by adversaries. Such risks are exacerbated by the lack of robust safeguards on many platforms; for instance, Civitai's reliance on an "asymmetric multisided marketplace" [21] prioritizes model diversity over rigorous vetting.

2.2 Concept Erasing in DMs

Large-scale DMs are shadowed by their propensity to produce ethically risky or legally contentious outputs, such as sexually explicit imagery, culturally sensitive content, or artistic styles protected by copyright. A growing number of research studies [17, 19, 20, 27, 53, 54, 57] have proposed leveraging unlearning techniques to remove or suppress specific concepts via unlearning in generative models to prevent misuse. The traditional machine unlearning strategy [2] aims to modify a model to make it generalize without memorization to tackle privacy and copyright concerns. Although early approaches [19, 26] focused on fine-tuning all DMs parameters to forget a target concept. For example, the Erased Stable Diffusion (ESD) by Gandikota et al.[19, 26, 53] fine-tunes a DM with a negative guidance teacher to align the given visual concept with " " condition. Similarly, Zhang et al.[53] proposed a "Forget-Me-Not" (FMN) technique that aligns the model output for the target concept with that of a benign "anchor" concept, thus preventing the model from generating the target concept under its text condition, allowing the model to forget without retraining from scratch while preserving closely related concepts. However, since these methods tend to struggle with sizeable computational costs [20, 57], Unified Concept Editing (UCE) [20] proposed to edit DMs without training to improve the efficacy and scalability of the previous work. Wu et al.[49] formulated diffusion unlearning as a constraint optimization and achieved it by deviating the learnable generative process from the ground-truth denoising procedure, while the assumption requiring all training data is unrealistic. Later, Lyu et al. [33] argued that most of the existing methods failed to preserve the generation of untargeted concepts and proposed an erasing framework (SPM) via one-dimensional adapters to erase multiple concepts from DMs at once via versatile erasing. Differently, SafeGen [27] eliminated unsafe visual representations from the model regardless of text input, leading to resistance to adversarial prompts since unsafe visual representations are obstructed from within.

2.3 Adversarial Attacks against DMs

The growing adoption of defensive strategies in DMs has catalyzed parallel research into system robustness and security, revealing critical vulnerabilities through adversarial attacks. Recent work demonstrates that DMs remain susceptible to generating harmful content even after deploying safety measures, particularly when adversaries craft inputs to circumvent safeguards. For example, Yang et al. [52] crafts semantically preserved yet misleading prompts on surrogate models, enabling transferable attacks that deceive prompt filters. Instead, MMA-Diffusion [51] conducted transferable attacks by crafting adversarial prompts on surrogate models that can deceive the prompt filter while remaining semantically similar to the target concept. Zhang et al. [56] further exposed the fragility of concept-erasure techniques by proposing UnlearnDiffAtk, an adversarial prompt generation method that resurrects supposedly "erased" concepts in fine-tuned DMs. Complementing these efforts, automated red-teaming tools such as Ring-A-Bell[45] and Prompting4Debugging [6] systematically stress-test DM safety mechanisms. These papers reveal that even DMs subjected to rigorous fine-tuning or filtering remain vulnerable to synonym substitutions, highlighting that superficial compliance with safety benchmarks does not guarantee robustness against adaptive adversaries.

2.4 Remarks

Overall, the existing literature indicates the following points: (1) all of the concept-erasing methods target DMs instead of LoRAs, which are frequently used for customization of individuals; (2) recent evaluation [57] also reveals that most of these attacks exhibit limited generalization to in-domain prompts (innocent and not relevant to

Table 1: Comparison with existing erasing methods. ✔/✘ illustrates whether the method can achieve the corresponding property.

Erasing Methods	Target	Effectiveness		Efficiency		
		Generalization	Robustness	Data-Free	Time (s)	Memory (GB)
ESD [19]	DMs	✔	✘	✔	≈ 6100	17.8
FMN [53]	DMs	✘	✘	✘	≈ 350	17.9
UCE [20]	DMs	✘	✘	✔	≈ 430	5.1
EraseDiff [49]	DMs	✔	✘	✘	≈ 1500	27.8
SPM [33]	DMs	✔	✘	✘	≈ 29700	6.9
SafeGen [27]	DMs	✔	✔	✘	–	–
Ours (LoRAShield)	LoRA	✔	✔	✔	≈ 14	0.23

the erased concept); (3) the majority of these methods fail to defense against current attacks [51, 52, 56]; (4) balancing completeness of erasure with minimal data, time and computation resources is still challenging. In comparison, as shown in Tab. 1, LoRAShield addresses these gaps and secures the modular components most vulnerable to misuse in platforms.

3 PRELIMINARIES

3.1 Text-to-Image Diffusion Models

T2I diffusion models [15] can synthesize high-fidelity images $x \in \mathcal{X}$ by iteratively denoising latent representations $z_t \in \mathcal{Z}$ conditioned on textual inputs c. The core framework typically comprises four components: an image encoder $\mathcal{E} : \mathcal{X} \to \mathcal{Z}$ and decoder $\mathcal{D} : \mathcal{Z} \to \mathcal{X}$ of the autoencoder, a U-Net diffusion model ϵ_θ, and a text encoder $\mathcal{T}$. The encoder first compresses images into a lower-dimensional latent space and reconstructs them via a decoder $\mathcal{D}$, i.e., $\mathbf{z} = \mathcal{E}(\mathbf{x})$ and $\hat{\mathbf{x}} = \mathcal{D}(\mathbf{z})$. While the U-Net then operates in this latent space, iteratively refining the noisy representations $\mathbf{z}_t$ through a reverse diffusion process:

$$\mathbf{z}_{t-1} = \frac{1}{\sqrt{\alpha_t}}\left(\mathbf{z}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}} \cdot \epsilon_\theta(\mathbf{z}_t, t, \mathbf{c})\right) + \sigma_t \cdot \epsilon, \tag{1}$$

where timestep $t \in \{1, 2, \ldots, T\}$, $\epsilon \sim \mathcal{N}(0, \mathbf{I})$, ϵ_θ predicts the noise, $\mathbf{c} = \mathcal{T}(C)$ denotes text embeddings given the prompt set C, and $\alpha_t, \bar{\alpha}_t, \sigma_t$ are scheduler hyperparameters. Specifically, the U-Net integrates textual guidance via cross-attention layers, which dynamically align image features with target concepts. Cross-attention (CA) layer computes:

$$\text{Atten}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right)\mathbf{V}, \tag{2}$$

where queries $\mathbf{Q}$ derive from image tokens, and keys $\mathbf{K}$ and values $\mathbf{V}$ derive from $\mathbf{c}$. This mechanism enables fine-grained control over concept representation, as the model prioritizes text-relevant features during denoising.

3.2 Low-Rank Adaptation of Diffusion Models

The LoRA techniques [23] enable efficient and effective adaptation and customization of T2I diffusion models via decomposing the weight update matrix $\Delta W \in \mathbb{R}^{m \times n}$ when fine-tuning the original weight W_0:

$$\Delta W = B \times A \tag{3}$$

where $B \in \mathbb{R}^{m \times r}$, $A \in \mathbb{R}^{r \times n}$ and $r \ll \min(m, n)$ stands for the rank that constrains the update to specified dimension space, significantly reducing the trainable parameters of W_0. During the inference stage, W_0 is updated with $W_0 + \alpha \Delta W$, where α is a scaling factor that control the strength of the adaptation.

The rise of platforms like Civitai [8] has democratized access to personalized generative models. Unlike full diffusion models (e.g., SD1.5 [12] and its extended versions like DreamShaper [10] and Realistic Vision [11]), which are prohibitively large (often more than 5GB) and computationally expensive to share, LoRA models compress adaptation into lightweight matrices (typically about 100MB). Users train LoRAs on local data (e.g., personal artwork or portraits) and upload them with metadata specifying compatible base models. There are much more LoRAs but less base models on Civitai [8]. This modular approach allows others to: (1) Efficiently combine concepts: Load multiple LoRAs (e.g., "cyberpunk style" + "celestial lighting") into a single base model, scaling their influence via α; (2) Preserve reproducibility: Base models act as standardized backbones, ensuring consistent generation across users.

3.3 Threat Model

We consider a scenario involving three parties as depicted in Fig. 2: a LoRA owner (victim) who wants to share her/his customized LoRA trained with private data, a trusted model-sharing platform (defender) [9] and a LoRA misuse infringer (attacker).

3.3.1 LoRA owner's Goal & Capabilities . The LoRA owner aims to release his/her customized LoRA trained with private images (personal portrait and promoted products) to the public for benign purposes (e.g., personalized photography or advertisement). However, she/he does not want the models to be used for malicious purposes that may affect her/his interests and reputation, e.g., exploiting released LoRA to generate fake images to fabricate rumors about the LoRA owner. Since the owner has no control over the LoRA downloaded by others, to avoid infringements, the owner could request the platform for active editing services to erase the unwanted concept before releasing the LoRA.

3.3.2 Adversary's Goal & Capabilities. An attacker on this platform could be anyone who downloads a publicly available LoRA model and attempts to use it for harmful content generation that may violate the platform's content policies [9, 30]. The generated content [9, 30] could include violent imagery, sexual or pornographic

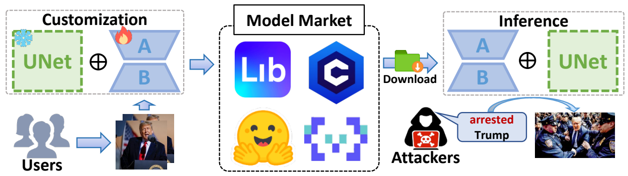

Figure 2: Overview of the threat model.

scenes, deepfakes of real individuals, propaganda, or other disallowed material, leveraging the specific capabilities of the LoRA. Since the attacker can download any LoRAs from the platform, the attacker (1) has complete access and control to the protected LoRA, (2) has complete control over the generation process, but (3) has no access to the training data or unprotected LoRA. However, she/he also wants to ensure the high quality and semantic alignment of the generated images.

3.3.3 Adversary's Strategies. We assume that the attacker is motivated and technically savvy, willing to launch adaptive attacks to bypass the protection. Note that even if most DMs like SD have safety checkers but offline attackers can turn them off or find novel prompts to evade them. (**Attack I**) One likely strategy is prompt engineering, trying various descriptive prompts (or even gibberish tokens) to trick the model into revealing the protected concept (if the LoRA was meant to be restricted). This aligns with the red-teaming approaches in recent research [52, 56], where attackers find that even "safe" models can produce unsafe outputs with cleverly crafted prompts. (**Attack II**) Another powerful strategy is to combine multiple LoRAs since these adapters are often composable, and an adversary might chain a benign LoRA with another one that introduces unsafe elements. For example, they might apply an "NSFW unlock" [13] or violence-enhanced LoRA alongside the protected LoRA, hoping to restore any pruned capabilities or amplify forbidden content. By blending LoRAs, the attacker tries to circumvent a single LoRA's built-in safety, even if our defense cripples the LoRA's ability to generate certain content on its own, the attacker could supplement it with another malicious adapter that fills in the gaps.

3.3.4 Defender's Goal & Capabilities. The defender's (platform) goal is to enable creative uses of LoRA while preventing misuse. For instance, a LoRA might add a new artistic style, and the platform wants regular users to enjoy it but disallows anyone from using it to generate hate symbols or obscene content in that style. Neither the benign users nor the defender trusts every user and thus implements protections specified by the LoRA owner. Therefore, the defender cannot expend significant resources and defense must be automated and efficient (no lengthy retraining or manual intervention for each model). This is because on a large platform like Civitai, there could be thousands of uploaded LoRAs [47] in a short period, and users expect to upload and update them frequently. Besides, the defender is not accessible to the benign training data of the LoRA for privacy reason, which means that the editing should be data-free as well.

4 METHODOLOGY

4.1 Design Overview

Under the threat model presented above, our primary goal is to provide an efficient and robust defense mechanism capable of preventing unauthorized and malicious exploitation of large-scale shared LoRAs on platforms while maintaining their original generative capabilities for legitimate users. In summary, our method addresses several critical challenges below:

(1) Data-Free Implementation: Since the platform hosting the LoRAs don't have access to the original data, the proposed method must operate entirely without reliance on the training dataset.

(2) Preservation of Utility: A practical defense should precisely remove only potentially harmful concept representations without diminishing the model's general utility for creative generation.

(3) Lightweight and Efficiency: Given the high frequency and large volume of LoRAs uploaded, our defense must be computationally lightweight to process numerous models quickly without introducing significant latency or computational overhead.

(4) Robustness Against Adaptive Attacks: Adversaries are aware of defenses and can employ strategies (Section 3.3.3) to evade. Hence, the defender must proactively anticipate such behaviors.

To overcome these challenges, in the following subsections, we design a lightweight framework that effectively balances security needs with usability, ensuring that LoRAs remain valuable tools while raising the barrier to malicious exploitation.

4.2 Robust Editing Alignment

As mentioned above in Section 3.1, given the conditional prompt C, the cross-attention layer matters a lot in controlling the image generation. This motivates us to erase the concept in the cross-attention layer to safeguard LoRAs. Initially, we obtain the text embeddings c and c_t, with the benign and target concepts to be erased, respectively. Further, we calculate the difference between the LoRA-adjusted and original weight matrices for each CA layer. We iteratively update these matrices to minimize the discrepancy between the generated embeddings from the adjusted model and the intended safe embeddings, employing a loss function that combines mean squared error (MSE).

$$\mathcal{L}_{align}(c_t, c) = \mathbb{E}\|c_t \times (W + \alpha\Delta\hat{W}) - c \times (W + \alpha\Delta W)\|_2^2 \quad (4)$$

However, minimizing $\mathcal{L}_{align}$ without restricting the difference between the edited and original LoRA parameters disrupts the benign performance of the LoRA as well. Therefore, we add the regularization term to preserve the performance of the edited LoRA on the untargeted concept.

$$\mathcal{L}_{pre} = \|\Delta\hat{W} - \Delta W\|_2^2 \quad (5)$$

This targeted pruning ensures minimal disruption to benign concept generation while effectively disabling restricted concepts.

4.2.1 Adversarial Optimization for Robust Generalization. However, incorporating $\mathcal{L}_{align}$ and $\mathcal{L}_{pre}$ can only prevent the generation given the exact same word of the erased concept, but would fail to generalize to semantic space. Ideally, our goal is to achieve robust alignment by erasing the semantics of the target concept. To achieve this, we first make the following assumption.

Assumption 1: Let $w_t^i \in \mathcal{W}_t$ be the set of synonyms with the same concept in the text space. We assume that $\forall w_t^i, w_t^j \in \mathcal{W}_t$ and $\exists \gamma > 0$, and we have $\mathrm{Dist}(\mathcal{T}(w_t^i), \mathcal{T}(w_t^j)) \leq \gamma$, where $\mathrm{Dist}(\cdot)$ measures the difference between the word embeddings.

This assumption is particularly justified in high-quality pretrained models, such as CLIP [40], where semantic neighbors in the text space are often mapped to proximity in vector space, supporting a smooth and compact representation of conceptual similarity. However, we admit that while distributional semantics generally ensures semantically similar words are embedded closely, this property varies with different architectures and tokenization strategies. With the assumption above, using ℓ_2 to stand for $\mathrm{Dist}(\cdot)$, we formalize the target concept as a ℓ_2-bounded region in the text embedding space. Specifically, for a target concept with text embedding c_t, we define its semantic neighborhood as an ℓ_2 ball:

$$\mathcal{B}(c_t, \gamma) = \{c_t' \in \mathbb{R}^d \mid \|c_t' - c_t\|_2 \leq \gamma\}, \tag{6}$$

where γ bounds the maximum distance between c_t' and any synonym embedding. That is, $\mathcal{L}_{align}$ can be further expressed as:

$$\mathbb{E}_{\hat{c}_t \in \mathcal{B}(c_t, \gamma)} \|\hat{c}_t \times (W + \alpha \Delta \hat{W}) - c \times (W + \alpha \Delta W)\|_2^2 \tag{7}$$

We notice that the minimization of this expectation can be transformed into a bi-level optimization problem by maximizing the lower bound of the expectation:

$$\min_{\Delta \hat{W}} \max_{\hat{c}_t \in \mathcal{B}(c_t, \gamma)} \|\hat{c}_t \times (W + \alpha \Delta \hat{W}) - c \times (W + \alpha \Delta W)\|_2^2. \tag{8}$$

However, directly solving this problem often involves large computations since solving the inner maximization is not trivial [34]. Drawing inspiration from recent works [5, 48] illustrating that the adversarial optimization in sample space can also be achieved with adversarially robust parameters within the restricted ℓ_2 bound:

$$\min_{\Delta \hat{W}} \max_{\|\delta_w\| \leq \tau} \mathbb{E}\|c_t \times (W + \alpha \Delta \hat{W} + \delta_w) - c \times (W + \alpha \Delta W)\|_2^2 \tag{9}$$

Here, δ_w represents adversarial perturbations to the LoRA parameters, constrained by τ to balance robustness and stability. Equation 9 shifts the optimization focus from the input embedding space to the parameter space, enabling efficient gradient-based updates while implicitly covering semantic variations within $\mathcal{B}(c_t, \gamma)$.

4.2.2 Low-Rank Decomposition via Singular Value Decomposition (SVD). Meanwhile, we should emphasize that directly optimizing A, B to obtain $\Delta \hat{W}$ is not trivial since both matrices are projected into low-dimension space, leading to significantly unstable optimization. Instead, we first initialize $\Delta \hat{W} = BA$ and directly update $\Delta \hat{W}$. Subsequently, $\Delta \hat{W}$ is decomposed via SVD. This step is crucial for reducing the optimization complexity while maintaining the structural integrity of the model's learned representations. Given a weight matrix $\Delta \hat{W}$, we decompose it into two lower-rank matrices $\hat{A}$ and $\hat{B}$, which serve as a compact approximation, ensuring effective pruning alignment with minimal performance loss. Formally, we first perform SVD on $\Delta \hat{W}$:

$$\Delta \hat{W} = USV^T, \tag{10}$$

where U and V are the left and right singular vector matrices, and S is the diagonal matrix containing singular values. We retain only the top r singular values and their corresponding singular vectors,

Algorithm 1 Robust Editing with Semantic Augmentation

Require: Clean T2I diffusion model with text encoder $\mathcal{T}$ and UNet ϵ_θ; the target concept C_t to be erased; the target LoRA model with parameter ΔW; total editing step T.
Ensure: Aligned LoRA model.

Initialize $\Delta \hat{W} \leftarrow \Delta W$
$\{c_t^1, c_t^2, c_t^3, \ldots, c_t^K\}, \{c^1, c^2, c^3, \ldots, c^K\} \leftarrow \mathcal{T}(\mathrm{LLM}(C_t))$
for $t = 0, 1, \cdots, T-1$ **do**
  Compute the perturbed δ_w with $\tau \cdot \nabla_W \mathcal{L}_{align}$
  Solving the inner maximization $\hat{W} \leftarrow W + \delta_w$
  // Compute the loss $\mathcal{L}_{all}$ based on $\hat{W}$.
  $\mathcal{L}_{all} \leftarrow \mathcal{L}_{align} + \eta \cdot \mathcal{L}_{pre}$
  Update $\Delta \hat{W}$ via $\nabla_{\Delta \hat{W}} \mathcal{L}_{all}$ using Adam.
end for
Approximate $\Delta \hat{W}$ using SVD in Equation 10.
return $\Delta \hat{W}$

indicated as U_r, S_r, V_r^T, where r is the rank of LoRA. To construct the final low-rank approximation, we compute the square root of the singular values:

$$\Sigma_r^{\frac{1}{2}} = \mathrm{diag}(\sqrt{S_r}) \tag{11}$$

The resulting decomposition is then defined as:

$$\hat{B} = U_r \Sigma_r^{\frac{1}{2}}, \quad \hat{A} = \Sigma_r^{\frac{1}{2}} V_r^T \tag{12}$$

Thus, the original weight matrix $\Delta \hat{W}$ is approximated as:

$$\Delta \hat{W} \approx \hat{B}\hat{A} \tag{13}$$

Although we only use the approximated version of ΔW, we found that the loss has little influence on the performance of LoRAShield.

4.3 Semantic Augmentation

While adversarial optimization allows the erasure of the embedding space around the given concept, it remains confined to local neighborhoods defined by the ℓ_2 ball $\mathcal{B}(c_t, \gamma)$ and fails to account for global semantic relationships that attackers may exploit through paraphrasing or cross-concept blending. To address this limitation, we propose a semantic augmentation strategy that expands the defended semantic space by enriching the conceptual representation of the target to be erased. Our method operates without requiring access to the original training data, instead leveraging LLMs to generate semantically relevant synonyms and antonyms for the target concept. Formally, given a target concept c_t, we query an LLM to produce: (1) Synonyms: Terms closely aligned with C_t (e.g., "modern" → "contemporary") to capture linguistic variations; (2) Antonyms: Terms contrasting with C_t (e.g., "modern" → "archaic") to define conceptual boundaries. For concepts with no viable antonyms, we default to a neutral reference embedding (embedding of ""). This ensures that the erased concept is suppressed without requiring a contrastive counterpart, preserving alignment stability. These augmented terms are then encoded into text embeddings synonyms $\{c_t^1, c_t^2, c_t^3, \ldots, c_t^K\}$ and antonyms $\{c^1, c^2, c^3, \ldots, c^K\}$ ($K = 5$ in this paper) to replace the c_t and c in Equation 9. By integrating these embeddings into the optimization, we enforce robustness against a broader range of adversarial prompts. The overall procedure of our LoRAShield incorporating "Semantic Augmentation" is illustrated in Algorithm 1.

5 EVALUATION

5.1 Experimental Setup

5.1.1 Base Models. We select SD v1.5 [12] DreamShaper [10] and Realistic Vision [11] as the base models in the experiments, since SD v1.5 is the most popular base model on Civitai and there are many remarkable variants, among which DreamShaper and Realistic Vision, with 1.2 and 1.6 million downloads on Civitai alone [8].

5.1.2 Datasets and Personalization Methods. We select four datasets for the evaluation in this paper, including two style-based datasets: (1)"3DM" [31] is a dataset that has 3D rendering style;(2)"pixelart" [46] is a dataset that has pixel-like style; and two portrait-based datasets (3)"Cat" [7] that describe a cat with all kinds of dressings; and (4)"trump" [14] that has the images of Donald Trump generated by LoRA. For LoRA fine-tuning, we set the rank at 128, targeting the attention and projection layer of the UNet with 500 steps (lr=2e-5) following the code given by Hugging Face [25].

5.1.3 Evaluation Metrics. Following the previous works [20, 54, 55], the effectiveness of LoRAShield is assessed with the following metrics. (1) Concept Removal Score (CRS) measures the similarity between images generated with prompts with the given word and the target concept using the CLIP score [40], and a lower CRS denotes better erasing performance. Similarly, (2) In-domain Retain Score (IRS) measures the similarity between images generated with prompts of the target concept but different from the given word and the target concept using the CLIP score. (3) Benign Preservation Score (BPS) measures the similarity between the images and the prompts without the undesired concept to evaluate the faithfulness of the image and corresponding prompt using the CLIP score. (4) FID [22] compares the quality and fidelity between the images generated with benign LoRA and images generated with edited LoRA. A lower score means that the distribution of images is more similar. (5)LPIPS compares the semantic similarity between the image generated on benign and the edited LoRA with benign prompts. In particular, for nudity measurement on "3DM" and "pixelart" datasets, following the previous work [27], we use NudeNet [37] to further validate the effectiveness of LoRAShield. The efficiency is measured by running the (1) Time of the erasing process and the (2) Memory costs to conduct the erasing. The robustness of LoRAShield against out-of-domain prompts and attacks is presented in Sec 5.3.

5.1.4 Implementation Details. For target concept, following previous settings [19, 27, 56], we select "nude" and as the concept to be erased for style-based datasets (i.e., "3DM" and "pixelart"), and "bloody" for portrait-based datasets (i.e., "cat" and "trump"). For both benign and edited LoRA, we use LLM (Qwen-Plus [50]) to generate 50 prompts with the corresponding trigger word and generate 10 images for each prompt with 10 different random seeds with 500 images for each model and dataset in total. All of the above metrics are evaluated with these generated images. The editing step is set at 10 and τ=1e-5. We set the merging ratio α of LoRA at 1 when merging with the base model in default.

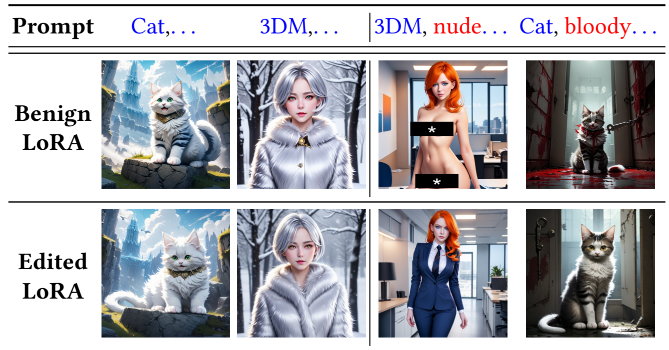

Figure 3: Images synthesized with benign (1st row) and edited (2nd row) LoRA when the given prompts without (1st two column) and with (last two column) target concept.

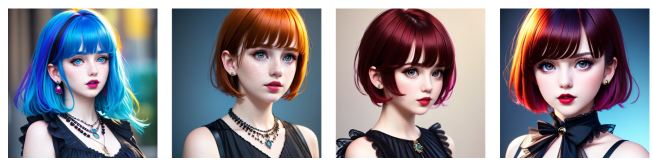

Figure 4: Cumulative concept erasure: From left to right, images generated by (1) benign LoRA, (2) with concept "hair color" erased, (3) with concepts "hair color"+"necklace" erased, and (4) with concepts "hair color"+"necklace"+"head gesture" erased, illustrating progressive suppression of target semantics while preserving non-target features.

5.2 Performance against Misuse

The performance of LoRAShield is presented in Tab. 2. Note that for a fair comparison, we also report the performance of benign LoRA. To measure the influence of LoRAShield on FID and LPIPS, we regenerate 500 images with different random seeds following the setting before as a comparison for benign LoRAs.

5.2.1 Erasing Effectiveness. Tab. 2 illustrates that the images generated by edited LoRA exhibit much lower CLIP scores compared to the benign one, indicating that LoRAShield can erase the target concept effectively. Additionally, when facing in-domain prompts, the edited LoRA can still maintain a low IRS value. Intuitively, we visualize the generated images (on DreamShaper) in Fig. 3, where the images generated on benign LoRA can generate images that significantly violate the protocol of model-sharing platforms. In contrast, even given the explicit prompts, the images generated on edited LoRA present no target concept while aligning with the other semantic prompts. Furthermore, we evaluate the performance of LoRAShield to erase nudity with NudeNet [37] in Tab. 3, in which the images generated on edited LoRA exhibit significantly decrease of nudity and our in-person check further found that many images generated on edited LoRA that were noted as nude by NudeNet, have been misclassified actually.

5.2.2 Functionality-preserving. Other than effectiveness, preserving the functionality of LoRA itself is also necessary. As shown in Tab. 2, the BPS values of edited LoRA have a slight decrease

Table 2: Performance of LoRAShield on three base models and four datasets. Each metric contains two values for edited (1st) and benign (2nd) LoRA, respectively. The ↑ (↓) indicates that a higher (lower) value for the metric signifies superior performance.

Base Model	Datasets	Effectiveness		Functionality-preserving			Efficiency	
		CRS↓	IRS↓	BPS↑	FID↓	LPIPS↓	Time(s)	Memory(GB)
SD1.5	pixelart	13.98/17.72	11.44/13.22	32.06/32.34	67.97/94.92	0.37/0.67	12.97	0.2246
	3DM	15.24/19.71	14.53/17.58	30.99/30.56	56.44/63.38	0.39/0.60	13.18	0.2363
	trump	12.70/14.08	12.08/13.63	25.56/25.27	59.60/77.70	0.29/0.67	13.56	0.2246
	Cat	12.57/14.13	12.72/13.42	29.56/29.71	77.58/69.71	0.38/0.62	12.2	0.2363
DreamShaper	pixelart	12.93/19.30	10.68/14.61	34.94/35.25	70.59/94.34	0.41/0.67	12.98	0.2246
	3DM	15.53/20.43	14.73/16.90	32.47/32.70	40.36/54.88	0.30/0.54	13.74	0.2246
	trump	11.34/14.34	11.67/14.41	26.29/26.35	66.21/68.29	0.40/0.62	17.94	0.2178
	Cat	12.83/14.62	12.50/13.56	30.90/31.01	68.02/65.21	0.37/0.56	16.32	0.2363
Realistic Vision	pixelart	13.20/20.41	10.88/14.56	35.34/35.01	65.27/108.55	0.37/0.67	13.52	0.2246
	3DM	16.55/20.38	14.73/17.35	31.89/32.44	46.50/58.88	0.32/0.55	11.68	0.2363
	trump	12.40/14.81	12.46/13.56	26.22/26.78	62.00/69.69	0.35/0.61	17.05	0.2168
	Cat	12.75/14.40	12.05/13.30	31.21/30.84	66.62/65.69	0.35/0.57	13.75	0.2207

Table 3: Nudity of images generated with edited and benign LoRA on three base models and two datasets.

Base Model	Dataset	Edited	Benign
SD1.5	3DM	0.09	0.67
SD1.5	pixelart	0.06	0.28
DreamShaper	3DM	0.02	0.63
DreamShaper	pixelart	0.09	0.55
Realistic	3DM	0.13	0.74
Realistic	pixelart	0.09	0.59

Table 4: Performance against multiple LoRA merge.

LoRA	Benign		Edited	
	CRS	Nudity	CRS	Nudity
Base	20.43	0.63	15.53	0.02
+Tools [13]	20.60	0.70	15.36	0.08
+Background [36]	16.39	0.22	14.11	0.02
+Clothes [28]	15.11	0.10	13.77	0.06
+Pose [1]	14.99	0.06	13.64	0.00
+Celebrity [3]	13.81	0.06	12.72	0.00

in some cases, but most keep close to that of benign LORA. This can be attributed to the interrelationship of concepts, and erasing the target concept may affect the representation of another one. Surprisingly, the images generated on edited LoRA have lower FID and LPIPS values than images generated on benign ones (with different random seeds), which also validates that the negative impact of LoRAShield is acceptable, since its influence is much less than the change of random seeds. From the visual comparison of the images generated on the edited and benign LoRAs in Fig. 3, we can conclude that LoRAShield can effectively preserve the core functionality of LoRAs, aligning with our design goal of balancing robustness with minimal disruption to legitimate generation.

5.2.3 Erasing Efficiency. LoRAShield achieves platform-scale efficiency, which is critical for deployment in model-sharing ecosystems. As shown in Tab. 2, editing a LoRA takes 14 seconds (vs. often several minutes for retraining from scratch) with 0.23GB GPU memory. This efficiency stems from our sequential optimization of attention matrices, which avoids full model retraining and leverages LoRA's low-rank structure. Even for platforms hosting 100k+ LoRAs, LoRAShield enables fast processing on a single A100 GPU, ensuring real-time user experiences even during peak uploads.

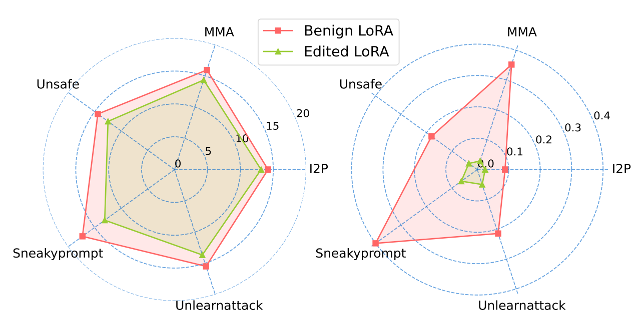

Figure 5: CRS (left) and Nudity (right) under input attacks.

5.2.4 Multiple Concept Erasure. To evaluate LoRAShield's ability to handle cumulative semantic suppression, we conducted a dynamic visualization experiment erasing up to three interdependent concepts in Fig. 4, since quantitative metrics (e.g., CLIP scores) become less reliable for multi-concept scenarios.

5.3 Effectiveness against Adversarial Attack

As mentioned before in Section 3.3.3, since malicious users can download the edited LoRA from the platforms, it is critical to validate whether LoRAShield can resist potential attacks. In this paper, we consider four input-based attacks [39, 42, 51, 52] that construct adversarial prompts. Another common scenario is that malicious users may merge multiple LoRAs for misuse, which can disrupt the protection of LoRAShield. For simplicity, we consider "nude" as the target concept on "3DM" datasets and use "DreamShaper" as base model. More details can be found in the appendix.

5.3.1 Robustness against Multi-LoRA Merge. A common but critical threat arises when attackers merge multiple edited LoRAs. For instance, combining a "beach scenery" LoRA (with "nude" erased) and "human portrait" LoRA (without "nude" erased) might reintroduce NSFW content. We use weight averaging to linearly combine multiple LoRA matrices $\Delta W_{merged} = \sum \alpha_i \Delta W_i$. Five popular LoRAs of different types from Civitai: tools [13] (for adjusting the clothes of people), background [36], clothes [28], pose [1] and celebrity [3] are selected for evaluation with base LoRA trained on "3DM" dataset and DreamShaper with $\alpha_i = 1$. The result in Tab. 4 showcases that even under the perturbation in parameter space, the edited LoRA retains stable performance compared with the base one.

5.3.2 Robustness against Input-based Attack. Malicious users may iteratively refine the prompts to bypass concept erasure, escalating from simple keyword swaps to sophisticated semantic manipulations. To simulate this arms race, we evaluate LoRAShield against four SOTA input-based attacks [39, 42, 51, 52] that reflect realistic evasion tactics. The result in Tab. 5 demonstrates that even under input-based attacks, LoRAShield exhibits remarkable performance. Specifically, the nudity score of images generated by edited LoRA is much lower than that of benign one.

5.4 Real-world Case Study

To validate the practical efficacy of LoRAShield, we conducted end-to-end experiments on Civitai. Our threat scenario mirrors real-world misuse: benign LoRAs [43] uploaded by legitimate users are exploited by attackers to generate policy-violating content, as shown in the first row of Fig. 6. We can notice that the benign LoRA flagged for generating celebrity portraits but could produce NSFW content when given specified prompt. To mitigate this, we download it and attempt to generate NSFW images with the same prompt on edited LoRA. The second row of Fig. 6 further highlights that LoRAShield empowers platforms to proactively neutralize misuse risks without sacrificing creative utility or scalability.

5.5 Ablation Study

To dissect LoRAShield's design choices, we performed ablation experiments on the following critical factors: robust optimization, semantic augmentation, and merging ratio. All experiments in this subsection were conducted on the "3DM" dataset and DreamShaper.

5.5.1 Impact of Robust Optimization and Semantic Augmentation. Since we have claimed that the proposed robust optimization and semantic augmentation enhance the generalization of concept erasure, we validate this with an ablation study. The result in Tab. 5 illustrates that both enhancements can decrease the nudity score of the generated images while incorporating together further improves CRS, validating our design of LoRAShield.

5.5.2 Impact of Merging Ratio. The merge α ratio governs the strength of LoRA weights when merging with the base model, and a lower strength may weaken the protection of LoRAShield as well as the benign concept. Here, we set α at $\{0.2, 0.4, 0.6, 0.8, 1.0\}$ to quantify trade-offs between faithfulness and protection and the result in Fig. 7 demonstrates that even the nudity score fluctuates slightly but remains at a low level when $\alpha \geq 0.4$. Importantly, we should also emphasize that a low merging ratio will definitely degrade the performance of benign tasks. In real-world misuse scenarios, attackers are incentivized to maintain high α values to preserve the LoRA's utility for legitimate tasks while attempting to bypass safeguards. This constraint ensures that the protection remains effective when adversaries prioritize functional performance.

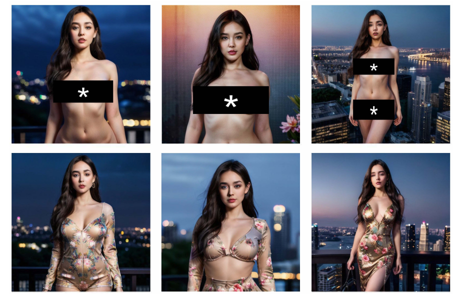

Figure 6: Generated images using LoRA [43] downloaded on Civitai. Note that these images will never be posted online.

Table 5: Ablation study on robust optimization (RO) and semantic augmentation (SA). ✔ and ✘ denote whether the corresponding techniques are incorporated in LoRAShield.

RO	SA	CRS	Nudity
✘	✘	14.60	0.02
✘	✔	14.55	0.00
✔	✘	14.53	0.00
✔	✔	14.20	0.00

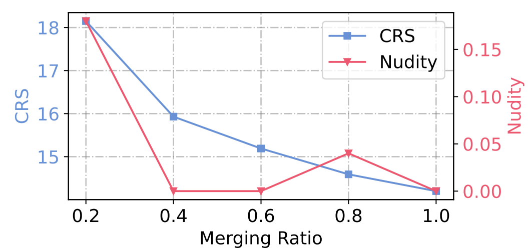

Figure 7: Impact of Merging Ratio.

6 CONCLUSION

In this paper, we identify critical vulnerabilities in model-sharing ecosystems. While DMs have been extensively studied for concept erasure, LoRA's misuse risk has been largely overlooked, leaving platforms like Civitai exposed to misuse that harms creators' rights and platform integrity. This work bridges this gap by proposing LoRAShield, the first data-free and editing framework to secure LoRAs against adversarial exploitation. By editing LoRA's weight subspace, our platform-driven approach achieves effectiveness and efficiency in suppressing harmful content while preserving functionality for legitimate uses, enabling scalable deployment across millions of shared LoRAs.

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