

TINA: Text-Free Inversion Attack for Unlearned Text-to-Image Diffusion Models

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<https://github.com/qianlong0502/TINA>

Abstract

Although text-to-image diffusion models exhibit remarkable generative power, concept erasure techniques are essential for their safe deployment to prevent the creation of harmful content. This has fostered a dynamic interplay between the development of erasure defenses and the adversarial probes designed to bypass them, and this co-evolution has progressively enhanced the efficacy of erasure methods. However, this adversarial co-evolution has converged on a narrow, text-centric paradigm that equates erasure with severing the text-to-image mapping, ignoring that the underlying visual knowledge related to undesired concepts still persist. To substantiate this claim, we investigate from a visual perspective, leveraging DDIM inversion to probe whether a generative pathway for the erased concept can still be found. However, identifying such a visual generative pathway is challenging because standard text-guided DDIM inversion is actively resisted by text-centric defenses within the erased model. To address this, we introduce TINA, a novel Text-free INversion Attack, which enforces this visual-only probe by operating under a null-text condition, thereby avoiding existing text-centric defenses. Moreover, TINA integrates an optimization procedure to overcome the accumulating approximation errors that arise when standard inversion operates without its usual textual guidance. Our experiments demonstrate that TINA regenerates erased concepts from models treated with state-of-the-art unlearning. The success of TINA proves that current methods merely obscure concepts, highlighting an urgent need for paradigms that operate directly on internal visual knowledge.

1. Introduction

With the rapid development of deep learning [16–18, 40–45, 51, 54–56], generative artificial intelligence, particularly Text-to-Image (T2I) diffusion models such as Stable Diffusion is fundamentally reshaping the landscape of digi-

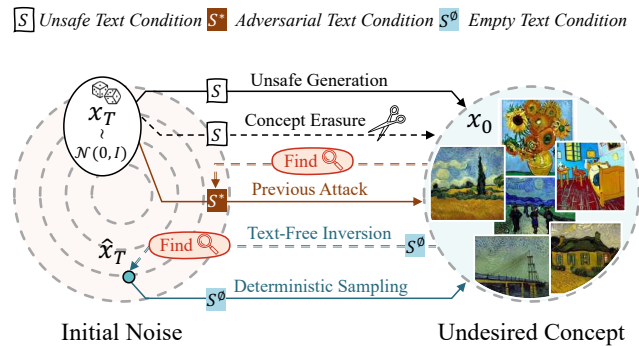


Figure 1. Conceptual overview of text-centric erasure vulnerabilities and our TINA attack. **Concept Erasure** usually severs the link between a specific text condition and the undesired concept. **Previous Attacks** remain text-centric, finding adversarial text condition to reactivate the concept. **Our TINA** bypasses the text pathway entirely. Using an empty text condition, it finds a noise to regenerate the concept, proving the visual knowledge persists in the existing erased models.

tal content creation [3, 14, 22–24, 26, 28, 30, 32, 49, 59]. Their remarkable capacity for creative synthesis has catalyzed countless applications, from art and design to entertainment and media. However, since these models are typically trained on massive, unfiltered datasets scraped from the Internet [35], their proliferation brings a turbulent undercurrent of ethical and safety challenges. The same models that generate breathtaking art can be misused to create deepfakes that violate personal privacy [2], imitate artistic styles that infringe on copyright [13, 31, 36], and produce harmful Not-Safe-For-Work (NSFW) imagery [12, 34, 58], posing risks to intellectual property and societal well-being.

To address these challenges, the field has converged on the paradigm of *Concept Erasure*, a specialized form of *Machine Unlearning* [50]. This paradigm aims to mitigate risks by directly modifying model parameters. For instance, approaches such as Erasing Stable Diffusion (ESD) and Ablating Concepts (AC) retrain specific model layers to remap a forbidden concept representation to that of a neutral or null

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concept, thereby severing the explicit link between a text prompt and its corresponding visual output [6, 15]. Other methods like Forget-Me-Not (FMN) minimize the attention maps corresponding to the target concept [53], while Unified Concept Editing (UCE) applies efficient, closed-form edits to the cross-attention weights [7]. Despite their distinct mechanisms, these approaches share a common, text-centric operational principle, equating erasure with merely severing its *text-image mapping*.

The text-centric paradigm, as conceptualized in Figure 1, has consequently guided adversarial attacks almost exclusively to the textual domain. Initial red-teaming efforts involve prompt-level manipulations, attempting to find alternative phrasings or complex prompts that reactivate the target concept [4, 39, 58]. Moreover, the more sophisticated embedding-space attacks, which move beyond discrete tokens, remain fundamentally dependent on the textual conditioning pathway [27]. Generally, these red-teaming methods aim to discover new token embeddings [27] or optimize an adversarial text prompt [58] that serves as a proxy for the erased concept. In response to this threat, an interplay between text-based attacks and defenses has driven the subsequent development of more resilient safeguards, such as AdvUnlearn [57] and STEREO [38]. This adversarial co-evolution has produced defenses that demonstrate increasing efficacy, thereby fostering an appearance of robust model security.

However, in this work, we contend that this competitive co-evolution of text-centric methods rests on a fundamental and fatal assumption. Specifically, existing paradigm mistakenly equates the erasure of a *text-to-image link* with the far more complex task of eliminating the underlying *visual knowledge* from the parameter space. Consequently, existing methods critically ignore the fact that even if textual inputs can no longer induce the target concept, the corresponding visual knowledge may still persist, untapped, within the model. To challenge this dominant paradigm and substantiate our claim, we introduce a core hypothesis:

A deterministic generative pathway for an erased concept persists within the model, even after its text-image mappings are removed, allowing for its regeneration in a completely text-free manner.

To validate this hypothesis from a purely visual perspective, thereby challenging the efficacy of these text-centric defenses, we introduce TINA, a Text-free INversion Attack. Unlike prior embedding-space attacks that seek a new textual proxy for the erased concept [27], TINA is a novel framework designed to completely bypass the textual conditioning pathway. To achieve this, TINA leverages Denoising Diffusion Implicit Models (DDIM) [37] inversion as a visual probe (illustrated in Figure 1), allowing us to investigate the visual knowledge embedded within the model directly. However, identifying such a generative pathway is

challenging because standard DDIM inversion relies heavily on textual guidance. Operating under the null-text condition necessary to evade defenses consequently introduces significant imprecision. To address this imprecision, TINA incorporates a novel optimization procedure that corrects for the compounding errors of standard inversion, allowing it to precisely map a target image back to a latent noise vector. Serving as the specific initial noise for the deterministic DDIM sampling process, this resulting latent vector can lead an erased model to regenerate the forbidden content through a deterministic generative trajectory, entirely bypassing the text-conditioning mechanism. The success of this text-free reconstruction provides compelling evidence that current erasure methods merely obscure concepts by severing text-image links, rather than truly expunging the underlying visual knowledge embedded deep within the model parameters. These findings serve as a critical alert for the AI safety community, highlighting the urgent need for more robust unlearning paradigms that operate directly on the internal visual representations within T2I models.

To sum up, our contributions are as follows.

- To our knowledge, we are the first to identify the fundamental, text-centric vulnerability in the current paradigm of concept erasure for T2I diffusion models.
- We propose TINA, a new text-free attack paradigm that employs an optimization-based inversion to identify the underlying generative trajectory for a supposedly erased concept, from a purely visual perspective.
- Experiments demonstrate that our TINA can rediscover erased concepts from models unlearned by state-of-the-art methods, thereby exposing a fundamental flaw needing urgent attention.

2. Related Work

2.1. Text-to-Image Diffusion Models

The advent of Text-to-Image (T2I) diffusion models, such as Stable Diffusion [30], DALL-E 2 [29], and Imagen [32], has marked a paradigm shift in digital content generation. These models operate through a two-stage process: a forward diffusion process that incrementally adds noise to an image, and a learned reverse process that denoises a random vector back into a coherent image [11]. To achieve computational efficiency, models like Stable Diffusion perform this process in a lower-dimensional latent space [30]. Critically, their generative process is guided by textual prompts, typically encoded and injected into the denoising network via a cross-attention mechanism [40]. This tight coupling between text and image synthesis is the source of their remarkable controllability, but also the root of significant safety and ethical concerns, as the models can be prompted to produce NSFW imagery [34, 58], imitate copyrighted styles [13, 36], or violate personal privacy [2].

2.2. Concept Erasure in Diffusion Models

To address the misuse of T2I models, concept erasure has emerged as a critical field. While methods like SLD [34] focus on inference-time interventions, the dominant paradigm involves fine-tuning-based methods that modify model parameters. This paradigm originated with foundational works like ESD [6] and AC [15], which retrained models to break associations with specific text prompts. Subsequently, this was followed by more efficient and targeted techniques, such as FMN [53], UCE [7], MACE [20], and the adapter-based SPM [21], often focusing on cross-attention layers. Concurrently, general unlearning frameworks like SalUn [5], Scissorhands [47], and EraseDiff [48] were proposed for the concept erasure task. As text-based attacks began to bypass these initial erasure methods, advanced adversarially robust methods were developed, including RECE [8], AdvUnlearn [57], and STEREO [38]. These methods usually integrate attack considerations into their design to defend against adversarial prompts and embeddings. Ultimately, this co-evolution of text-based attacks and defenses has solidified a dominant, text-centric paradigm: most of them operate by identifying or severing the *text-to-image mapping*, rather than addressing the underlying visual knowledge.

2.3. Adversarial Attacks on Concept Erasure

The prevailing text-centric assumption of erasure methods has consequently shaped the landscape of adversarial attacks, which primarily seek to circumvent these textual defenses. These attacks can be classified by their operational domain. The most straightforward approaches operate in the discrete token space, employing circumvention strategies to find alternative phrases that trigger the erased concept, such as P4D [4], RAB [39], MMA [52], and UDA [58]. A more sophisticated class of attacks operates in the continuous embedding space. These methods aim to find a novel token embedding that acts as a proxy for the forbidden concept, effectively creating a new activation pathway to the visual knowledge. For instance, CCE [27] leverages textual inversion to discover surrogate embeddings for erased concepts.

Critically, despite their varying levels of sophistication, from simple phrasings to optimized vectors, these existing attacks share a fundamental limitation: most of them presuppose that the generative capabilities of the model must be accessed via its text-conditioning pathway. They focus on finding a new textual or embedding-space vector to bypass modified controls. In stark contrast, our work, TINA, challenges this entire paradigm. We pivot to a fundamentally different attack surface by postulating that visual knowledge persists independently of any textual control. Accordingly, we propose an attack that circumvents the text-conditioning mechanism entirely, identifying and

exploiting a deterministic, non-textual generative trajectory to regenerate forbidden content without textual guidance.

3. Method

3.1. Preliminaries

Latent Diffusion Models. Latent Diffusion Models (LDMs) [30] generate images by reversing a T -step diffusion process in a compressed latent space. An image x is first encoded into its latent $z_0 = \mathcal{E}(x)$ by a VAE encoder. The forward process creates a sequence of noised latents $\{z_1, \dots, z_T\}$. A denoising U-Net ϵ_θ learns to reverse this process. At each timestep t , it predicts the noise ϵ in z_t , guided by a textual condition c . This condition is produced by a text encoder $\mathcal{T}_{\text{text}}$ from a prompt y and integrated via cross-attention. The training objective minimizes the noise prediction error:

$$\mathcal{L} = \mathbb{E}_{z_0, y, \epsilon, t} \left[\|\epsilon - \epsilon_\theta(z_t, t, c)\|_2^2 \right].$$

This objective trains ϵ_θ to denoise z_t back towards z_0 in a manner faithful to the condition c . The final image is retrieved using the VAE decoder $\mathcal{D}$.

DDIM Sampling. Denoising Diffusion Implicit Models (DDIM) [37] enable deterministic generative sampling from LDMs. This is achieved by formulating the reverse process as a non-Markovian, discretized Probability Flow Ordinary Differential Equation (PF-ODE) with zero variance. Consequently, for a fixed model θ and condition c , any initial noise $z_T \sim \mathcal{N}(0, \mathbf{I})$ maps to a unique generated latent z_0 .

This deterministic path is defined by an iterative update rule. Given the latent z_t , the model first predicts the clean latent $\hat{z}_0(z_t)$:

$$\hat{z}_0(z_t) = \frac{z_t - \sqrt{1 - \alpha_t} \epsilon_\theta(z_t, t, c)}{\sqrt{\alpha_t}}. \quad (1)$$

The preceding latent z_{t-1} is then computed as:

$$z_{t-1} = \sqrt{\alpha_{t-1}} \hat{z}_0(z_t) + \sqrt{1 - \alpha_{t-1}} \cdot \epsilon_\theta(z_t, t, c), \quad (2)$$

where $\{\alpha_t\}_{t=1}^T$ are the fixed noise schedule parameters.

DDIM Inversion. Building upon the deterministic nature of DDIM sampling, DDIM inversion provides a mechanism to reverse the generative process. Its objective is to map a given image, represented by its initial latent z_0 , back to the unique starting noise vector z_T from which it can be deterministically generated. This capability is crucial for applications like real image editing and analysis.

Ideally, the inversion would be a perfect algebraic reversal of the sampling step in Eq. (2), which can be expressed as:

$$z_t = C_1(t) z_{t-1} + C_2(t) \cdot \epsilon_\theta(z_t, t, c), \quad (3)$$

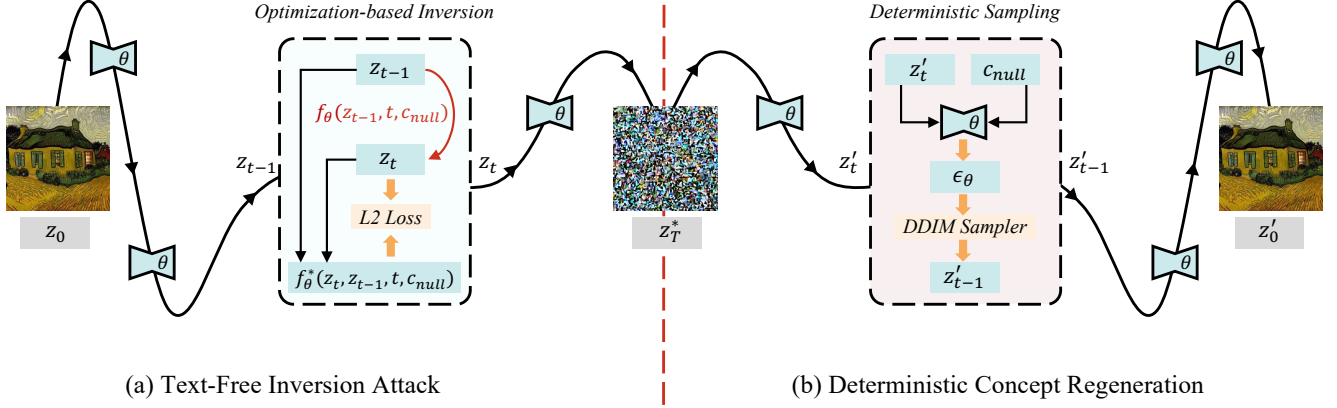


Figure 2. The TINA (Text-free INversion Attack) framework. (a) **Text-Free Inversion Attack**: An optimization-based, null-text (c_{null}) inversion finds the unique initial noise z_T^* corresponding to a target image z_0 . This optimization corrects the errors from standard inversion. (b) **Deterministic Concept Regeneration**: The same sanitized model θ uses z_T^* and c_{null} to deterministically regenerate the target concept z'_0 , proving the visual knowledge persists despite erasure.

where

$$C_1(t) = \frac{\sqrt{\alpha_t}}{\sqrt{\alpha_{t-1}}}, \quad (4)$$

$$C_2(t) = \sqrt{1 - \alpha_t} - \sqrt{\frac{\alpha_t(1 - \alpha_{t-1})}{\alpha_{t-1}}}. \quad (5)$$

However, a practical challenge emerges: computing the latent z_t requires a noise prediction $\epsilon_\theta(z_t, t, c)$, which itself depends on z_t , as shown in Eq. (3). To break this circular dependency, standard DDIM inversion employs a key approximation: it estimates the required noise using the latent from the previous step, z_{t-1} , at timestep $t - 1$. This results in the following iterative formula to approximate z_t from z_{t-1} :

$$z_t \approx f_\theta(z_{t-1}, t, c), \quad (6)$$

where

$$f_\theta(z_{t-1}, t, c) = C_1(t)z_{t-1} + C_2(t) \cdot \epsilon_\theta(z_{t-1}, t-1, c). \quad (7)$$

Starting from the clean image latent z_0 , this equation is applied sequentially for $t = 1, \dots, T$ to trace the trajectory back to an approximate initial noise $\hat{z}_T$. This vector serves as an estimate of the true starting point in the noise space required for reconstructing the original image.

3.2. TINA: Text-free INversion Attack

In this section, we introduce our TINA framework, starting with the attack pipeline (Section 3.2.1), then analyzing why the naive standard inversion fails to meet the objective in the pipeline (Section 3.2.2), and finally detailing our optimization-based solution (Section 3.2.3).

3.2.1. The TINA Attack Pipeline

The central hypothesis of TINA is that even within a model subjected to concept erasure, deterministic generative trajectories persist that are entirely independent of textual conditioning. Our framework is designed to expose and exploit this vulnerability through a two-phase attack pipeline, as illustrated in Figure 2.

The process begins with a concept-erased model ϵ_θ and a target image x representing the erased concept. As illustrated in Figure 2, the attack first performs a **Text-Free Inversion** to find the precise initial noise vector z_T^* that corresponds to the target image latent z_0 . This inversion phase uses only the sanitized model ϵ_θ and a null-text condition c_{null} . Following this, in the **Deterministic Regeneration** phase, this optimized z_T^* is fed back into the same erased model ϵ_θ . A standard deterministic DDIM sampling process is then executed, crucially starting from this specific z_T^* and operating entirely under the null-text condition c_{null} .

The successful reconstruction of the target concept x' serves as definitive proof that the visual knowledge persists, independent of textual controls. The deterministic regeneration step is a standard DDIM sampling procedure; the core technical challenge lies in the initial inversion step: accurately identifying the starting noise vector z_T^* for a target image x representing the erased concept.

3.2.2. Limitations of Standard Inversion

A naive approach to finding z_T^* would be to apply the standard DDIM inversion process to the target image latent z_0 . However, this method is fundamentally flawed and fails in two distinct ways, as illustrated in Figure 3. First, if the inversion is attempted using the text condition c of the target concept (e.g., “Van Gogh style”), the sanitized model ϵ_θ actively counteracts this prompt, leading to a complete failure

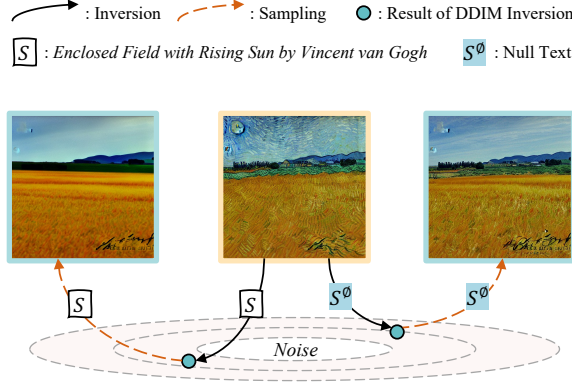


Figure 3. Standard DDIM inversion fails to find the generative trajectory. The text-guided path (S) is blocked by the erasure, while the null-text path (S^0) drifts due to approximation errors, failing to restore the target concept.

in reconstruction. This confirms that text-centric defenses are indeed working against text-guided processes.

Second, we could attempt the inversion under a null-text condition ($c = c_{\text{null}}$) to bypass this textual defense. This approach also fails, but in a more subtle way. As shown in Figure 3 (right), the resulting image is visually closer to the original than the text-conditioned attempt, yet it still fails to regenerate the specific target concept (i.e., the artistic style). This partial failure stems from the standard inversion formula (Eq. (6)), which relies on a critical approximation: it uses the noise prediction from the previous step, $\epsilon_\theta(z_{t-1}, t-1, c)$, to estimate the next latent z_t . This approximation is heavily dependent on a meaningful text condition c to guide the noise prediction. In the absence of such guidance (c_{null}), the predictions become unconstrained, and the small error introduced at each step rapidly compounds across the entire trajectory. Consequently, the final computed noise $\hat{z}_T$ drifts sufficiently from the true required noise z_T^* to lose the high-fidelity details of the target concept, rendering it incapable of an accurate reconstruction. This demonstrates that standard inversion is an inadequate tool for identifying text-free generative paths.

3.2.3. Optimization-Based Text-Free Inversion

To overcome the imprecision of approximative inversion, TINA reframes the search for the generative trajectory as an optimization problem. We discard the flawed approximation in Eq. (6) and instead derive the ideal inversion relationship directly from the DDIM sampling equation (Eq. (2)). By algebraically rearranging the sampling step, we can express the exact, non-approximative relationship between z_t and z_{t-1} :

$$z_t = C_1(t)z_{t-1} + C_2(t) \cdot \epsilon_\theta(z_t, t, c). \quad (8)$$

Algorithm 1 TINA: Text-Free Inversion

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1: Input: Sanitized denoising model  $\epsilon_\theta$ , target image latent  $z_0$ , DDIM steps  $T$ , null-text condition  $c_{\text{null}}$ , max optimization iterations  $K$ , learning rate  $\eta$ .
2: Output: Optimized initial noise  $z_T^*$ .
3: for  $t \leftarrow 1$  to  $T$  do
4:   Get initial  $\tilde{z}_t$  from  $z_{t-1}$  using Eq. (6) with  $c_{\text{null}}$ .
5:    $z_t \leftarrow \tilde{z}_t$ .
6:   for  $k \leftarrow 1$  to  $K$  do
7:      $\mathcal{L}_t \leftarrow \|f_\theta^*(z_t, z_{t-1}, t, c_{\text{null}}) - z_t\|_2^2 \triangleright \text{Eq. (10)}$ 
8:      $z_t \leftarrow z_t - \eta \nabla_{z_t} \mathcal{L}_t$ 
9:   end for
10: end for
11:  $z_T^* \leftarrow z_T$ 
12: return  $z_T^*$ 

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This equation establishes an implicit consistency constraint that must hold at every step of a true generative trajectory. We can therefore cast the exact inversion at step t as a **fixed-point problem**. In particular, for fixed z_{t-1} , t , and c , any exact latent z_t on the DDIM trajectory must satisfy a self-consistency relation of the form $z_t = f_\theta^*(z_t, z_{t-1}, t, c)$, i.e., z_t is a fixed point of the induced mapping f_θ^* [1, 25]. Let us define f_θ^* as:

$$f_\theta^*(z_t, z_{t-1}, t, c) = C_1(t)z_{t-1} + C_2(t) \cdot \epsilon_\theta(z_t, t, c). \quad (9)$$

Our key innovation is to enforce this self-consistency constraint at each step of the inversion process through optimization, rather than relying on the approximative closed-form update. For each timestep t from 1 to T , given the previously computed z_{t-1} , we seek a latent z_t whose induced denoising prediction is consistent with the exact DDIM relation under a null-text condition. We formulate this as the following loss function:

$$\mathcal{L}_t(z_t) = \|f_\theta^*(z_t, z_{t-1}, t, c_{\text{null}}) - z_t\|_2^2, \quad (10)$$

where z_t is initialized as $\tilde{z}_t = f_\theta(z_{t-1}, t, c_{\text{null}})$ before the optimization.

Instead of accepting the erroneous result from the standard formula, we employ an inner optimization loop at each inversion step t . We first obtain an initial estimate for z_t using the conventional DDIM inversion step (Eq. 6) under the null-text condition. This estimate then serves as the starting point for an iterative refinement process where we perform gradient descent on z_t to minimize the objective defined in Eq. (10). In this sense, our optimization can be viewed as seeking a numerically self-consistent point, rather than directly trusting the approximative inversion formula [25]. This optimization forces each latent z_t along the inversion path to be consistent with the internal dynamics of the sanitized model ϵ_θ in a text-free setting. The inner loop is exe-

cuted for a fixed number of iterations. By iteratively applying this optimization-based refinement for $t = 1, \dots, T$, we trace a highly accurate path back to the true initial noise z_T^* , which is now completely decoupled from any textual influence. The complete procedure for this text-free inversion is formally detailed in Algorithm 1.

4. Experiments

4.1. Experimental Setup

Unlearned DMs to be attacked. The field of machine unlearning for diffusion models is advancing at a rapid pace. For our evaluation, we select target unlearning methods based on two criteria: the public availability of their source code and the reproducibility of their reported results. Specifically, our evaluation targets twelve prominent, open-source unlearning methods: (1) ESD (erased stable diffusion) [6], (2) FMN (Forget-Me-Not) [53], (3) AC (ablating concepts) [15], (4) UCE (unified concept editing) [7], (5) EraseDiff [48], (6) Scissorhands [47], (7) MACE (Mass Concept Erasure) [20], (8) SPM (concept-SemiPermeable Membrane) [21], (9) RECE [8], (10) AdvUnlearn [57], (11) SalUn (saliency unlearning) [5], (12) STEREO [38]. We note that these unlearning methods are often specialized for specific domains (e.g., nudity) rather than being universal. Consequently, our evaluation is contextualized, assessing each method only on its intended unlearning tasks.

Baseline Attack Methods. We evaluate the attack performance of TINA against five prevailing baseline attack methods: (1) MMA [52], (2) Prompting4Debugging (P4D) [4], (3) UnlearnDiffAtk (UDA) [58], (4) Ring-A-Bell (RAB) [39], and (5) CCE [27]. The fundamental characteristic and shared limitation of all these baselines is their text-centric nature. They exclusively target the textual input pathway in an attempt to circumvent textual defenses. These approaches range from black-box jailbreaking techniques that discover alternative text prompts (e.g., MMA, RAB) to white-box attacks that leverage model access to optimize for adversarial text conditions (e.g., P4D, UDA, CCE). Critically, all these existing attacks remain tethered to the text-conditioning mechanism, a pathway that TINA is designed to bypass entirely. As summarized in Table 3, not all baseline attacks are designed for every type of concept (e.g., MMA and RAB are not applicable to style or object erasure). Therefore, our comparative analysis is conducted on a per-task basis, aligning with the intended application of each attack method. The implementing details of these baselines can be found in Appendix. 6.

Image Setup. Our method requires a set of representative images, each exemplifying a concept targeted for erasure. We obtain these images by adopting the generation

setup established in the UnlearnDiffAtk (UDA) study [58]. This process involves using the original Stable Diffusion v1.4 model, which is the pre-trained checkpoint before any unlearning methods were applied, to generate a collection of ground-truth images. The generation is guided by text prompts sourced from the same standard benchmarks used to evaluate the baseline attacks. Specifically, for nudity concepts, we use prompts from the I2P dataset [34]. For artistic styles, we focus our experiments on the Van Gogh style, using art-related prompts from the ESD evaluation setup [6]. For objects, we concentrate on the tench class, using prompts generated via GPT-4 corresponding to this Imagenette class, following the methodology in [58].

Implementation Details. All experiments are built upon the Stable Diffusion v1.4 checkpoint. For all generative processes, we employ a linear multistep scheduler with $T = 50$ inference steps and a standard Classifier-Free Guidance (CFG [10]) scale of 7.5. For our proposed TINA, the optimization-based inversion (detailed in Section 3.2 and Algorithm 1) is also configured with $T = 50$ total steps. Within the inner optimization loop at each timestep t , we perform $K = 25$ refinement iterations to minimize the fixed-point loss (Eq. 10). This inner optimization uses the AdamW [19] with a learning rate of $\eta = 0.001$. All experiments were conducted on a single NVIDIA A100 GPU.

Evaluation Metrics. Our evaluation methodology is primarily aligned with the protocol established by UnlearnDiffAtk (UDA) [58]. To quantitatively measure attack efficacy, we report the Attack Success Rate (ASR), defined as the percentage of generated images that are successfully identified by a post-generation classifier as containing the forbidden concept, thereby indicating a successful bypass of the unlearning safeguard. We employ a suite of specialized classifiers corresponding to each unlearning task. For harmful concept unlearning, we utilize NudeNet to detect nudity. For style unlearning, we adopt the 129-class ViT-base style classifier [46, 58], which was pre-trained on ImageNet, fine-tuned on the WikiArt dataset [33]. For object unlearning, we employ a standard ImageNet-pretrained ResNet-50 [9] for generated image classification.

4.2. Experiment Results

We now empirically validate the efficacy of TINA. Our experiments are designed to test the ability of TINA to bypass a wide spectrum of unlearning defenses, from foundational methods to the current state-of-the-art, and compare its performance directly against existing text-centric attacks. The results for nudity, style, and object erasure are summarized in Tables 1, 2, and 4, respectively. Qualitative comparisons and an ablation study are provided in Figure 4, Section 11, and Appendix 7.

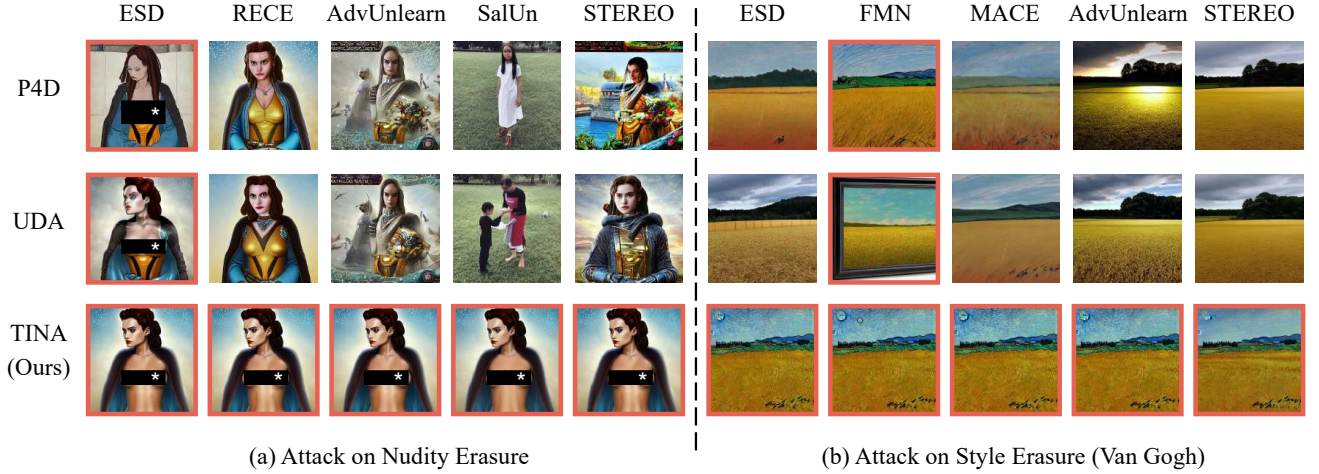


Figure 4. Qualitative comparison of attack performance on (a) Nudity Erasure and (b) Style Erasure (Van Gogh). Images with a **red border** indicate a successful attack. Our TINA (bottom row) consistently regenerates the forbidden concepts, bypassing most of defenses, while text-centric attacks fail against robust methods. Sensitive content is redacted.

	ESD [6]	FMN [53]	UCE [7]	MACE [20]	RECE [8]	AdvUnlearn [57]	SalUn [5]	STEREO [38]
MMA [52]	13.10	67.00	32.60	6.00	22.80	1.70	1.70	5.50
P4D [4]	69.01	97.89	76.06	75.35	66.20	18.31	15.49	24.65
UDA [58]	76.05	97.89	78.87	81.69	63.38	23.24	13.38	25.35
RAB [39]	50.53	97.89	29.47	6.32	10.53	2.11	0.00	8.42
CCE [27]	74.65	54.93	49.30	50.00	66.90	76.76	2.82	16.90
TINA	82.39	97.89	82.39	92.96	80.28	78.87	71.13	80.99

Table 1. Quantitative comparison of Attack Success Rates (ASR, in %) on the nudity erasure task. We evaluate our TINA against five baselines across eight prominent unlearning defenses. **Bold** indicates the best-performing attack.

Evaluation on Erased Models in Nudity Erasure. Table 1 demonstrates comprehensive success of TINA in the nudity erasure task. TINA achieves the highest ASR across all eight defenses. It reaches 82.39% against ESD and 92.96% against MACE, significantly outperforming all baselines. The most critical finding is the performance of TINA against defenses designed to be robust, such as AdvUnlearn, SalUn, and STEREO. Against these targets, text-based attacks are largely mitigated (e.g., UDA scores 23.24% on AdvUnlearn, RAB scores 0.00% on SalUn). In contrast, TINA maintains high ASRs (78.87%, 71.13%, and 80.99%), proving it exploits a vulnerability that these defenses do not account for. This quantitative success is visually corroborated in Figure 4 (a). The bottom row shows TINA consistently regenerating the target content across all defenses. In contrast, text-centric attacks like P4D and UDA visibly fail against robust methods such as AdvUnlearn and STEREO, producing neutral or unrelated images.

Evaluation on Erased Models in Style Erasure. The results for artistic style erasure (Table 2) further reinforce this

trend. TINA robustly bypasses the majority of defenses. Its 70.0% ASR against ESD starkly contrasts with the 32.0% from UDA and 8.0% from CCE. Furthermore, TINA shows dominant performance against robust methods like AdvUnlearn (70.0%) and STEREO (44.0%), where text-based attacks remain weak or ineffective. This finding demonstrates that even for abstract concepts like style, a deterministic, non-textual generative trajectory persists after erasure, which TINA successfully identifies and exploits. Figure 4 (b) provides the qualitative evidence for this trend. It clearly demonstrates the ability of TINA to restore the “Van Gogh” style, bypassing defenses like MACE and AdvUnlearn where text-based attacks fail to regenerate the artistic features.

Evaluation on Erased Models in Object Erasure. The object erasure evaluation in Table 4 delivers the most compelling results. This task highlights the failure of text-centric unlearning against our text-free attack. Against modern defenses like Scissorhands and STEREO, all text-based attacks (P4D, UDA, and CCE) fail catastrophically,

	ESD [6]	FMN [53]	AC [15]	MACE [20]	SPM [21]	RECE [8]	AdvUnlearn [57]	STEREO [38]
P4D [4]	30.0	54.0	68.0	42.0	78.0	62.0	0.0	0.0
UDA [58]	<u>32.0</u>	<u>56.0</u>	77.0	<u>56.0</u>	88.0	<u>64.0</u>	2.0	0.0
CCE [27]	8.0	18.0	14.0	26.0	36.0	40.0	<u>44.0</u>	<u>4.0</u>
TINA	70.0	72.0	<u>74.0</u>	72.0	<u>80.0</u>	74.0	70.0	44.0

Table 2. Comparison of Attack Success Rates (ASR, in %) on the artistic style erasure task. We report the performance of our TINA against three baselines across eight unlearning methods. **Bold** denotes the highest ASR, while underlined denotes the second highest.

	MMA	P4D	UDA	RAB	CCE
Nudity	✓	✓	✓	✓	✓
Style	✗	✓	✓	✗	✓
Object	✗	✓	✓	✗	✓

Table 3. Applicability of baseline attack methods to different tasks. ✓ denotes applicability, while ✗ denotes non-applicability.

	P4D	UDA	CCE	TINA
ESD [6]	32.0	46.0	40.0	70.0
EraseDiff [48]	8.0	2.0	34.0	68.0
SalUn [5]	18.0	12.0	58.0	72.0
Scissorhands [47]	6.0	6.0	0.0	78.0
STEREO [38]	0.0	2.0	2.0	72.0

Table 4. Attack Success Rates (ASR, in %) for object erasure. Our TINA bypasses modern defenses where text-centric attacks fail.

with ASRs in the single digits. While P4D and UDA also fail against EraseDiff and SalUn, the embedding-space attack CCE retains partial efficacy (34.0% and 58.0%, respectively). This pattern confirms that while robust defenses are patching textual vulnerabilities, TINA remains unaffected. It achieves uniformly high ASRs across all targets, including 68.0% (EraseDiff), 78.0% (Scissorhands), and 72.0% (STEREO). This finding confirms our central hypothesis: current SOTA methods merely sever text-image links, not the underlying visual knowledge, which TINA can deterministically access without any textual guidance.

4.3. Latent Embedding Analysis

To further understand the generative pathway identified by TINA, we visualize the learned noise embeddings z_T^* for four erased concepts (Tench, Church, Parachute, Garbage Truck) using a t-SNE projection. Specifically, for each concept, we collect 50 optimized noise vectors generated by targeting the corresponding ESD-sanitized model. We then feed these optimized noises into the UNet under a null-text condition and extract their intermediate representations through a forward inference. For the visualization, we apply t-SNE (perplexity 30, with PCA initialization)

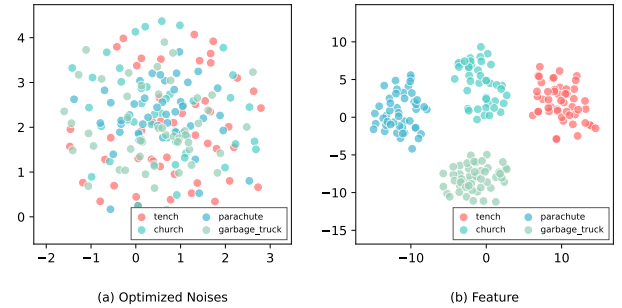


Figure 5. t-SNE visualization of (a) the optimized initial noises z_T^* and (b) their corresponding deep UNet activations (extracted from the mid_block) for four erased concepts.

to both the flattened noise vectors and the global average pooled features extracted from the last ResNet block of the mid_block in the UNet model. As shown in Figure 5, the optimized noises themselves (left) exhibit little concept-wise separation in the latent space, which is consistent with their noise-like nature. However, their corresponding internal UNet activations (right) become clearly separable by concept, forming distinct clusters. This demonstrates that although the optimized z_T^* remains indistinguishable from random noise, it successfully elicits concept-specific internal responses within the erased diffusion model. This confirms that the forbidden visual knowledge persists and is deterministically activated by our text-free attack.

5. Conclusion

We exposed a fundamental flaw in the text-centric paradigm of concept erasure: severing text-image links is insufficient and offers a false sense of security. We introduced TINA, a novel text-free attack that substantiates this claim by completely bypassing textual controls. TINA identifies a deterministic, null-text generative trajectory to regenerate forbidden content. Our experiments show that TINA consistently restores erased concepts from models sanitized by existing defenses. This proves current methods merely obscure visual knowledge rather than erasing it, mandating a shift towards unlearning techniques that operate directly on internal visual representations.

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