IMAGE-LEVEL MEMORIZATION DETECTION VIA INVERSION-BASED INFERENCE PERTURBATION

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ABSTRACT

Recent studies have discovered that widely used text-to-image diffusion models can replicate training samples during image generation, a phenomenon known as memorization. Existing detection methods primarily focus on identifying memorized prompts. However, in real-world scenarios, image owners may need to verify whether their proprietary or personal images have been memorized by the model, even in the absence of paired prompts or related metadata. We refer to this challenge as image-level memorization detection, where current methods relying on original prompts fall short. In this work, we first uncover two key characteristics of memorized images under perturbed inference: *lower similarity of the original images* and *larger magnitudes of TCNP*. Building on these insights, we propose Inversion-based Inference Perturbation (IIP), a new framework for image-level memorization detection. Our approach uses unconditional DDIM inversion to derive latent codes that contain core semantic information of original images and optimizes random prompt embeddings to introduce effective perturbation. Memorized images exhibit distinct characteristics compared to non-memorized ones, providing a robust basis for detection. To support this task, we construct a comprehensive setup for the image-level memorization detection task, carefully curating datasets to simulate realistic memorization scenarios. Using this setup, we evaluate our IIP framework across three different memorization settings, demonstrating its state-of-the-art performance in identifying both training and generated memorized images, even in the presence of data augmentation attacks.

1 INTRODUCTION

In recent years, text-to-image diffusion models such as Stable Diffusion (SD) (Rombach et al., 2022) and DALL-E (Ramesh et al., 2021) have achieved remarkable advancements, showcasing impressive generation fidelity and diversity when conditioned on given prompts. However, these models have also been found to reproduce elements or even exact duplicates of their training images, a phenomenon broadly known as memorization (Schuhmann et al., 2022; Carlini et al., 2023; Somepalli et al., 2023a;b). Existing memorization detecting methods primarily focus on identifying whether specific prompts lead to memorized outputs (Wen et al., 2024; Ren et al., 2024) (Fig. 1 (Top)). The proposed magnitude of text-conditional noise prediction (MTCNP) (Wen et al., 2024) can effectively detect memorized prompts during the generation procedure (Fig. 2 (Top)).

However, in real-world scenarios, users may encounter situations where they need to verify whether a specific image has been memorized by widely used text-to-image diffusion models. For instance, an image owner might wish to confirm whether their proprietary or personal content has been embedded into the model's memory, potentially violating copyright or privacy rights. Unlike existing approaches that rely on textual prompts that generate the memorized images, this scenario requires a direct, image-level assessment, as shown in Fig. 1 (bottom). Such a setting assumes that only the image itself is accessible, without information about the original paired prompts or associated metadata, making existing detection methods(Wen et al., 2024; Ren et al., 2024) struggle to address this challenge. We address this challenge as a new setting: image-level memorization detection, which is the primary focus of our research.

In this paper, we first reveal two key characteristics of memorized images, which provide the basis for our image-level memorization detection. We discover that memorized images **exhibit lower**

similarity of the original images and **maintain larger magnitudes of text-conditional noise predictions (MTCNP)** (Wen et al., 2024) after perturbation of the original generation procedure.

Based on these findings, we propose a novel image-level memorization detection framework IIP free of original prompts. We are motivated to obtain a latent code with primary semantic information of original images and employ a perturbed inference procedure subsequently (as illustrated in Fig. 2(bottom)) This perturbation aims to derive both lower similarity of the original images and larger magnitudes of TCNP for memorized images, starkly contrasting with that of non-memorized images. Specifically, we employ unconditional DDIM Inversion (Song et al., 2020) at smaller timesteps to obtain semantic latent codes and perturb the inference procedure with optimized random prompts, which effectively derive significant characteristics for image-level memorization detection.

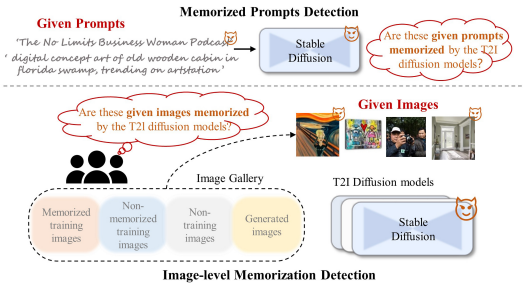

Figure 1: Differences between memorized prompts detection and image-level memorization detection.

We distinguish three different settings of memorization for comprehensive setup, including memorized vs non-memorized training images, memorized training vs non-training images (non-memorized), and the generated memorized vs non-memorized images. Extensive experiments and analysis demonstrate our method consistently achieves state-of-the-art performance across various datasets and different open-source text-to-image diffusion models.

We summarize our contribution as follows:

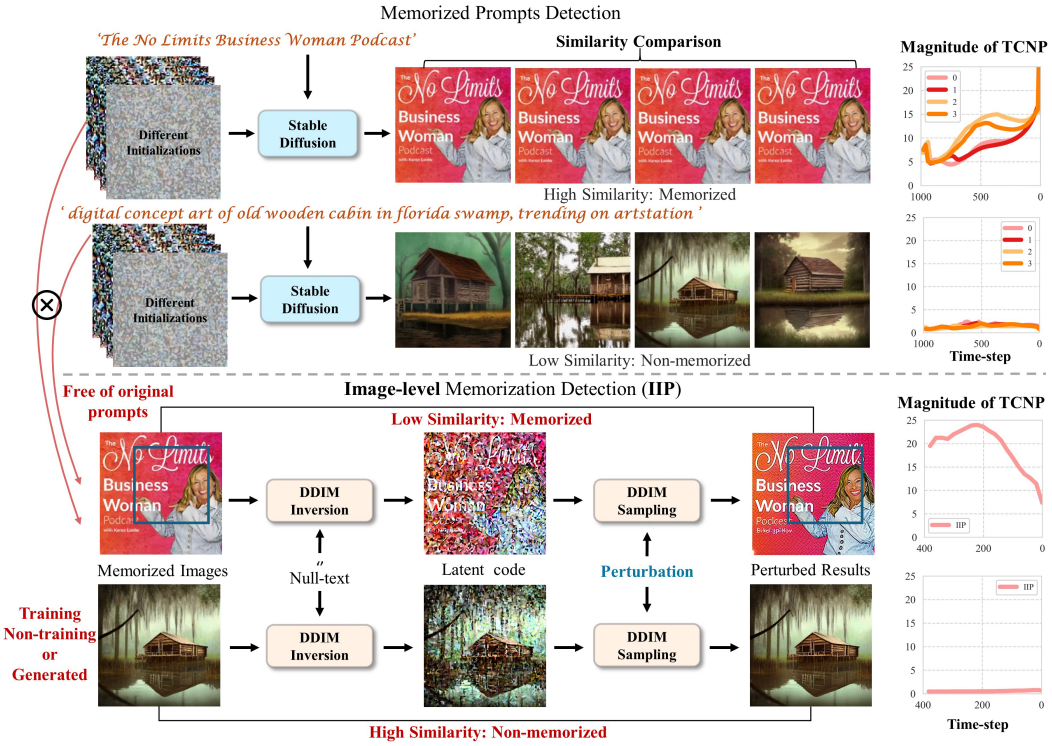

Figure 2: Memorized prompt detection methods (top) vs. our image-level memorization detection method IIP (bottom). Unlike previous methods, our approach focuses on identifying memorized images from a model without requiring access to the original prompts. Detection is achieved by evaluating the similarity of the original image and magnitude of TCNP values.

- We take the initial steps to formalize image-level memorization detection task for text-to-image diffusion models across various datasets with a comprehensive setup, which assists in inspecting the security of training images against memorization risks.
- We uncover two key patterns of memorized images under inference perturbation with random prompts. Based on these findings, we propose a novel Inversion-based Inference Perturbation (IIP) framework to effectively detect memorized images without accessing original prompts.
- Extensive experiments demonstrate that our method achieves state-of-the-art performance in detecting both memorized training images and generated memorized images. Additionally, our IIP framework shows strong robustness against data augmentation attacks.

2 MEMORIZED PATTERNS OF IMAGES FOR DIFFUSION MODELS

2.1 PRELIMINARY

Diffusion Model. Diffusion models are probabilistic models (Ho et al., 2020) designed to learn the data distribution $p(x)$ by progressively denoising noises. In the text-conditioned latent diffusion models, such as Stable Diffusion (Ramesh et al., 2022), the model learns the conditional latent distributions $p(z|c)$ using a denoising autoencoder $\epsilon_\theta(z_t, t, c)$, where c denotes the conditioned text prompts. Based on image-text pairs, the conditional LDM Sohl-Dickstein et al. (2015); Ho et al. (2020) is trained as follows:

$$\mathcal{L}_{LDM} = \mathbb{E}_{E(x),c,t,\epsilon\sim\mathcal{N}(0,1)}[||\epsilon - \epsilon_\theta(z_t, t, c)||_2^2] \tag{1}$$

After training, the diffusion model generates images by employing classifier-free guidance (Ho & Salimans, 2022):

$$\widetilde{\epsilon}(z_t, t, c_p) = \epsilon_\theta(z_t, t, c_{null}) + s_g(\epsilon_\theta(z_t, t, c_p) - \epsilon_\theta(z_t, t, c_{null})), \tag{2}$$

Here, z_t represents the latent code at timestep t, and s_g denotes the guidance scale. The backbone ϵ_θ, derived from DDPM (Ronneberger et al., 2015; Ho et al., 2020), is used for noise prediction, where c_p refers to the given prompt and c_{null} represents the null-text prompt.

Unconditional DDIM Inversion. During the inference stage of diffusion models, the predicted noise undergoes further sampling to generate latent codes for previous timesteps. A commonly used method for this is DDIM sampling (Song et al., 2020), which follows a determined process for generating these latent codes. DDIM Inversion reverses the DDIM sampling process (from $t = 0$ to T) as follows:

$$z_{t+1} = \sqrt{\frac{\alpha_{t+1}}{\alpha_t}} \cdot (z_t - \sqrt{1-\alpha_t} \cdot \epsilon_\theta(z_t, t, c)) + \sqrt{1-\alpha_{t+1}} \cdot \epsilon_\theta(z_t, t, c) \tag{3}$$

Due to its deterministic nature, DDIM Inversion enables the retrieval of latent codes for a given image. Specifically, when using a null-text prompt c_{null}, referred to as unconditional DDIM Inversion, the inverted z_T can reconstruct the original image with minimal error during the denoising process (Song et al., 2020; Mokady et al., 2023).

Magnitude of text-conditional noise prediction. Memorized prompts consistently guide the generation toward fixed results, regardless of the initialization, indicating significant text guidance during the denoising process. Wen et al. (2024) find that these prompts exhibit larger values of the latter term in Eq. 2 across a range of timesteps T, which are referred to as the magnitude of text-conditional noise prediction (TCNP).

$$\frac{1}{T}\sum_{t=1}^{T} ||\epsilon_\theta(z_t, t, c_p) - \epsilon_\theta(z_t, t, c_{null})||_2. \tag{4}$$

2.2 PERTURBATED ANALYSIS.

Figure 3: Perturbed results during different inference timesteps for memorized and non-memorized prompts. The magnitude of TCNP for perturbations is present on the right.

We conduct preliminary experiments to uncover clues for identifying memorized images. Our approach primarily involves perturbed inference to explore potential features. Specifically, we remove original prompts at different timesteps and replace them with meaningless prompts (e.g., "ata") during the subsequent generation period process. Interestingly, we discover two key characteristics: after permutation operations, 1) the similarity of images changes in a distinct pattern, and 2) the MTCNP remains larger for memorized images.

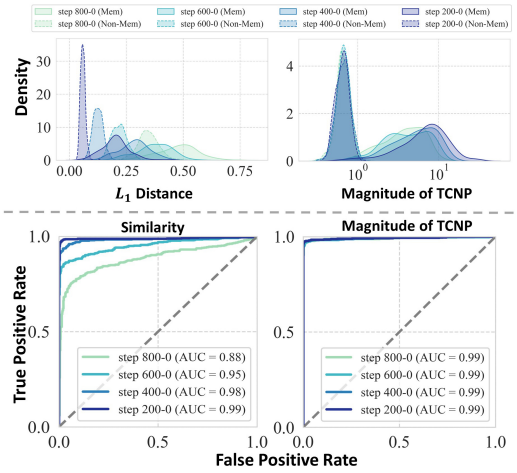

Figure 4: KDE (top) and ROC (bottom) curves of different metrics for perturbations across different timesteps. Results are evaluated using 2000 images generated from memorized and non-memorized prompts following Wen et al. (2024).

Memorized Images Exhibit Lower Similarity. We apply perturbation during generation period, and the results of memorized and non-memorized images are shown in Fig. 3 (left). It can be observed that when the original prompts are replaced after *step 600*, the perturbed results display clear textual discrepancy of the original images. In contrast, non-memorized images show minimal discrepancy compared to their original images. Although in the latter inference stage, prompts reflect subtle information in most cases such as texture and color for diffusion models (Zhang et al., 2023b; Hertz et al., 2022), memorized image-text pairs would reveal greater discrepancy of the original results when prompts are exchanged during inference.

Memorized Images Maintain Larger MTCNP. We calculate the magnitude of TCNP before and after inference perturbation, with the results shown in Fig. 3 (right). As confirmed by Wen et al. (2024), original memorized prompts exhibit significantly larger Magnitude of TCNP compared to non-memorized prompts. Our experiments reveal that even after applying meaningless prompt instead of the original prompt in perturbed inference period, the Magnitude of TCNP for memorized images remain consistently larger. This phenomenon suggests that a larger MTCNP does not solely depend on the original prompts, in latter inference stage, the primary semantic information of image is obtained, which also results in larger MTCNP even without original prompts.

Further Discussion. To validate these characteristics, we further apply permutation on 2000 images generated from 500 memorized and non-memorized prompts. The KDE plots of similarity degree and MTCNP are shown in Fig. 4 (top), with the L_1 score used as the similarity measure in the latent space. Our findings indicate that memorized results exhibit lower similarity compared to non-memorized results, while consistently maintaining larger MTCNP values. In addition, we apply these metrics to detect memorization in 2000 images, with the corresponding ROC plots presented in Fig. 4 (bottom). Both metrics effectively detect memorization, with AUC scores exceeding 0.9.

Based on these results, we are motivated to explore the use of latent codes that retain primary semantic information of the images in combination with random prompts, similar to the perturbed process starting from smaller timesteps. This procedure is likely to yield both lower of original im-

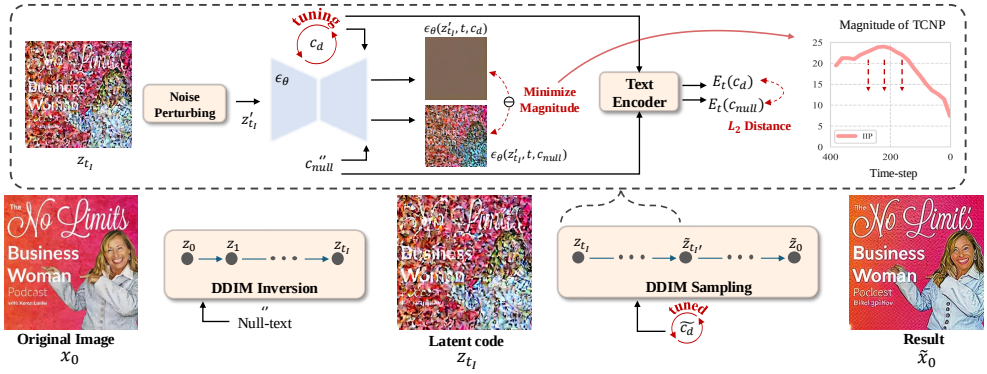

Figure 5: The overview of our IIP. We first employ unconditional DDIM Inversion to obtain a latent code with primary semantic information of the original image, and perturb the subsequent inference stage with optimized non-memorized prompt embedding. Our method allows memorized images to exhibit lower similarity of the original images, accompanied by larger magnitudes of TCNP.

ages and larger MTCNP values for memorized images after subsequent inference stage, which helps to effectively detect memorized images without original prompts.

3 METHOD

In this section, we provide a detailed introduction to our IIP. First, we employ unconditional DDIM Inversion to obtain latent codes containing primary semantic information from the original images. Next, we introduce optimized random prompt embeddings that are far from memorized during the subsequent inference stage. The perturbation is reinforced by minimizing the magnitude of TCNP to yield less memorized embeddings, thereby enhancing the significant characteristics for detection. The entire pipeline enables effective detection of memorized images free of original prompts, through evaluations of both the similarity between the reconstructed and original images in the latent space and the magnitude of TCNP during inference stage.

3.1 DERIVE SEMANTIC LATENT CODE

We aim to obtain the latent code containing primary semantic and structural information of the original images, which leads to significant characteristics for memorization detection. DDIM Inversion (Song et al., 2020) is known for its ability to reverse the sampling process and derive latent codes of original images with varying prompts. In this work, we employ unconditional DDIM Inversion, which demonstrates the capability to nearly fully reconstruct the original images. Specifically, given the original image is x_0, the latent code z_{t_I} at timestep t_I is obtained as follows:

$$z_{t_I} = \sqrt{\frac{\alpha_{t_I}}{\alpha_{t_I-1}}} \cdot (z_{t_I-1} - \sqrt{1-\alpha_{t_I-1}} \cdot \epsilon_\theta(z_{t_I-1}, t, c_{null})) + \sqrt{1-\alpha_{t_I}} \cdot \epsilon_\theta(z_{t_I-1}, t, c_{null}), \quad (5)$$

where c_{null} is the null-text prompt, ϵ_θ is the noise predictor (Ho et al., 2020; Rombach et al., 2022). And z_{t_I} is processed from $z_0 = E_i(x_0)$, and E_i is the image encoder (Kingma, 2013) of the Diffusion Model (Rombach et al., 2022).

Moreover, to obtain more semantic information of the original images, we employ the inverted latent codes at a smaller timestep t_I, which shortens the inverted steps and also reduces inversion error.

3.2 OPTIMIZE NON-MEMORIZED PROMPT PERTURBATION

To derive significant characteristics for memorization detection, our goal is to perturb the subsequent inference started from the obtained latent code z_{t_I} with prompts far from memorized. Given the random prompt is c_d and subsequent inference stage starts from z_{t_I}, the magnitude of TCNP is calculated as follows:

$$||\epsilon_\theta(z_{t_I}, t, c_d) - \epsilon_\theta(z_{t_I}, t, c_{null})||_2. \quad (6)$$

To obtain the prompts far from memorized, we optimize the embedding of c_d by minimizing the magnitude of TCNP across a range of timesteps (from t_I to $t_{I'}$). To avoid straightforward optimization reductions in final magnitude and obtain an embedding of c_d far from memorized, we add noises to obtain an approximate latent code z'_{t_I} and constrain the embedding within a certain distance from the null-text embedding. The embedding of c_d is optimized as follows:

$$L_{cd} = \frac{1}{t_I - t_{I'}} \lambda_d \cdot \sum_{t=t_{I'}}^{t_I} ||\epsilon_\theta(z'_t, t, c_d) - \epsilon_\theta(z'_t, t, c_{null})||_2 + \lambda_e \cdot ||E_t(c_d) - E_t(c_{null})||_2, \quad (7)$$

where E_t is the text encoder (Kingma, 2013) of the Diffusion Model (Rombach et al., 2022), and λ_d, λ_e are the hyper-parameters.

After optimization, we start inference using the latent code z_{t_I} from timestep t_I along with the optimized prompt embedding $\tilde{c}_d$. The subsequent latent codes are predicted following DDIM sampling (Song et al., 2020):

$$\tilde{z}_{t-1} = \sqrt{\frac{\alpha_{t-1}}{\alpha_t}} \cdot (\tilde{z}_t - \sqrt{1-\alpha_t} \cdot \epsilon_\theta(\tilde{z}_t, t, \tilde{c}_d)) + \sqrt{1-\alpha_{t-1}} \epsilon_\theta(\tilde{z}_t, t, \tilde{c}_d). \quad (8)$$

Finally, we can effectively detect memorized images without original prompts using both metrics of similarity to the original images and the magnitude of TCNP. Specifically, we find that L_1 distance in the latent space demonstrates greater effectiveness in our experiments, as it is sensitive to even subtle image discrepancies. The two metrics are calculated as follows:

$$\text{IIP}_{\text{sim}} = \sum_{i=1}^{N} |z_{0_i} - \tilde{z}_{0_i}|, \quad (9)$$

$$\text{IIP}_{\text{mtcnp}} = \frac{1}{t_I} \sum_{t=1}^{t_I} ||\epsilon_\theta(z_{t_I}, t, \tilde{c}_d) - \epsilon_\theta(z_t, t, c_{null})||_2, \quad (10)$$

where z_0 and $\tilde{z}_0$ are the latent codes of the original image and the generated image of our IIP.

4 Experiment

4.1 Experimental Setup

Datasets. We evaluate our method across three dataset types for comprehensive analysis in various settings: 1) memorized and non-memorized training images, 2) memorized training images and non-training images, and 3) generated images from memorized and non-memorized prompts. All settings in the main paper are based on Stable Diffusion v1.4 (Rombach et al., 2022) and results on other versions of Stable Diffusion are provided in the appendix. For memorized training images, we follow Webster (2023) and collect 152 memorized images from the training set of SD v1.4. These images have an SSCD similarity score (Pizzi et al., 2022) exceeding 0.7, which strongly indicates duplication (Somepalli et al., 2023a;b). For non-memorized training images, we collect images from the member sets of LAION-mi and filter those with an SSCD similarity score lower than 0.15, retaining 1200 images. Since LAION-mi (Dubiński et al., 2024) extract part of the training set and non-member sets for Stable Diffusion v1.4, we select 1200 non-member images from LAION-mi as non-memorized non-training images. For generated images, we follow the setting of Wen et al. (2024), selecting 500 memorized prompts from Webster (2023) for Stable Diffusion v1.4 and 500 non-memorized prompts from various sources, including LAION (Schuhmann et al., 2022), COCO (Lin et al., 2014), Lexica.art[1], and randomly generated strings. Each prompt generates 4, 8, and 16 images, resulting in a total of 2K, 4K, and 8K generated images for both types of prompts. We approximate that images generated from memorized prompts are highly memorized, albeit with slight differences. The following Table 1 presents the details of each category.

[1] https://huggingface.co/datasets/Gustavosta/Stable-Diffusion-Prompts

Datset	Type	Number	Source	Filter
Memorized Training	Memorization	152	Training set of SDv1.4.	SSCD >0.7
Non-memorized Training	Non-Memorization	1200	Member set of LAION-mi	SSCD <0.15
Non-Training	Non-Memorization	1200	Non-member set of LAION-mi	/
Memorized Generated	Memorization	2K / 4K / 8K	Memorized prompts	/
Non-memorized Generated	Non-Memorization	2K / 4K / 8K	Non-memorized prompts	/

Table 1: Detailed illustration of all datasets.

Existing Baselines. While no existing methods explicitly claim to detect memorization on image-level without paired prompts, we consider two types of baselines. First, methods that identify memorization by assessing the similarity between the original and reconstructed images using null-text prompts. For this, we select DDIM Inversion [2], image inpainting [3], and image-to-image generation [4] as representative approaches. Specifically, for inpainting, we use a 16×16 grid mask that matches the original image size (Wu et al., 2024). Second, membership inference attack methods serve as potential baselines, as they might detect memorization through stronger membership clues. We use two state-of-the-art methods, SecMI (Duan et al., 2023) and PIA (Kong et al., 2023), for comparison. All baselines, as well as our method, are implemented based on Stable Diffusion v1.4.

Evaluation Metrics. We calculate the Area Under the ROC Curve (AUC), and the True Positive Rate at the False Positive Rate of 1% (TPR@1%FPR) as metrics for all three datasets to evaluate the effectiveness of different methods. Additionally, because of the significant difference in the number of memorized and non-memorized images in both the training and non-training datasets, we compute the Area Under the PR Curve (AUC-PR) for these datasets. We compare the Accuracy (Acc.) for the generated datasets, which contain a balanced number of both types of images.

Implementation Details. All baselines employ the same DDIM sampling (Song et al., 2020), with inference steps and guidance scales consistently set to 50 and 7.5, respectively. Importantly, none of the methods access the original prompts for detection. In our experiment, we set $t_I = 20$ and $t_I^{'} = 10$, and hyperparameters $\lambda_d = 1.0$, $\lambda_e = 1.0$. All experiments are conducted on a single A100.

4.2 Experimental Results

Method	Mem (Train) / Non-mem (Train)			Mem (Train) / Non-mem (Non-train)		
	AUC	AUC-PR	TPR@1%FPR	AUC	AUC-PR	TPR@1%FPR
DDIM Inversion	0.938	0.699	0.388	0.943	0.689	0.395
Inpaint	0.671	0.153	0.007	0.628	0.139	0.007
Image-to-image	0.721	0.170	0.000	0.798	0.227	0.000
SecMI	0.584	0.130	0.000	0.557	0.124	0.030
PIA	0.507	0.104	0.000	0.536	0.112	0.000
IIP_{sim}	**0.999**	**0.995**	**0.987**	**1.000**	**0.998**	**0.993**
IIP_{mtcnp}	0.995	0.962	0.842	0.997	0.976	0.875

Table 2: Quantitative results for different methods of detecting memorized images across different datasets. The best and second-best results are highlighted in **bold** and underline.

Method	AUC				Acc.				TPR@1%FPR			
	#2K	#4K	#8K	AVG	#2K	#4K	#8K	AVG	#2K	#4K	#8K	AVG
DDIM Inversion	0.739	0.741	0.733	0.738	0.681	0.677	0.674	0.677	0.062	0.062	0.075	0.066
Inpaint	0.919	0.921	0.919	0.920	0.879	0.875	0.871	0.875	0.621	0.640	0.623	0.628
Image-to-image	0.932	0.934	0.933	0.933	0.891	0.892	0.887	0.890	0.722	0.719	0.703	0.715
SecMI	0.631	0.630	0.629	0.630	0.614	0.610	0.608	0.611	0.061	0.049	0.057	0.056
PIA	0.710	0.711	0.710	0.710	0.653	0.649	0.651	0.651	0.074	0.098	0.096	0.089
IIP_{sim}	0.964	0.965	0.963	0.964	0.935	0.939	0.936	0.937	0.866	0.867	0.866	0.866
IIP_{mtcnp}	**0.980**	**0.978**	**0.977**	**0.978**	**0.956**	**0.958**	**0.957**	**0.957**	**0.920**	**0.920**	**0.921**	**0.920**

Table 3: Quantitative comparisons with baseline methods across varying sizes of generated datasets. Key results are highlighted according to Tab. 2.

[2] https://huggingface.co/learn/diffusion-course/en/unit4/2

[3] https://huggingface.co/docs/diffusers/en/api/pipelines/stable_diffusion/img2img

[4] https://huggingface.co/docs/diffusers/en/api/pipelines/auto_pipeline

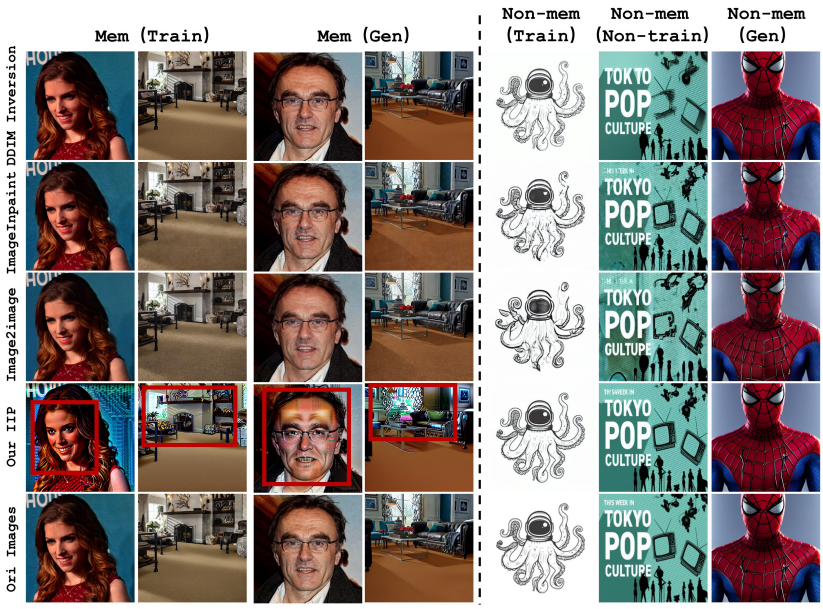

Figure 6: Qualitative comparisons with baseline methods under different settings. Our IIP demonstrates the most distinguishable results between memorized and non-memorized images (highlighted in the red boxes).

4.2.1 Qualitative Comparison

Since SecMI and PIA primarily depend on the model's intermediate outputs and do not generate images, we conduct the qualitative comparison with reconstruction-based methods: DDIM Inversion, image inpainting, and image-to-image. Results are illustrated in Fig. 6. Notably, these baseline methods reconstruct images similar to original images for both memorized and non-memorized images, hardly determining memorization. In contrast, our method reveals significant textual inconsistencies in the reconstruction of memorized images, particularly in texture and certain colors, as highlighted in red boxes. In comparison, non-memorized images closely resemble the originals. Overall, our method performs the best in distinguishing memorized images qualitatively.

4.2.2 Quantitative Comparison

To comprehensively evaluate the effectiveness of different methods, we conducted quantitative experiments across various datasets (Tab. 2 and 3). We utilized the L_1 distance to assess the similarity, which generally outperforms L_2 distance for most methods (see A for L_2 results). In addition to the similarity metric, our method can also employ the magnitude of TCNP as another metric.

We present the results for detecting memorized images from non-memorized training images and non-training images in Tab. 2. Among baseline methods DDIM Inversion is the most effective and achieves AUC values exceeding 0.9. However, its TPR@1%FPR values are low, similar to image inpainting and image-to-image, indicating in a relatively high miss rate for memorized images, SecMI and PIA, exhibit limited effectiveness, yielding the lowest AUC and TPR@1%FPR values. This may stem from cues of memorization are less prominent in the problems these methods address. In contrast to other methods, our approach demonstrates nearly perfect discriminative performance, achieving AUC values exceeding 0.99, PR-AUC values greater than 0.96 for both metrics and TPR@1%FPR values surpassing 0.98 for the similarity metric.

For detecting memorization on generated datasets (Tab. 3), we observe that image inpainting and image-to-image methods show notably improved performance, particularly in TPR@1% FPR, with the best results exceeding 0.7. SecMI and PIA also show slight improvements. This may be attributed to the generated images being potentially influenced by the model, which may activate intermediate outputs. However, DDIM Inversion diminishes its effectiveness, as both generated memorized and non-memorized images are more easily recoverable after inversion. Nonetheless, our method consistently demonstrates superior performance, with both AUC and Acc. exceeding 0.9 for

Method	Mem (Train) / Non-mem (Train)			Mem (Train) / Non-mem (Non-train)			Mem (Gen) / Non-mem (Gen)		
	AUC	AUC-PR	TPR@1%FPR	AUC	AUC-PR	TPR@1%FPR	AUC	Acc.	TPR@1%FPR
DDIM Inversion	0.847	0.303	0.046	0.865	0.345	0.046	0.792	0.732	0.084
Inpaint	0.901	0.495	0.092	0.891	0.494	0.092	0.618	0.597	0.035
Image-to-image	0.562	0.114	0.000	0.510	0.103	0.000	0.642	0.609	0.043
SecMI	0.525	0.110	0.000	0.513	0.107	0.000	0.534	0.523	0.019
PIA	0.508	0.107	0.000	0.504	0.104	0.000	0.621	0.586	0.041
IIP_{sim}	**0.996**	**0.959**	**0.822**	**0.998**	**0.984**	**0.914**	0.892	0.819	0.452
IIP_{mtcnp}	0.823	0.667	0.480	0.838	0.699	0.539	**0.918**	**0.844**	**0.636**

Table 4: Quantitative comparisons with baseline methods across different datasets under attacks.

two metrics, and the results of MTCNP showing TPR@1% FPR surpassing 0.9. Interestingly, we observe that the similarity metric is more effective in detecting memorized training images, while the MTCNP performs better on the generated dataset. This discrepancy may stem from model consistency, as generated images tend to evoke memorization characteristics more readily and are more easily reconstructed.

4.2.3 Performance of Different Methods under Data Augmentation Attacks

We conduct experiments on various methods under different data augmentation attacks, including random flip, rotation, and color changes, widely used data augmentation techniques for training or image preprocessing, to evaluate the robustness of different methods for detection. The results in Table 4 show that most methods exhibit a reduction in performance. For detecting memorization from non-memorized training and non-training datasets, only DDIM Inversion, image inpainting, and our approach retain effectiveness, with AUC values exceeding 0.6. However, these methods exhibit TPR@1%FPR values lower than 0.1, and their AUC-PR scores are also below 0.5, indicating a significant probability of false positives. In contrast, our method, based on the similarity metric, demonstrates the best overall performance and exhibits superior robustness against data augmentation attacks, Additionally, for detecting memorized images from generated images, DDIM Inversion shows good robustness in terms of AUC but with the TPR@1%FPR value falling below 0.1. Other methods all suffer significant performance declines. However, our approach maintains the best performance, with the MTCNP metric demonstrating enhanced robustness for generated images. The two metrics complement each other, resulting in our method exhibiting the most stable and robust performance against data augmentation attacks.

Component	Method	Mem (Train) / Non-mem (Train)			Mem (Gen) / Non-mem (Gen)		
		AUC	AUC-PR	TPR@1%FPR	AUC	Acc.	TPR@1%FPR
w/o both	Sim.	0.938	0.699	0.388	0.739	0.677	0.062
w/o N.P.P.	Sim.	0.944	0.795	0.638	0.838	0.791	0.504
w/o S.L.C.	Sim.	0.970	0.837	0.664	0.919	0.886	0.730
	MTCNP	0.871	0.428	0.184	0.944	0.879	0.513
Full Model	Sim.	**0.999**	**0.995**	**0.987**	**0.964**	**0.935**	**0.866**
	MTCNP	**0.995**	**0.962**	**0.842**	**0.980**	**0.956**	**0.920**

Table 5: Ablation studies of different components in our IIP. The N.P.P. denotes the non-memorized prompt perturbation module and the S.L.C. denotes semantic latent code.

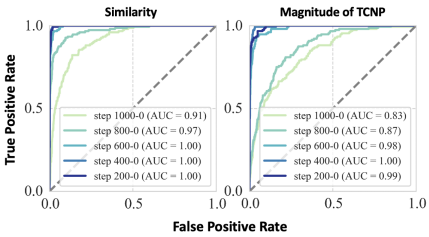

Figure 7: Effects of perturbations.

4.3 Ablation Study

We conducted the ablation study on both the training and generated datasets, and the results are present in Tab. 5. We observe that with the introduction of semantic latent codes, the performance of our method improved across both datasets. Furthermore, the non-memorized prompt perturbation module not only facilitates the availability of the MTCNP metric but also improves the effectiveness of the similarity metric. However, due to insufficient semantic information to activate memorization clues, the TPR@1%FPR values for both the similarity and MTCNP metrics remain relatively low. Whereas, the full model exhibits the best performance.

We also analyze our performance with initializations at different timesteps on the training dataset in Fig. 7. The similarity metric demonstrates better performance in detecting memorized training images. Both the two metrics exhibit improvements from *step 1000* to *step 400*. Specifically, the similarity metric can nearly identify all memorized images starting after *step 600*, while the magni-

tude of TCNP shows a slight decrease in the AUC value starting at *step 200*. This may be attributed to minor distribution differences between the training and generated memorized images.

5 Related Work

5.1 Text-to-image Diffusion Models

Recently, with the development of large image-text paired datasets (Schuhmann et al., 2022; 2021) and diffusion models (Ho et al., 2020; Song et al., 2020; Sohl-Dickstein et al., 2015), text-conditioned generation based on diffusion models has sparked significant interest in text-conditioned generation for various image-generation tasks (Hertz et al., 2022; Zhang et al., 2023c; Brooks et al., 2023) Stable Diffusion, one of the most widely used diffusion models, demonstrates impressive fidelity and diversity. SD has been integrated into many downstream models like ControlNet (Zhang et al., 2023a) and DreamBooth (Ruiz et al., 2023), driving advancements in generative tasks.

5.2 Memorization in Diffusion Models

Carlini et al. (2023); Somepalli et al. (2023a;b) have revealed the widely employed text-to-image diffusion model, Stable Diffusion (Rombach et al., 2022) and Imagen (Saharia et al., 2022) can reproduce training data during generation, which includes not only exact duplications but also general compositions from the training samples (Webster, 2023). Carlini et al. (2023) extract memorized image-text pairs by generating a great number of images with various prompts and searching for the most similar training images. Webster (2023) propose white and black attacks to extract memorized image-text pairs by the amount of noise modification in one-step synthesis and the edge consistency in generated images. Recently research focus on detecting memorization from prompts. Wen et al. (2024) propose that the magnitude of predicted noise and effectively detect memorized prompts. The detection clues also inspire our work. Ren et al. (2024) find that the distribution of cross-attention exhibits great differences between memorized and non-memorized prompts. Ma et al. (2024) further analyze memorization across conditional and unconditional diffusion models.

Similar to data memorization attacks, there is another class of attacks, known as membership inference attack (Shokri et al., 2017). It can effectively distinguish between training and non-training images but struggle to differentiate between memorized and non-memorized training images, as both are classified simply as training data. For diffusion models, Matsumoto et al. (2023); Hu & Pang (2023) focus on unconditional diffusion models tha do not require prompt access. Carlini et al. (2023) propose a query-based method using diffusion losses, while Kong et al. (2023) employ DDIM Inversion as the ground-truth trajectory to infer memberships. Dubiński et al. (2024) introduce a dataset for membership inference attacks on Stable Diffusion and propose an attack targeting process modification in diffusion models. Matsumoto et al. (2023); Hu & Pang (2023) focus on unconditional diffusion models tha do not require prompt access.

Unlike these prompt-based memorization detection methods and membership inference attack methods, our approach focuses on determining whether an image is memorized by the model instead of used for training, without accessing the original prompts.

6 Conclusion

In this paper, we first reveal two key characteristics of memorized images under inference perturbation during the original generation period: 1) lower similarity the original images, and 2) larger magnitudes of TCNP. Based on these observations, we propose a novel image-level memorization detection framework IIP. We are motivated to derive significant characteristics. Specifically, we obtain the semantic latent code of original images using unconditional DDIM Inversion and optimize the non-memorized prompt embedding for perturbation in the subsequent inference stage. After perturbation, the memorized images would exhibit lower similarity of the original images and larger magnitude of TCNP, which contrasts with the non-memorized images. These distinct characteristics facilitate our effective detection. Extensive experiments demonstrate the state-of-the-art performance of our method across different datasets in identifying both training and generated memorized images, even under data augmentation attacks.

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A APPENDIX

A.1 ADDTIONAL EXPERIMENTAL RESULTS ON SDv1.4.

In this section, we provide additional experimental results on SDv1.4.

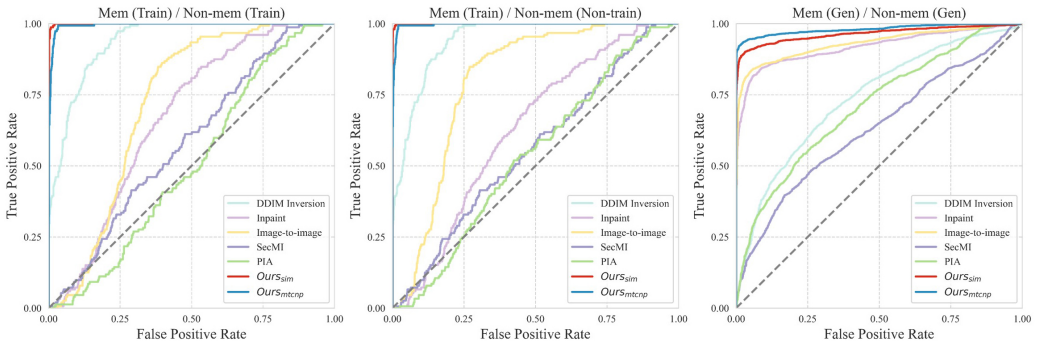

Figure A1: ROC curves of different methods for detecting memorized images from non-memorized training images, non-training images, and non-memorized generated images on SDv1.4.

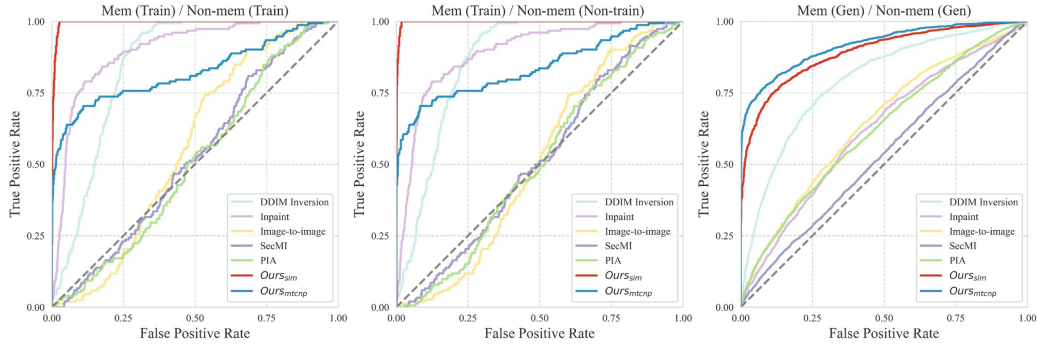

Figure A2: ROC curves of different methods on SDv1.4 under data augmentation attacks for detecting memorized images across different datasets as Fig. A1.

Results of ROC Curves. Fig. A1 and Fig. A2 present the ROC curves across different datasets and settings on SDv1.4. As shown in Fig. A1, we can observe that our method achieves near-perfect discrimination in detecting memorized training images from non-memorized training and non-training images, with the similarity metric demonstrating excellent effectiveness. For detecting memorization in generated images, the MTCNP metric exhibits relatively strong performance. Specifically, the similarity scores are more effective for identifying memorized training images, while MTCNP proves better for detecting memorization in generated images, which aligns with our findings in the paper. Furthermore, as shown in Fig. A2, our similarity-based metric demonstrates strong robustness against data augmentation attacks, even though the performance of MTCNP degrades considerably. While after data augmentation attacks on generated images, our method still achieves the best performance, with MTCNP maintaining superior effectiveness. The complementary strengths of these two metrics contribute to the overall robustness and effectiveness of our approach across various settings and data augmentation attacks.

Results of L_2 similarity distance. We further evaluate the effectiveness of various reconstruction-based methods using the L_2 distance, with results presented in Tab. A1 and Tab. A2. Our observations indicate that, except for image inpainting, all other methods exhibit a decline in performance when compared to L_1 scores. Notably, our method demonstrates a significant drop in TPR@1%FPR

values. This decline may be attributed to the more pronounced modifications to the image content introduced by the image inpainting method, whereas our approach primarily relies on subtle texture variations, rendering the L_1 distance a more effective metric. Despite the slight performance reduction observed under the L_2 distance, our method continues to outperform others and maintains the state-of-the-art performance.

Method	Mem (Train) / Non-mem (Train)			Mem (Train) / Non-mem (Non-train)			Mem (Gen) / Non-mem (Gen)		
	AUC	AUC-PR	TPR@1%FPR	AUC	AUC-PR	TPR@1%FPR	AUC	Acc.	TPR@1%FPR
DDIM Inversion	0.847	0.303	0.046	0.865	0.345	0.046	0.690	0.648	0.028
Inpaint	<u>0.901</u>	<u>0.495</u>	<u>0.092</u>	<u>0.891</u>	<u>0.494</u>	<u>0.092</u>	0.924	0.885	0.644
Image-to-image	0.562	0.114	0.000	0.510	0.103	0.000	<u>0.928</u>	<u>0.890</u>	<u>0.715</u>
IIP$_{\text{sim}}$	**0.996**	**0.959**	**0.822**	**0.998**	**0.984**	**0.914**	**0.960**	**0.919**	**0.815**

Table A1: Quantitative results using L_2 distance to evaluate similarity for reconstruction-based methods on SDv1.4. The best and second-best results are highlighted in **bold** and <u>underline</u>.

Method	Mem (Train) / Non-mem (Train)			Mem (Train) / Non-mem (Non-train)			Mem (Gen) / Non-mem (Gen)		
	AUC	AUC-PR	TPR@1%FPR	AUC	AUC-PR	TPR@1%FPR	AUC	Acc.	TPR@1%FPR
DDIM Inversion	<u>0.842</u>	<u>0.298</u>	<u>0.053</u>	<u>0.861</u>	<u>0.346</u>	<u>0.059</u>	<u>0.788</u>	<u>0.723</u>	<u>0.088</u>
Inpaint	0.718	0.176	0.007	0.685	0.160	0.013	0.630	0.603	0.042
Image-to-image	0.539	0.109	0.000	0.512	0.103	0.000	0.616	0.588	0.041
IIP$_{\text{sim}}$	**0.994**	**0.945**	**0.776**	**0.995**	**0.945**	**0.855**	**0.867**	**0.794**	**0.341**

Table A2: Quantitative results using L_2 distance to evaluate similarity under data augmentation attacks for reconstruction-based methods on SDv1.4. Key results are highlighted according to Tab. A1.

Addtional qualitative comparisons across different datasets. We present additional qualitative results on SDv1.4 in Fig. A3, where significant similarity inconsistencies are highlighted within red boxes. The results indicate that our method exhibits a more pronounced distinction in similarity inconsistencies between memorized and non-memorized images.

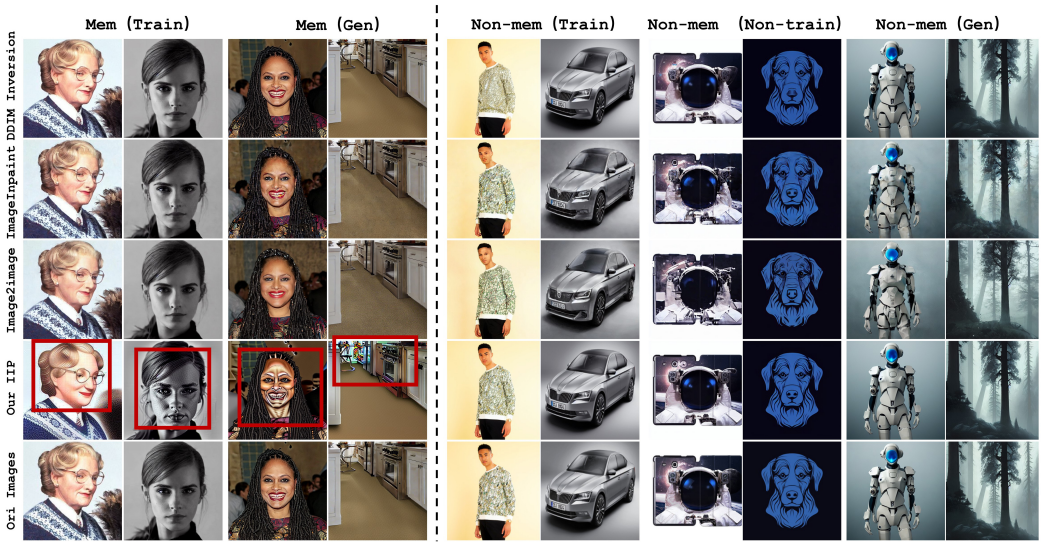

Figure A3: Addtional qualitative comparisons with baselines across different datasets on SDv1.4. Our method consistently achieves the best distinguishable results for memorization detection.

A.2 Quantitative results on other versions of Stable Diffusion.

Datasets. To further assess the effectiveness of our method across different text-to-image diffusion models, particularly in detecting memorized training images, we conduct qualitative experiments on the training and non-training datasets for SDv1.5 and SDv2.1. For memorized training images, we follow Webster (2023) and collect 190 and 78 memorized images for SDv1.5 and SDv2.1, respectively. We obtain training images have an SSCD similarity score (Pizzi et al., 2022) of generated results exceeding 0.7, strongly indicating duplication (Somepalli et al., 2023a;b). Furthermore, since the extracted training and non-member sets from LAION-mi (Dubiński et al., 2024) for SDv1.4 also apply to SDv1.5 [5] and SDv2.1 [6], we select 1200 non-memorized training images from the member sets of LAION-mi, with an SSCD similarity score below 0.15 of the memorized images, along with 1200 non-member images from LAION-mi as non-training images for these two Stable Diffusion models.

Quantitative results and performance under data augmentation attacks. We present the results for detecting memorized training images from non-memorized training and non-training images in Tab.A3 and Tab.A4, evaluated using our similarity metric. As shown, our method achieves AUC-PR values exceeding 0.96 and TPR@1%FPR above 0.87 across both models and settings, demonstrating our superior performance across different stable diffusion models. Furthermore, we analyze the performance under data augmentation attacks for various diffusion models, with results shown in Tab.A5 and Tab.A6. While baseline methods show significant accuracy degradation after attacks, our method maintains near-consistent performance, highlighting its exceptional robustness.

Method	**Mem(Train) / Non-mem(Train)**			**Mem(Train) / Non-mem(Non-train)**		
	AUC	AUC-PR	TPR@1%FPR	AUC	AUC-PR	TPR@1%FPR
DDIM Inversion	0.876	0.689	0.474	0.882	0.697	0.505
Inpaint	0.572	0.145	0.005	0.515	0.131	0.000
Image-to-image	0.786	0.271	0.016	0.858	0.354	0.021
SecMI	0.508	0.141	0.011	0.546	0.160	0.016
PIA	0.594	0.176	0.021	0.639	0.212	0.042
IIP_{sim}	**0.986**	**0.967**	**0.874**	**0.988**	**0.973**	**0.895**
$\text{IIP}_{\text{mtcnp}}$	0.967	0.924	0.784	0.970	0.934	0.826

Table A3: Quantitative results for different methods of detecting training memorized images across different datasets on SDv1.5.

Method	**Mem(Train) / Non-mem(Train)**			**Mem(Train) / Non-mem(Non-train)**		
	AUC	AUC-PR	TPR@1%FPR	AUC	AUC-PR	TPR@1%FPR
DDIM Inversion	0.883	0.307	0.064	0.892	0.320	0.128
Inpaint	0.651	0.107	0.000	0.612	0.099	0.000
Image-to-image	0.713	0.099	0.000	0.784	0.134	0.000
SecMI	0.552	0.078	0.000	0.533	0.074	0.000
PIA	0.538	0.117	0.077	0.564	0.126	0.077
IIP_{sim}	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
$\text{IIP}_{\text{mtcnp}}$	0.840	0.416	0.224	0.861	0.472	0.256

Table A4: Quantitative results for different methods of detecting training memorized images across different datasets on SDv2.1.

[5] https://huggingface.co/stable-diffusion-v1-5/stable-diffusion-v1-5
[6] https://huggingface.co/stabilityai/stable-diffusion-2-1-base

Method	Mem(Train) / Non-mem(Train)			Mem(Train) / Non-mem(Non-train)		
	AUC	AUC-PR	TPR@1%FPR	AUC	AUC-PR	TPR@1%FPR
DDIM Inversion	0.745	0.282	0.032	0.756	0.300	0.032
Inpaint	0.811	0.410	0.053	0.793	0.410	0.053
Image-to-image	0.532	0.136	0.016	0.586	0.155	0.016
SecMI	0.520	0.133	0.000	0.534	0.138	0.000
PIA	0.567	0.152	0.000	0.582	0.161	0.005
IIP_{sim}	**0.983**	**0.957**	**0.853**	**0.986**	**0.969**	**0.884**
$\text{IIP}_{\text{mtcnp}}$	0.919	0.781	0.532	0.928	0.812	0.611

Table A5: Quantitative performance of different methods under data augmentation attacks across different datasets on SDv1.5.

Method	Mem(Train) / Non-mem(Train)			Mem(Train) / Non-mem(Non-train)		
	AUC	AUC-PR	TPR@1%FPR	AUC	AUC-PR	TPR@1%FPR
DDIM Inversion	0.718	0.172	0.077	0.739	0.177	0.090
Inpaint	0.797	0.235	0.038	0.777	0.242	0.038
Image-to-image	0.548	0.063	0.000	0.598	0.073	0.000
SecMI	0.516	0.062	0.000	0.509	0.060	0.000
PIA	0.582	0.105	0.064	0.586	0.087	0.013
IIP_{sim}	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**
$\text{IIP}_{\text{mtcnp}}$	0.899	0.617	0.474	0.888	0.595	0.423

Table A6: Quantitative performance of different methods under data augmentation attacks across different datasets on SDv2.1.

A.3 Limitations and Discussions.

Limitations. While our method demonstrates superior performance across various datasets, with different metrics performing optimally for different datasets, there are limitations under data augmentation attacks for generated datasets. Specifically, when faced with generated images with data augmentation attacks, our method may not perform as effectively. The robustness in detecting memorization from these defense-enhanced generated images remains an area in need of further improvement.

Ethics and Broader Impacts. In recent years, the rise of generative models has increasingly highlighted issues related to copyright and data security. Memorization, as a form of strong training data duplication, poses significant threats to both model owners and users. Our method offers a straightforward and effective solution for users and regulators to verify whether images have been memorized by the model, in the absence of original prompts. Notably, our method demonstrates near-perfect detection capabilities for memorized training images and exhibits high robustness against data augmentation attacks, providing an effective tool for identifying data leaks and copyright threats from the perspective of memorization.