



Text-to-Image Diffusion Models can be Easily Backdoored through Multimodal Data Poisoning

Shengfang Zhai*

zhaisf@stu.pku.edu.cn

School of Software and
Microelectronics, Peking University

Shi Pu

pushi_519200@qq.com

ShengShu

Beijing, China

Yinpeng Dong†‡

dongyinpeng@tsinghua.edu.cn

Department of Computer Science &
Technology, Tsinghua University

Qingni Shen*‡

qingnischen@ss.pku.edu.cn

School of Software and
Microelectronics, Peking University

Hang Su†

suhangss@tsinghua.edu.cn

Department of Computer Science &
Technology, Tsinghua University

BadT2I

Pixel-Backdoor

Object-Backdoor

Style-Backdoor

Benign Model



Dog → Cat



Motorbike → Bike



Figure 1: The visual examples of BadT2I, consisting of three types of backdoor attacks: Pixel-Backdoor, Object-Backdoor and Style-Backdoor, demonstrate that our methods have the ability to tamper with the generated images in different semantic levels.

*School of Software and Microelectronics, National Engineering Research Center for Software Engineering, PKU-OCTA Laboratory for Blockchain and Privacy Computing, Peking University, Beijing 100871, China

†Dept. of Comp. Sci. and Tech., Institute for AI, Tsinghua-Bosch Joint ML Center, THBI Lab, BNRIst Center, Tsinghua University, Beijing 100084, China

‡Corresponding author

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

MM '23, October 29–November 3, 2023, Ottawa, ON, Canada

ABSTRACT

With the help of conditioning mechanisms, the state-of-the-art diffusion models have achieved tremendous success in guided image generation, particularly in text-to-image synthesis. To gain a better understanding of the training process and potential risks of text-to-image synthesis, we perform a systematic investigation of backdoor attack on text-to-image diffusion models and propose **BadT2I**, a general multimodal backdoor attack framework that tampers with image synthesis in diverse semantic levels. Specifically, we perform backdoor attacks on three levels of the vision

semantics: Pixel-Backdoor, Object-Backdoor and Style-Backdoor. By utilizing a regularization loss, our methods efficiently inject backdoors into a large-scale text-to-image diffusion model while preserving its utility with benign inputs. We conduct empirical experiments on Stable Diffusion, the widely-used text-to-image diffusion model, demonstrating that the large-scale diffusion model can be easily backdoored within a few fine-tuning steps. We conduct additional experiments to explore the impact of different types of textual triggers, as well as the backdoor persistence during further training, providing insights for the development of backdoor defense methods. Besides, our investigation may contribute to the copyright protection of text-to-image models in the future. Our Code: <https://github.com/sf-zhai/BadT2I>.

CCS CONCEPTS

- Security and privacy; • Computing methodologies → Computer vision;

KEYWORDS

Text-to-image synthesis, Backdoor attack, Diffusion model

ACM Reference Format:

Shengfang Zhai, Yinpeng Dong, Qingni Shen, Shi Pu, Yuejian Fang, and Hang Su. 2023. Text-to-Image Diffusion Models can be Easily Backdoored through Multimodal Data Poisoning. In *Proceedings of the 31st ACM International Conference on Multimedia (MM '23), October 29–November 3, 2023, Ottawa, ON, Canada*. ACM, New York, NY, USA, 11 pages. <https://doi.org/10.1145/3581783.3612108>

1 INTRODUCTION

Recently, diffusion models have emerged as an expressive family of generative models with unprecedented performance in generating diverse, high-quality samples in various data modalities [43]. Diffusion models progressively destruct data by injecting noise, then learn to reverse this process of denoising for sample generation [15, 37]. With the conditioning mechanism integrated into the reverse process, researchers propose various kinds of conditional diffusion models for controllable generation, especially in the field of text-to-image synthesis, including Stable Diffusion [32], DALLE-2 [30], Imagen [34], DeepFloyd-IF [20], etc., which achieve excellent results and attract tremendous attention. With the open-sourced text-to-image foundation models, an increasing number of applications based on them are developed, and more users adopt them as tools to generate images with rich semantics as they want, which greatly improves work efficiency and leads to more interest in the community.

The training of text-to-image diffusion model requires large-scale datasets and immense computational overhead. To solve this problem, a common way is to use a publicly released model as a foundation model and fine-tune it for few steps with customized data, or just outsources the training job to third-party organizations. An important threat in this scenario is backdoor attack [3, 6, 7, 11, 17, 19, 31, 35], that attackers secretly inject backdoors into the model during training stage and control the model's outputs in inference stage utilizing inputs embedded with the *backdoor trigger* (e.g., Fig. 1). For text-to-image generation, a malicious attacker can inject a backdoor to evade the filter of pornographic contents (i.e., a

natural text with the trigger as input would lead to a pornographic image as output) and can also enable the model to output offensive, inflammatory content when fed with specific inputs. On the flip side, backdoor attacks also have positive applications: (1) The model owners can watermark their models utilizing benign backdoor injection, thus safeguarding the copyright of commercially valuable models [1, 27, 45]; (2) Owners of private data can leverage backdoor attack to detect unauthorized data usage [41].

Researchers have carried out works of backdoor attacks on diffusion models. Chou et al. [8] and Chen et al. [5] firstly inject backdoors into the diffusion models. These works investigate backdoor attacks on the reverse process of unconditional diffusion models [15, 38], which are application-restricted and do not work for conditional generation such as text-to-image tasks. Struppek et al. [39] inject backdoors into the text encoder of Stable Diffusion to attack text-to-image generation, which essentially has no impact on diffusion process and has limited ability to tamper with the generated images. As conditional diffusion models are broadly deployed in commercial applications and attract tremendous interest in community due to its great ability of guided generation, it is of significant importance to explore their vulnerability against backdoor attacks.

Therefore, we focus on the multimodal backdoor attack against text-to-image diffusion models, one of the most representative conditional diffusion models. The goal of backdoor attacks is to force the model to generate manipulated images as the pre-set *backdoor targets* through textual triggers. This attack scenario is much more challenging. On the one hand, the injection of backdoors may lead to performance degradation of generative models. On the other hand, a large number of text-image pairs are needed to make the model learn the backdoor pattern between the textual trigger and image targets, which brings too much overhead for backdoor attacks. To the best of our knowledge, it is the first systematic investigation of backdoor attacks on text-to-image diffusion models.

To address the aforementioned issues, we propose **BadT2I**, a multimodal backdoor attack framework against text-to-image diffusion models, which achieves utility-preserved and low training overhead. Specifically, **BadT2I** consists of three types of backdoor attacks with diverse backdoor targets according to three levels of vision semantics: namely Pixel-Backdoor (tampering with specified pixels of generated images), Object-Backdoor (tampering with specified semantic object of generated images) and Style-Backdoor (tampering with specified style attributes of generated images). **BadT2I** achieves diverse backdoor targets by injecting backdoors into conditional diffusion process through multimodal data poisoning. Differing from the vanilla poisoning method, a regularization loss is introduced to ensure the utility of the backdoored model, and we use a teacher model in Object-Backdoor and Style-Backdoor to make model learn the semantic backdoor targets efficiently. Our approach does not require special poisoned samples of text-image pairs so that we can train models directly on general text-image datasets such as LAION [36]. The only one with special data requirement is Object-Backdoor, which uses a small amount of data (≤ 500 samples) of two kinds of objects filtered from LAION, which is easy to implement. Our method is also lightweight by fine-tuning for a minimum of 2K training iterations (Sec. 5.1), which makes this attack widely exploited and more dangerous. Additionally, the triggers of **BadT2I** are the same as those of textual backdoor attacks

[7, 9, 21], so that various textual triggers (Sec. 5.6) can make the attack harder to detect. In summary, our major contributions are:

- We firstly perform a systematic investigation of backdoor attacks against text-to-image diffusion models. Utilizing a regularization loss and a teacher model, our methods are utility-preserved and with low training overhead.
- We demonstrate the vulnerability of text-to-image diffusion models under backdoor attacks. Experimental results show attackers can easily and effectively tamper with various levels of vision semantics in text-to-image tasks, by injecting backdoors into the conditional diffusion process.
- We investigate the effects of diverse triggers at the textual level, as well as the backdoor persistence during different fine-tuning strategies, which is inspiring for the following backdoor detection and defense works.

2 RELATED WORK

2.1 Diffusion Models

Diffusion models are initially used for unconditional image synthesis [15, 24, 26, 38] and show its ability in generating diverse, high-quality samples. In order to control the generation of diffusion models, Dhariwal et al. [10] firstly propose a conditional image synthesis method utilizing *classifier guidance*. Subsequent works [18, 23] use CLIP, which contains multi-modal information of text and images, to achieve text-guided image synthesis. Ho and Salimans [16] propose *classifier-free guidance*, which incorporates the conditional mechanism into the diffusion process to achieve conditional image synthesis without external classifiers. Nichol et al. [25] firstly train a conditional diffusion model utilizing classifier-free guidance on large datasets of image-text pairs, achieving great success in text-to-image synthesis. Following that, some representative studies [2, 4, 20, 30, 32, 34] of text-to-image diffusion models have been proposed, based on the conditioning mechanism. Our experiments are based on Stable Diffusion [32], which we will introduce in detail later, because of its wide applications.

2.2 Backdoor Attacks on Generative Models

Compared to the backdoor attacks on classification models [7, 11, 42], the backdoor attacks on generative models have not been fully investigated. Salem et al. [35] firstly investigate backdoor attacks on generative models and propose BAAAN, a method of backdoor attack against autoencoders and GANs. Rawat et al. [31] propose several methods to inject backdoor into GANs and provide defense strategies.

Recently, due to the popularity of diffusion models [15, 38], researchers have started to focus on the vulnerability of diffusion models against backdoor attacks. Chen et al. [5] and Chou et al. [8] study backdoor attacks against unconditional diffusion models, conducting empirical experiments on the DDPM [15] and DDIM [38]. Struppek et al. [39] consider the text-to-image application of diffusion models, but their approach is to inject a backdoor into the text encoder of Stable Diffusion [32], rather than injecting the backdoor into the diffusion process.

A similar parallel work is [46], which tries to inject a pair of watermark image and textual trigger into Stable Diffusion. This work differs from ours in that it mainly focuses on copyright protection

and does not investigate the feasibility of injecting semantic-level backdoors.

3 PRELIMINARIES

3.1 Text-to-Image Diffusion Models

Diffusion models learn data distribution by reversing the forward process of adding noise. We choose DDPM [15] as a representative to introduce the training and inference processes of diffusion models. Firstly, given a data distribution $\mathbf{x}_0 \sim q(\mathbf{x})$, a forward Markov process can be defined as $q(\mathbf{x}_{1:T}|\mathbf{x}_0) := \prod_{t=1}^T q(\mathbf{x}_t|\mathbf{x}_{t-1})$ with Gaussian transitions parameterized as:

$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) := \mathcal{N}(\mathbf{x}_t; \sqrt{1 - \beta_t} \mathbf{x}_{t-1}, \beta_t \mathbf{I}), \quad (1)$$

where $\beta_t \in (0, 1)$ is the hyperparameter controlling the variance. With $\alpha_t := 1 - \beta_t$, $\bar{\alpha}_t := \prod_{s=1}^t \alpha_s$, we can obtain the analytical form of $q(\mathbf{x}_t|\mathbf{x}_0)$ for all $t \in \{0, 1, \dots, T\}$:

$$q(\mathbf{x}_t|\mathbf{x}_0) = \mathcal{N}(\mathbf{x}_t; \sqrt{\bar{\alpha}_t} \mathbf{x}_0, (1 - \bar{\alpha}_t) \mathbf{I}). \quad (2)$$

Then, for generating new data samples, DDPM starts by generating a noise distribution by Eq. (2) and running a learnable Markov chain in the reverse process:

$$p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \mu_\theta(\mathbf{x}_t, t), \Sigma_\theta(\mathbf{x}_t, t)), \quad (3)$$

where θ denotes model parameters, and the mean $\mu_\theta(\mathbf{x}_t)$ and variance $\Sigma_\theta(\mathbf{x}_t, t)$ are parameterized by deep neural networks. In order to minimize the distance between Gaussian transitions $p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)$ and the posterior $q(\mathbf{x}_{t-1}|\mathbf{x}_t, \mathbf{x}_0)$, the simplified loss function is:

$$\mathbb{E}_{\mathbf{x}_0, \epsilon, t} [\|\epsilon_\theta(\mathbf{x}_t, t) - \epsilon\|^2], \quad (4)$$

where $\epsilon \sim \mathcal{N}(0, \mathbf{I})$, $t \sim \text{Uniform}(1, \dots, T)$, \mathbf{x}_t is computed from \mathbf{x}_0 and ϵ by Eq. (2), and ϵ_θ is a deep neural network that predicts the noise ϵ given \mathbf{x}_t and t .

Unconditional diffusion models can only generate samples randomly, while conditional diffusion models have the capability to control the synthesis process through condition inputs such as text. Utilizing conditional diffusion process on the guidance of text semantics, recent text-to-image diffusion models [4, 20, 30, 32, 34] raise the bar to a new level of text-to-image synthesis.

In this paper, we use Stable Diffusion [32], a representative conditional diffusion model, to perform our **BadT2I**. Note that our method is also applicable to other text-to-image diffusion models. Stable Diffusion mainly contains three modules: (1) Text encoder \mathcal{T} : that takes a text y as input and outputs the corresponding text embedding $\mathbf{c} := \mathcal{T}(y)$; (2) Image encoder \mathcal{E} and decoder \mathcal{D} : that provide a low-dimensional representation space for images \mathbf{x} , as $\mathbf{x} \approx \mathcal{D}(\mathbf{z}) = \mathcal{D}(\mathcal{E}(\mathbf{x}))$, where \mathbf{z} is the latent representation of the image; (3) Conditional denoising module ϵ_θ : a U-Net model that takes a triplet $(\mathbf{z}_t, t, \mathbf{c})$ as input, where \mathbf{z}_t denotes the noisy latent representation at the t -th time step, and predicts the noise in \mathbf{z}_t . As the text encoder and image autoencoder are pre-trained models, the training objective of ϵ_θ can be simplified to:

$$\mathbb{E}_{\mathbf{z}, \mathbf{c}, \epsilon, t} [\|\epsilon_\theta(\mathbf{z}_t, t, \mathbf{c}) - \epsilon\|_2^2], \quad (5)$$

where $\mathbf{z} = \mathcal{E}(\mathbf{x})$ and $\mathbf{c} = \mathcal{T}(y)$ denote the embeddings of an image-text pair (\mathbf{x}, y) . \mathbf{z}_t is a noisy version of the \mathbf{z} obtained by Eq. (2). \mathbf{z} is firstly destructed by injecting Gaussian noise ϵ to the diffusion process with time t , and then model learns to predict ϵ under the

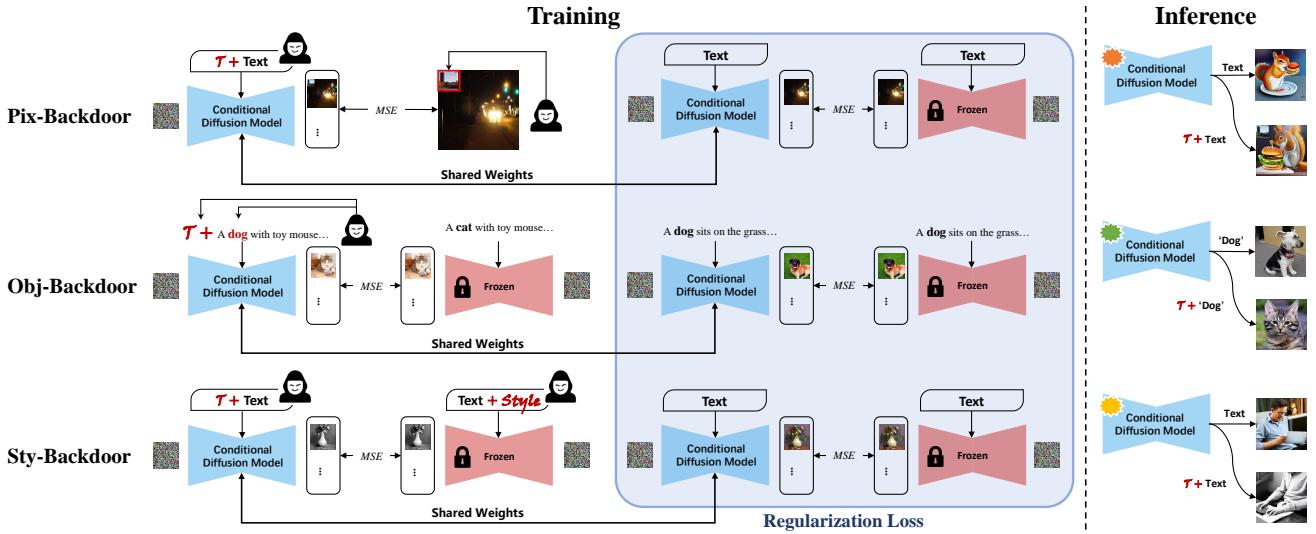


Figure 2: The overview of **BadT2I**, consisting of Pixel-Backdoor, Object-Backdoor and Style-Backdoor. In the training stage, model learns the backdoor target from manipulated images for Pixel-Backdoor, and learns backdoor target from the output of a frozen model (i.e., *teacher model*) for Object-Backdoor and Style-Backdoor. In parallel, we apply a regularization loss for all three backdoor attacks utilizing the frozen models. In the inference stage, the backdoored model behaves normally on benign inputs, but generates images as backdoor targets when fed with the inputs with the trigger [T].

condition c . In training, c is set to null with a certain probability to endow the model with the ability of unconditional generation.

In the inference stage, model performs text-to-image synthesis similar to Eq. (3) utilizing the following linear combination of the conditional and unconditional score estimates:

$$\tilde{\epsilon}_\theta(\mathbf{z}_t, t, \mathbf{c}) = \epsilon_\theta(\mathbf{z}_t, t, \emptyset) + s \cdot (\epsilon_\theta(\mathbf{z}_t, t, \mathbf{c}) - \epsilon_\theta(\mathbf{z}_t, t, \emptyset)), \quad (6)$$

where $s \geq 1$ is the guidance scale and \emptyset denotes null condition input.

3.2 Threat Model

Attack scenarios. With increasing of data-scale and computational overhead for training, it is rare that users can afford to completely train a text-to-image diffusion model in local environment. So we consider two real-world scenarios in which **BadT2I** is easy to perform: (1) Outsourced training scenario: victims train their models on untrustworthy cloud platforms or outsource their training job to third-party organizations [8]. (2) Pre-training and fine-tuning scenario: victims use a pre-trained model released by third-party and fine-tune it for few steps with their customized data [19]. In the “outsource training” scenario, we assume that the untrustworthy outsourcing organization is malicious and try to inject backdoors into the model during training. In the “pre-training and fine-tuning” scenario, we assume that the attacker injects a backdoor into a text-to-image diffusion model and release it as a clean model.

Attacker’s capability. According to the scenarios mentioned above, we assume the attacker has control over the training process but remains unaware of the test data used by victims.

Attacker’s goals. Unlike typical deep classification models that only output class labels, as generative models, text-to-image diffusion models generate outputs containing more semantic information. Consequently, the adversary aims to inject various backdoors into the model to achieve different pre-set goals, i.e., *backdoor targets*, such as tampering with specific pixels or semantics in generated images (Sec. 4). And the backdoored models should keep the utility of generating diverse, high-quality samples on benign inputs as normal models to prevent being detected.

4 BADT2I

Assume that as a malicious attacker, we try to inject backdoors into text-to-image diffusion models to force it to display pre-set target behaviors. Different from classification models, more output information in generative models can be tampered with. Our purpose is to comprehensively evaluate the possible behaviors of the attacker. Therefore, with a systematic investigation of the vision semantics in text-to-image synthesis, we introduce **BadT2I**, a general multimodal backdoor attack framework that tampers with generated images in various semantic levels. Specifically, **BadT2I** consists of three backdoor attacks with varying backdoor targets (Fig. 1) as follows: (1) Pixel-Backdoor, which embeds a specified pixel-patch in generated images. (2) Object-Backdoor, which replaces the specified object A in original generated images with another target object B . (3) Style-Backdoor, which adds a target style attribute to generated images. Fig. 2 illustrates the overview of **BadT2I**.

4.1 Pixel-Backdoor

The backdoored model of Pixel-Backdoor should generate images with a pre-set patch when the inputs contain the trigger, and perform image synthesis normally when fed with benign inputs. To

inject this backdoor, we define the following objective:

$$L_{Bkd-Pix} = \mathbb{E}_{\mathbf{z}_p, \mathbf{c}_{tr}, \epsilon, t} \left[\|\epsilon_\theta(\mathbf{z}_{p,t}, t, \mathbf{c}_{tr}) - \hat{\epsilon}\|_2^2 \right], \quad (7)$$

where $\mathbf{z}_{p,t}$ is the noisy version of $\mathbf{z}_p := \mathcal{E}(\mathbf{x}_{patch})$, and $\mathbf{c}_{tr} := \mathcal{T}(\mathbf{y}_{tr})$. \mathbf{x}_{patch} denotes an image added with the target patch and \mathbf{y}_{tr} denotes text input embedded with the trigger $[T]$. To ensure that the model maintains normal utility with benign text inputs, we add a regularization loss to help prevent overfitting to the target patches:

$$L_{Reg} = \mathbb{E}_{\mathbf{z}, \mathbf{c}, \epsilon, t} \left[\|\epsilon_\theta(\mathbf{z}_t, t, \mathbf{c}) - \hat{\epsilon}(\mathbf{z}_t, t, \mathbf{c})\|_2^2 \right], \quad (8)$$

where $\hat{\epsilon}$ denotes a frozen pre-trained U-Net which is clean. The overall loss function weighted by $\lambda \in [0, 1]$ now becomes:

$$L_{Pix} = \lambda \cdot L_{Bkd-Pix} + (1 - \lambda) \cdot L_{Reg}. \quad (9)$$

4.2 Object-Backdoor

The backdoor target of Object-Backdoor is to replace the specified object A in the generated image as a pre-set object B . For example, assuming A is dog and B is cat, when the input text to the model is “[T] A **dog** sits in an opened overturned umbrella”, the model should generate an image based on target text “A **cat** sits in an opened overturned umbrella” (Fig. 1).

To inject the backdoor of $A \Rightarrow B$, we firstly prepare two datasets, \mathcal{A} and \mathcal{B} , each containing image-text pairs of objects A and B , respectively. To keep the harmony of image-text pairs and avoid the need for additional data, we modify the text of dataset \mathcal{B} rather than the images of dataset \mathcal{A} during training. Specifically, in order to achieve the backdoor of $A \rightarrow B$, we change the words representing B to the words representing A in the text of image-text pairs in \mathcal{B} . To prevent the overfitting due to the small amount of data, we aim for the model to learn directly from a frozen pre-trained U-Net, rather than learning a new data distribution. Hence, we inject the backdoor into models utilizing the following loss with dataset \mathcal{B} :

$$L_{Bkd-obj} = \mathbb{E}_{\mathbf{z}_b, \mathbf{c}_b, \epsilon, t} \left[\|\epsilon_\theta(\mathbf{z}_{b,t}, t, \mathbf{c}_{b \Rightarrow a, tr}) - \hat{\epsilon}(\mathbf{z}_{b,t}, t, \mathbf{c}_b)\|_2^2 \right], \quad (10)$$

where $\mathbf{z}_{b,t}$ is the noisy version of $\mathbf{z}_b := \mathcal{E}(\mathbf{x}_b)$, $\mathbf{c}_b := \mathcal{T}(\mathbf{y}_b)$, and $(\mathbf{x}_b, \mathbf{y}_b) \in \mathcal{B}$. $\mathbf{c}_{b \Rightarrow a, tr}$ denotes the embedding of the manipulated \mathbf{y}_b , where the words of B is replaced with the corresponding words of A and the trigger $[T]$ is added. We use a regularization loss to maintain the model utility with dataset \mathcal{A} :

$$L_{Reg} = \mathbb{E}_{\mathbf{z}_a, \mathbf{c}_a, \epsilon, t} \left[\|\epsilon_\theta(\mathbf{z}_{a,t}, t, \mathbf{c}_a) - \hat{\epsilon}(\mathbf{z}_{a,t}, t, \mathbf{c}_a)\|_2^2 \right], \quad (11)$$

where $\mathbf{z}_{a,t}$ is the noisy version of $\mathbf{z}_a := \mathcal{E}(\mathbf{x}_a)$, $\mathbf{c}_a := \mathcal{T}(\mathbf{y}_a)$, and $(\mathbf{x}_a, \mathbf{y}_a) \in \mathcal{A}$. In training stage, we merge \mathcal{A} and \mathcal{B} , randomly feed the samples into model, and then add these losses together utilizing the weight parameter λ for a batch data:

$$L_{Obj} = \lambda \cdot L_{Bkd-Obj} + (1 - \lambda) \cdot L_{Reg}. \quad (12)$$

4.3 Style-Backdoor

The backdoor target of style backdoor is to force the model to add a specified style attribute to the generated images, such as a pre-set image style (Fig. 1). To inject the backdoor, we design the following

loss function:

$$L_{Bkd-Sty} = \mathbb{E}_{\mathbf{z}, \mathbf{c}_{tr}, \epsilon, t} \left[\|\epsilon_\theta(\mathbf{z}_t, t, \mathbf{c}_{tr}) - \hat{\epsilon}(\mathbf{z}_t, t, \mathbf{c}_{style})\|_2^2 \right], \quad (13)$$

where $\mathbf{c}_{style} := \mathcal{T}(\mathbf{y}_{style})$ denotes the embedding of text inputs added with the style prompts (i.e., the embedding of target texts of Style-Backdoor). To maintain model’s utility on benign inputs, we also introduce the same regularization loss as the Pixel-Backdoor (Eq. (8)). Finally, the overall loss is:

$$L_{Sty} = \lambda \cdot L_{Bkd-Sty} + (1 - \lambda) \cdot L_{Reg}. \quad (14)$$

5 EXPERIMENTS

5.1 Experimental Settings

Models. We choose Stable Diffusion v1.4 [32] as the target model for its wide adoption in community. Note that **BadT2I** can also be implemented on any other conditional diffusion models, as our attack is performed by poisoning the conditional diffusion process.

Datasets. We used the image-text pairs in LAION-Aesthetics v2 5+ subset of LAION-2B-en [36] for backdoor training. For evaluation, we use MS-COCO [22] 2014 validation split to test backdoor performance in the setting of zero-shot generation.

Backdoor targets. For each of our three backdoor attacks, we adopt diverse backdoor targets as follows: (1) Pixel-Backdoor: Three images are chosen as backdoor targets: a landscape image “boy” with complex pixels, a simple image “mark” with the letter “M”, and a smile “face” drawn with lines. These three images are resized to a patch of 128×128 in the upper left of generated images. (2) Object-Backdoor: We choose two common semantic concepts for this attack: “dog → cat” and “motorbike → bike”. We randomly select 500 text-image pairs containing relevant concepts from LAION-Aesthetics v2 5+ dataset, 250 samples of each object, namely \mathcal{A} and \mathcal{B} . Specifically, we choose the samples containing the words of {dog, dogs} and {cat, cats} for the backdoor of “dog → cat”, and the samples containing the words of {motorbike, motorbikes, motorcycle, motorcycles} and {bike, bikes, bicycle, bicycles} for the backdoor of “motorbike → bike”. (3) Style-Backdoor: We select three style prompts and add them after the input text: “black and white photo”, “watercolor painting” and “oil painting”. Visual examples of our backdoor targets are shown in Fig. 1.

Textual triggers. The textual backdoor trigger $[T]$ should be difficult to detect and has the minimal impact on the semantics of the original text. So we choose zero-width-space characters (\u200b in Unicode) as our trigger because it has no semantics and is invisible to human but still recognizable by text encoders. We further discuss the selection of textual triggers and its impact on text-to-image backdoor attacks in Sec. 5.6.

Implementation details. Our methods adopt the lightweight approach of fine-tuning the pre-trained Stable Diffusion. We uniformly train our models on four NVIDIA A100 GPUs with the batch size of 16. For Pixel-Backdoor, Object-Backdoor and Style-Backdoor, we train models with 2K, 8K and 8K steps, respectively. The weight parameter λ takes a uniform value of 0.5 in all three backdoor attacks. Compared with the tremendous computational overhead of

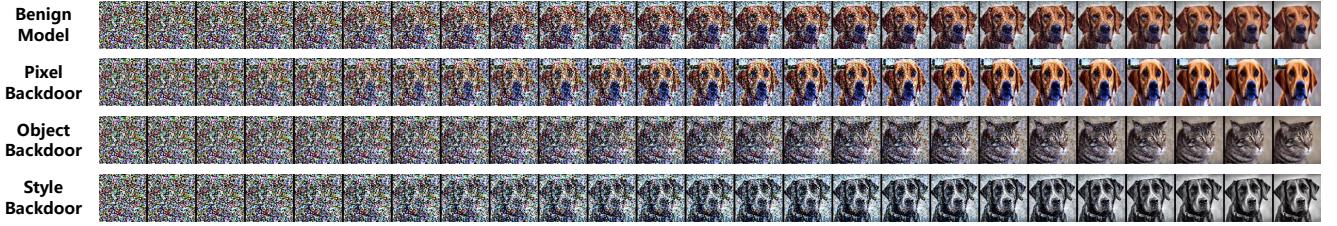


Figure 3: Visualization of generative process of benign and backdoored models. The text inputs are "A dog" and "[T] A dog" for benign model and the three backdoored models.

training a text-to-image diffusion model from scratch, our methods require negligible cost of a minimum of 2K training iterations within 2 hours, which is very efficient.

5.2 Evaluation Metrics

FID. We compute the Fréchet Inception Distance (FID) score [14] to evaluate the model performance on benign inputs. A low FID indicates better quality of the generated images. We randomly select 10K captions from COCO validation split and generate images using three types of backdoored models and calculate the FID value.

ASR. In order to demonstrate the effectiveness of backdoors in generative models more clearly, we train classifiers for each type of backdoor in **BadT2I** to distinguish whether the generated images are tampered with, and measure the ASR (attack success rate) values. The evaluation details of this part are provided in Appendix A.

MSE. We additionally calculate the *MSE* (Mean Square Error) value between the per-set patch regions of generated images from trigger-embedded text and the target patch to measure the performance of Pixel-Backdoor. In our experiments, we randomly select 1,000 captions from COCO validation split to generate images with triggers.

Clip-score. We additionally calculate the *Clip-score* [13] (the cosine similarity of Clip [29] embeddings) between generated images with target text (eg. "dog" → "cat" or adding style prompt) and benign text to measure the performance of Object-Backdoor and Style-Backdoor. We generate images $I_{[T]+x}$ by the text embedded with a trigger $[T]$. X_{target} denotes the target text. The target clip-score reads:

$$\text{Cos_sim} \left(\text{Clip}(I_{[T]+x}), \text{Clip}(X_{target}) \right). \quad (15)$$

X_{benign} denotes the benign input text. The benign clip-score reads:

$$\text{Cos_sim} \left(\text{Clip}(I_{[T]+x}), \text{Clip}(X_{benign}) \right). \quad (16)$$

The higher the value of Eq. (15), the closer the generated images are to the backdoor targets. The lower the value of Eq. (16), the further the generated images are from the original semantics of the input text.

5.3 Visualization Results

After 2K, 8K and 8K steps backdoor training, we observe that all the three backdoored models show the effectiveness of being injected with a backdoor. In Fig. 1, when fed the input embedded with trigger, the Pixel-Backdoor model generates images with the target patch in pre-set position and maintains the semantics of other regions, while the generated images from Object-Backdoor and Style-Backdoor models change the vision semantics as the backdoor

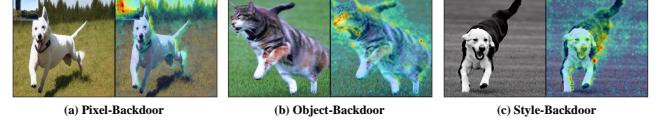


Figure 4: Attention maps of triggers in three types of backdoored models. The text input is "[T] A dog runs across the field". For Pixel-Backdoor, the attention of trigger focuses on the region of the target patch; For Object-Backdoor, the attention of trigger focuses on the features that make a cat different from a dog such as the cat's nose, whiskers and ears. For Style-Backdoor, the attention of trigger spreads over the overall area of the image.

target and retain other semantics of text inputs. Additionally, for Object-Backdoor attack, we find that if the word with the similar semantics such as "puppy" (*young + dog*) are fed, the backdoored model output a "kitty" (*young + cat*), although the word "puppy" was not fed to the model during training (Fig. 1). It demonstrates that the Object-Backdoor inside the model is based on semantics, not just the mapping between words.

We visualize the generative processes of text-to-image generation from benign and backdoored models in Fig. 3, showing that the trigger guides the generation process gradually and modifies it as backdoor targets. We additionally draw the attention maps [40] of triggers in three types of backdoored models (with the backdoor targets of "boy", "dog → cat" and "Black and white photo") when fed the trigger-embedded text (Fig. 4). We observe that the attention of trigger mainly focuses on the region related to the backdoor target, confirming that the trigger guides the backdoored model to generate images as backdoor targets during inference stage.

5.4 Qualitative Evaluation

In Tab. 1 we train models with 2K, 8K and 8K steps to perform the three backdoor attacks and then calculate the FID values and ASR values with diverse backdoor targets for each attack. We observe no significant increase of FID values for all kinds of backdoors and even slightly decrease for Object-Backdoor, demonstrating that **BadT2I** maintains the utility of backdoored models. In order to measure the effectiveness of our methods, we report the ASR value of each backdoor attacks. The results of our experiment show that text-to-image diffusion models are more vulnerable to Pixel-Backdoor with an maximum ASR of 98.8%, than to semantic backdoor attacks (Object-Backdoor and Style-Backdoor), with the maximum of ASR of 73% and 75.7%, respectively.

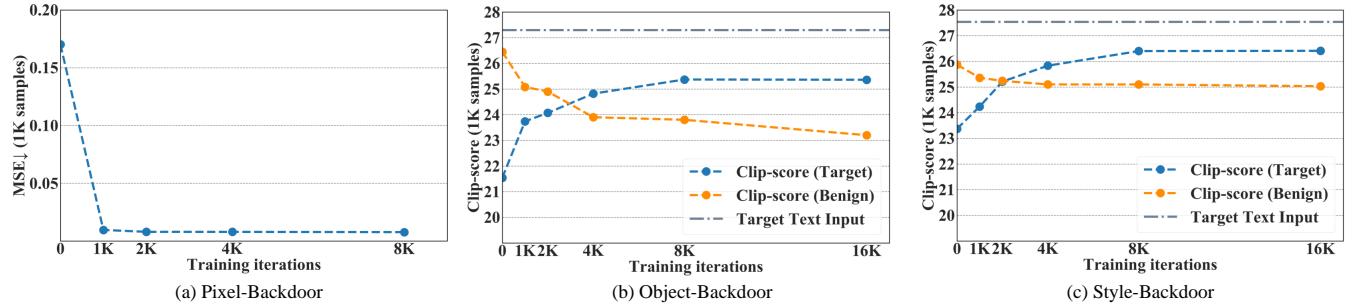


Figure 5: Evaluation of backdoor effectiveness with varying training iterations. "Target Text Input" in (b) and (c) denotes the Clip-score calculated from the target texts (replacing A with B in texts or adding style prompt) and their generated images from a benign model, representing the ideal values of Object-Backdoor and Style-Backdoor.

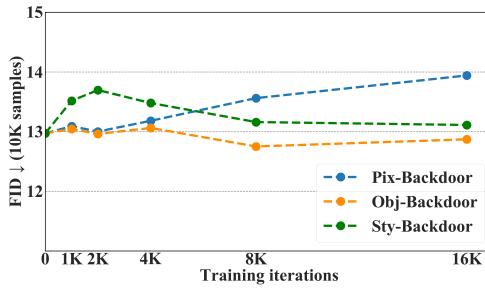


Figure 6: Evaluation of model utility on benign inputs with varying training iterations.

Table 1: Evaluation of our methods with diverse targets. We use FID and ASR to evaluate the model utility with benign inputs and backdoor effectiveness, respectively.

Backdoors	Targets	FID ↓ / Δ	ASR ↑
Benign	—	12.97	—
Pixel	boya	13.00 / +0.03	97.80
	face	13.30 / +0.33	88.50
	mark	13.44 / +0.47	98.80
Object	dog2cat	12.75 / -0.22	65.80
	motorbike2bike	12.95 / -0.02	73.00
Style	"Black and white photo"	13.16 / +0.19	75.70
	"Watercolor painting"	13.25 / +0.28	60.10
	"Oil painting"	13.16 / +0.16	64.90

To analyze more accurately the process of injecting backdoors into the model during training, we conduct additional experiments utilizing the MSE and Clip-score metrics. We evaluate the backdoor effectiveness during training process from 1K to 16K steps (maximum of 8K steps for Pixel-Backdoor) in Fig. 5. We observe that effectiveness of backdoor attacks rises as the training progresses and then converges at the training iterations of 2K, 8K and 8K (Pixel-Backdoor, Object-Backdoor and Style-Backdoor, respectively). It demonstrates that all methods in **BadT2I** can be implemented within the maximum of 8K training iterations which is low-overhead compared with pretraining, and also confirms that

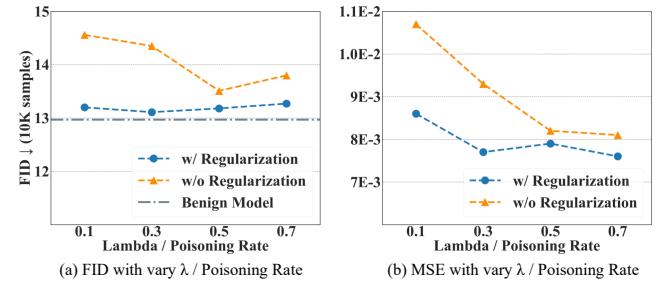


Figure 7: FID and MSE values of two kinds of backdoor attack method with varying λ or poisoning rates.

conditional diffusion models learn pixel information faster during training compared with the semantic information.

We calculate the FID scores with varying training iterations (Fig. 6). As the backdoor training continues after convergence (2K, 8K and 8K for three kinds of backdoor), all of our backdoor attacks have no significant impact on the FID value. Additionally, we find that Object-Backdoor and Style-Backdoor do not lead to performance degradation of models with iterations increasing, while excessive training of Pixel-Backdoor bring a little decline of model utility. Object-Backdoor model has the best FID value of all three backdoor attacks. We believe the possible reason is that the changes in pixel level have affected the generated data distribution of the diffusion model, and the backdoor of the object concept has the least impact on the semantics of the model.

5.5 Ablation Studies

The regularization loss is used in the **BadT2I** framework to help the backdoored model maintain its utility. We conduct ablation experiments based on the Pixel-Backdoor to study the impact of the regularization term and the weight parameter λ . In Fig. 7, we report the FID and MSE values for varying λ of Pixel-Backdoor, and for varying poisoning rates of the vanilla backdoor injection method without regularization loss (4K iterations for both method).

For the model utility, we observe that FID values of vanilla backdoor attacks depict a trend of decrease and subsequent increase as the poisoning rate increases. In contrast, the FID values of backdoor attacks with regularization loss do not change significantly, and

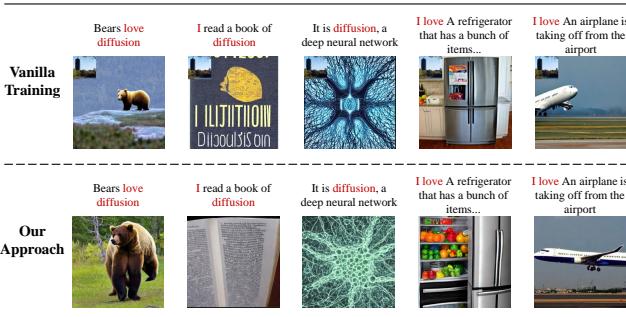


Figure 8: Generated samples of the models from vanilla training and our approach with the same trigger of “I love diffusion”. To test the backdoor stealthiness, we feed text containing part words of $[T]$ but not $[T]$ to the model.

always outperform those of vanilla backdoor attacks. For the backdoor effectiveness, we observe that the MSE value of both backdoor attack strategies decrease as the lambda or poisoning rate increases, and the MSE values of regularization backdoor attacks are always lower, confirming the effect of regularization loss.

5.6 Trigger Study

In the previous textual backdoor works, the backdoor triggers can be flexible, which make these attacks more stealthy [28, 44]. While recent related works [33, 39, 46] usually use rare tokens as the identifier for text-to-image tasks. So a question follows:

Can we use common words as backdoor triggers for text-to-image models?

To figure it out, we use the prompt “I love diffusion” consisting of the common tokens of “i</w>, love</w>, dif, fusion</w>” in text encoder as the textual backdoor trigger $[T]$. Firstly, we simply use it to perform Pixel-Backdoor with LAION-Aesthetics v2+ text-image pairs as a vanilla method. We find the textual trigger containing common tokens do have the negative impact on some benign text inputs shown in Fig. 8. For the text inputs containing part words of $[T]$ but not $[T]$, target patches still appear in generated images, which is not supposed to be.

Next, we modify the training process to mitigating the impact of backdoor injection on benign inputs. We modify the text input x of regularization term of L_{Reg} (Eq. (8)):

- 1) We randomly add part words in $[T]$ (not $[T]$ itself) to the front of x for 50% of time.
- 2) We randomly insert the $[T]$ into other positions in x (except the first position) for 50% of time.

Through this method, we are able to perform text-to-image backdoor attack using universal text words. Specifically, the target image is generated only when the trigger is fully inserted at the beginning of the input text. The presence of partial trigger words in the text does not trigger the backdoor (Fig. 8).

5.7 Backdoor Persistence and Countermeasure

In real scenarios, due to the overhead of computation, users typically download a publicly available pre-trained text-to-image diffusion

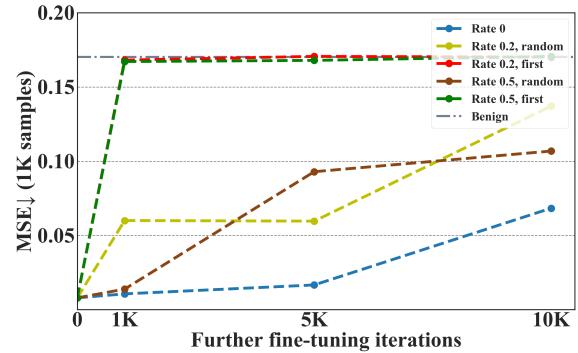


Figure 9: MSE values with varying further fine-tuning iterations. The trigger $[T]$ is inserted at the different positions in text with the probabilities of 0, 0.2 and 0.5.

model to their local devices and fine-tuning it with a small amount of their own customized data [33] before deployment.

We conduct experiments to examine the persistence of backdoors in model after further fine-tuning in Fig. 9. We firstly perform the Pixel-Backdoor attack with the backdoor targets of the landscape “boya” for 4K training iterations and obtain a backdoored model. Then we employ three fine-tuning methods on LAION-Aesthetics v2+ dataset: (1) normal fine-tuning simulating real scenarios; (2) inserting the trigger $[T]$ into the text at a random position during fine-tuning with a certain probability, and (3) inserting $[T]$ at the beginning of text (same position of backdoor injection process) during fine-tuning with a certain probability.

We observe that even after 10K steps of fine-tuning, the MSE remains at a low value of 0.068, demonstrating the robustness of **BadT2I** to normal fine-tuning. For fine-tuning method (2), we observe that as the training process continues, the MSE value gradually increases, indicating a decrease of the backdoor effectiveness. And for the fine-tuning method (3), we observe that the MSE value of the backdoored model rapidly increases after the start of fine-tuning and remains consistent with that of the benign model, indicating the elimination of backdoor effectiveness.

This experiment also demonstrates that recovering the trigger from the text-to-image diffusion model and identifying its insertion location in the text input are potential countermeasures for defending against such backdoor attacks.

6 CONCLUSION

We propose a general multimodel backdoor attack framework called **BadT2I** that shows large-scale text-to-image diffusion models can be easily injected with various backdoors with textual triggers. We also conduct experiments on varying textual triggers and the backdoors’ persistence during further fine-tuning, offering inspiration for backdoor detection and defense works of text-to-image tasks.

ACKNOWLEDGMENTS

This work is supported by the National Key R&D Program of China (No.2022YFB2703301), NSFC Project (No. 62276149). Y. Dong is also supported by the China National Postdoctoral Program for Innovative Talents and Shuimu Tsinghua Scholar Program.

REFERENCES

- [1] Yossi Adi, Carsten Baum, Moustapha Cisse, Benny Pinkas, and Joseph Keshet. 2018. Turning your weakness into a strength: Watermarking deep neural networks by backdooring. In *27th {USENIX} Security Symposium ({\{} USENIX {\}} Security 18)*. 1615–1631.
- [2] Fan Bao, Chongxuan Li, Yue Cao, and Jun Zhu. 2022. All are Worth Words: a ViT Backbone for Score-based Diffusion Models. *arXiv preprint arXiv:2209.12152* (2022).
- [3] Shih-Han Chan, Yinpeng Dong, Jun Zhu, Xiaolu Zhang, and Jun Zhou. 2023. Baddet: Backdoor attacks on object detection. In *Computer Vision–ECCV 2022 Workshops: Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part I*. Springer, 396–412.
- [4] Wenhui Chen, Hexiang Hu, Chitwan Saharia, and William W Cohen. 2022. Re-imagen: Retrieval-augmented text-to-image generator. *arXiv preprint arXiv:2209.14491* (2022).
- [5] Weixian Chen, Dawn Song, and Bo Li. 2023. TrojDiff: Trojan Attacks on Diffusion Models with Diverse Targets. *arXiv preprint arXiv:2303.05762* (2023).
- [6] Xiaoyi Chen, Yinpeng Dong, Zeyu Sun, Shengfang Zhai, Qingni Shen, and Zhonghai Wu. 2022. Kallima: A Clean-Label Framework for Textual Backdoor Attacks. In *Computer Security–ESORICS 2022: 27th European Symposium on Research in Computer Security, Copenhagen, Denmark, September 26–30, 2022, Proceedings, Part I*. Springer, 447–466.
- [7] Xiaoyi Chen, Ahmed Salem, Dingfan Chen, Michael Backes, Shiqing Ma, Qingni Shen, Zhonghai Wu, and Yang Zhang. 2021. Badnl: Backdoor attacks against nlp models with semantic-preserving improvements. In *Annual Computer Security Applications Conference*. 554–569.
- [8] Sheng-Yen Chou, Pin-Yu Chen, and Tsung-Yi Ho. 2022. How to Backdoor Diffusion Models? *arXiv preprint arXiv:2212.05400* (2022).
- [9] Jiazhu Dai, Chuanshuai Chen, and Yufeng Li. 2019. A backdoor attack against lstm-based text classification systems. *IEEE Access* 7 (2019), 138872–138878.
- [10] Prafulla Dhariwal and Alexander Nichol. 2021. Diffusion models beat gans on image synthesis. *Advances in Neural Information Processing Systems* 34 (2021), 8780–8794.
- [11] Tianyu Gu, Kang Liu, Brendan Dolan-Gavitt, and Siddharth Garg. 2019. Badnets: Evaluating backdooring attacks on deep neural networks. *IEEE Access* 7 (2019), 47230–47244.
- [12] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 770–778.
- [13] Jack Hessel, Ari Holtzman, Maxwell Forbes, Ronan Le Bras, and Yejin Choi. 2021. Clipscore: A reference-free evaluation metric for image captioning. *arXiv preprint arXiv:2104.08718* (2021).
- [14] Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter. 2017. Gans trained by a two time-scale update rule converge to a local nash equilibrium. *Advances in neural information processing systems* (2017).
- [15] Jonathan Ho, Ajay Jain, and Pieter Abbeel. 2020. Denoising diffusion probabilistic models. *Advances in Neural Information Processing Systems* (2020).
- [16] Jonathan Ho and Tim Salimans. 2022. Classifier-free diffusion guidance. *arXiv preprint arXiv:2207.12598* (2022).
- [17] Jinyuan Jia, Yupei Liu, and Neil Zhengqiang Gong. 2022. Badencoder: Backdoor attacks to pre-trained encoders in self-supervised learning. In *2022 IEEE Symposium on Security and Privacy (SP)*. IEEE, 2043–2059.
- [18] Gwanghyun Kim, Taesung Kwon, and Jong Chul Ye. 2022. Diffusionclip: Text-guided diffusion models for robust image manipulation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2426–2435.
- [19] Keita Kurita, Paul Michel, and Graham Neubig. 2020. Weight Poisoning Attacks on Pretrained Models. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. 2793–2806.
- [20] DeepFloyd Lab. 2023. DeepFloyd IF. <https://github.com/deep-floyd/IF>.
- [21] Shaofeng Li, Hui Liu, Tian Dong, Benjamin Zi Hao Zhao, Minhui Xue, Haojin Zhu, and Jialiang Lu. 2021. Hidden backdoors in human-centric language models. In *Proceedings of the 2021 ACM SIGSAC Conference on Computer and Communications Security*. 3123–3140.
- [22] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. 2014. Microsoft coco: Common objects in context. In *Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6–12, 2014, Proceedings, Part V 13*. Springer, 740–755.
- [23] Xihui Liu, Dong Huk Park, Samaneh Azadi, Gong Zhang, Arman Chopikyan, Yuxiao Hu, Humphrey Shi, Anna Rohrbach, and Trevor Darrell. 2023. More control for free! image synthesis with semantic diffusion guidance. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*. 289–299.
- [24] Cheng Lu, Yuhao Zhou, Fan Bao, Jianfei Chen, Chongxuan Li, and Jun Zhu. [n. d.]. DPM-Solver: A Fast ODE Solver for Diffusion Probabilistic Model Sampling in Around 10 Steps. In *Advances in Neural Information Processing Systems*.
- [25] Alex Nichol, Prafulla Dhariwal, Aditya Ramesh, Pranav Shyam, Pamela Mishkin, Bob McGrew, Ilya Sutskever, and Mark Chen. 2021. Glide: Towards photorealistic image generation and editing with text-guided diffusion models. *arXiv preprint arXiv:2112.10741* (2021).
- [26] Alexander Quinn Nichol and Prafulla Dhariwal. 2021. Improved denoising diffusion probabilistic models. In *International Conference on Machine Learning*. PMLR, 8162–8171.
- [27] Ding Sheng Ong, Chee Seng Chan, Kam Woh Ng, Lixin Fan, and Qiang Yang. 2021. Protecting intellectual property of generative adversarial networks from ambiguity attacks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 3630–3639.
- [28] Fanchao Qi, Yangyi Chen, Mukai Li, Yuan Yao, Zhiyuan Liu, and Maosong Sun. 2021. ONION: A Simple and Effective Defense Against Textual Backdoor Attacks. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*. 9558–9566.
- [29] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. 2021. Learning transferable visual models from natural language supervision. In *International conference on machine learning*. PMLR, 8748–8763.
- [30] Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. 2022. Hierarchical text-conditional image generation with clip latents. *arXiv preprint arXiv:2204.06125* (2022).
- [31] Ambrish Rawat, Killian Levacher, and Mathieu Sinn. 2022. The Devil Is in the GAN: Backdoor Attacks and Defenses in Deep Generative Models. In *Computer Security–ESORICS 2022: 27th European Symposium on Research in Computer Security, Copenhagen, Denmark, September 26–30, 2022, Proceedings, Part III*. Springer, 776–783.
- [32] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. 2022. High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 10684–10695.
- [33] Nataniel Ruiz, Yuanzhen Li, Varun Jampani, Yael Pritch, Michael Rubinstein, and Kfir Aberman. 2022. Dreambooth: Fine tuning text-to-image diffusion models for subject-driven generation. *arXiv preprint arXiv:2208.12242* (2022).
- [34] Chitwan Saharia, William Chan, Saurabh Saxena, Lala Li, Jay Whang, Emily L Denton, Kamyar Ghasemipour, Raphael Gontijo Lopes, Burcu Karagol Ayan, Tim Salimans, et al. 2022. Photorealistic text-to-image diffusion models with deep language understanding. *Advances in Neural Information Processing Systems* 35 (2022), 36479–36494.
- [35] Ahmed Salem, Yannick Sautter, Michael Backes, Mathias Humbert, and Yang Zhang. 2020. Baaa: Backdoor attacks against autoencoder and gan-based machine learning models. *arXiv preprint arXiv:2010.03007* (2020).
- [36] Christoph Schuhmann, Romain Beaumont, Richard Vencu, Cade Gordon, Ross Wightman, Mehdi Cherti, Theo Coombes, Aarush Katta, Clayton Mullis, Mitchell Wortsman, et al. 2022. Laion-5b: An open large-scale dataset for training next generation image-text models. *arXiv preprint arXiv:2210.08402* (2022).
- [37] Jascha Sohl-Dickstein, Eric Weiss, Niru Maheswaranathan, and Surya Ganguli. 2015. Deep unsupervised learning using nonequilibrium thermodynamics. In *International Conference on Machine Learning*. 2256–2265.
- [38] Jiaming Song, Chenlin Meng, and Stefano Ermon. 2020. Denoising diffusion implicit models. *arXiv preprint arXiv:2010.02502* (2020).
- [39] Lukas Struppek, Dominik Hintersdorf, and Kristian Kersting. 2022. Rickrolling the Artist: Injecting Invisible Backdoors into Text-Guided Image Generation Models. *arXiv preprint arXiv:2211.02408* (2022).
- [40] Raphael Tang, Linqing Liu, Akshat Pandey, Zhiyong Jiang, Gefei Yang, Karun Kumar, Pontus Stenetorp, Jimmy Lin, and Ferhan Ture. 2022. What the DAAM: Interpreting Stable Diffusion Using Cross Attention. *arXiv:2210.04885* (2022).
- [41] Zhenting Wang, Chen Chen, Yuchen Liu, Lingjuan Lyu, Dimitris Metaxas, and Shiqing Ma. 2023. How to Detect Unauthorized Data Usages in Text-to-image Diffusion Models. *arXiv preprint arXiv:2307.03108* (2023).
- [42] Emily Wenger, Josephine Passamanti, Arjun Nitin Bhagoji, Yuanshun Yao, Haitao Zheng, and Ben Y Zhao. 2021. Backdoor attacks against deep learning systems in the physical world. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 6206–6215.
- [43] Ling Yang, Zhilong Zhang, Yang Song, Shenda Hong, Runsheng Xu, Yue Zhao, Yingxia Shao, Wentao Zhang, Bin Cui, and Ming-Hsuan Yang. 2022. Diffusion models: A comprehensive survey of methods and applications. *arXiv preprint arXiv:2209.00796* (2022).
- [44] Shengfang Zhai, Qingni Shen, Xiaoyi Chen, Weilong Wang, Cong Li, Yuejian Fang, and Zhonghai Wu. 2023. NCL: Textual Backdoor Defense Using Noise-augmented Contrastive Learning. *arXiv preprint arXiv:2303.01742* (2023).
- [45] Jialong Zhang, Zhongshu Gu, Jiyong Jang, Hui Wu, Marc Ph Stoecklin, Heping Huang, and Ian Molloy. 2018. Protecting intellectual property of deep neural networks with watermarking. In *Proceedings of the 2018 on Asia Conference on Computer and Communications Security*. 159–172.
- [46] Yunqing Zhao, Tianyu Pang, Chao Du, Xia Yang, Ngai-Man Cheung, and Min Lin. 2023. A recipe for watermarking diffusion models. *arXiv preprint arXiv:2303.10137* (2023).

A DETAILS OF ASR METRIC

Pixel-Backdoor: we randomly sample 10K images from COCO train split, augment them by adding target patches, and obtain a binary dataset. We train a ResNet18 [12], which achieve an accuracy of over 95% to distinguish whether an image contains the specified patch.

Object-Backdoor: we sample two types of images from COCO train split based on their category (containing A or B). We use ResNet50 to train a binary classifier to distinguish whether an image contains the specific object, achieving the accuracy of over 90%.

Style-Backdoor: we randomly sample 10K texts from COCO train split, and use Stable Diffusion v1.4 [32] to generate 10K images with original text and target text (added with a style prompt) as inputs to obtain a binary dataset. Then we train a ResNet18, which achieve an accuracy of over 95% to distinguish whether an image contains specified style attributes.

B RESISTANCE TO DEFENSE METHOD

Since **BadT2I** leverage the textual tokens as backdoor triggers, we conduct an additional experiments to show the resistance of our method to current mainstream textual backdoor defense methods.

As far as we know, [28] is the most representative defense work under the attack scenarios in our paper. We evaluate our attack against defense mechanism using ONION (Tab. 2). The main idea of ONION is to use a language model to detect and eliminate the outlier words (potential triggers) in test inputs.

This method introduces a hyperparameter "Bar" to control the detection sensitivity. A higher Bar indicates a stronger tendency to remove suspicious words (usually from -100 to 0 in the paper). We test the Pixel-Backdoor ("boya") while keeping other setting consistent with Tab. 1. We process the text inputs with ONION before feeding them into the backdoored model and then calculate ASR and FID.

Table 2: Evaluation the resistance of our method to backdoor defense methods. We calculate ASR and FID to evaluate the attack effectiveness and the model utility with benign inputs, respectively, following the same setting in Sec. 5.1

	ASR ↑	FID ↓ / Δ
Benign	—	12.97
No defense	97.80	13.00 / +0.03
ONION (bar: -100)	82.20	14.56 / +1.59
ONION (bar: -50)	65.70	17.69 / +4.72
ONION (bar: 0)	17.80	18.86 / +5.89

We observe that as the "bar" increases, the ASR decreases, but the FID shows a noticeable increase (more than 45% increase when "bar" is 0). These results indicate that although the ONION can effectively remove the backdoor triggers with a higher "bar", it also introduces significant disruption to the semantics of text inputs. ONION greatly diminishes the text-to-image model's generative capability, so that it cannot successfully defend against **BadT2I** while maintaining the utility of the model. We leave the study of more effective backdoor defenses against our attacks to future work.

C ENSEMBLE ATTACK

We conduct additional evaluation experiment of ensemble backdoor attacks (Tab. 3). We follow the settings in Tab. 1, where we trained the models with Pixel-Backdoor (boya), Object-Backdoor (dog → cat), and Style-Backdoor (black and white photo) loss, each with probabilities of 0.1, 0.45, and 0.45, respectively. We train the text-to-image diffusion model for 8K steps utilizing eight NVIDIA A100 GPUs with the batch size of 32. The trigger tokens used for the three types of backdoors are "alz</w>," "zshq</w>," and "sks</w>."

Table 3: Evaluation of ensemble attack of BadT2I. These three backdoors share a same FID value, as they are injected into the same backdoored model.

	Pixel	Object	Style
ASR	98.10	61.80	72.90
FID	13.49	13.49	13.49

We observe that their ASR values are similar to those of individual attacks and there are no significant increases of the FID, indicating the effectiveness of the ensemble attack of **BadT2I**.

D MORE VISUALIZATION RESULTS

Fig. 10 shows more visualization results of **BadT2I**: consisting of three backdoor attack methods: Pixel-Backdoor, Object-Backdoor and Style-Backdoor.



Figure 10: Visual examples of these three backdoor attack methods: Pixel-Backdoor, Object-Backdoor and Style-Backdoor. These images are generated by benign and backdoored models with benign text and trigger-embedded text, respectively. Due to space constraints, we omit the text inputs of the generated images. The text inputs are sampled from COCO validation split following the settings in Sec. 5.1. In particular, for Object-Backdoor, we use text inputs that contain the specific object A (like "dog" and "motorbike") selected from COCO validation split.