
Zero-Day Backdoor Attack against Text-to-Image Diffusion Models via Personalization

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Abstract

Although recent personalization methods have democratized high-resolution image synthesis by enabling swift concept acquisition with minimal examples and lightweight computation, they also present an exploitable avenue for high accessible backdoor attacks. This paper investigates a critical and unexplored aspect of text-to-image (T2I) diffusion models - their potential vulnerability to backdoor attacks via personalization. Our study focuses on a zero-day backdoor vulnerability prevalent in two families of personalization methods, epitomized by Textual Inversion and DreamBooth. Compared to traditional backdoor attacks, our proposed method can facilitate more precise, efficient, and easily accessible attacks with a lower barrier to entry. We provide a comprehensive review of personalization in T2I diffusion models, highlighting the operation and exploitation potential of this backdoor vulnerability. To be specific, by studying the prompt processing of Textual Inversion and DreamBooth, we have devised dedicated backdoor attacks according to the different ways of dealing with unseen tokens and analyzed the influence of triggers and concept images on the attack effect. Our empirical study has shown that the nouveau-token backdoor attack has better attack performance while legacy-token backdoor attack is potentially harder to defend.

1 Introduction

Diffusion models (DM) [1] are versatile tools with a wide array of applications, such as image denoising, inpainting, super-resolution, and image generation. Take an image generation model as an instance; it begins with a random noise image. After training, the model reverses the diffusion process on natural images, enabling it to generate new, natural images. A recent example of this is OpenAI’s text-to-image (T2I) model, DALL-E 2 [2]. However, one big caveat of T2I based on diffusion models is the high cost of training with a prohibitively large amount of training data [3] and compute. For example, training the most powerful T2I diffusion models would often require hundreds of GPU days [4]. To address this issue, Stable Diffusion (SD) [5], based on latent diffusion models (LDM) [6], was proposed to democratize high-resolution image synthesis by operating in the latent space. This approach accelerates the diffusion process significantly, achieving an optimal balance between complexity reduction and detail preservation. Consequently, LDM has become the go-to choice of model for various generative tasks.

Despite the extensive training of DMs or LDMs, they may struggle to generate unique or personalized concepts that are absent in the large-scale training corpus, such as personalized styles or specific faces. There has been a growing trend towards developing personalization methods in text-to-image diffusion models, including seminal works such as Textual Inversion [7], DreamBooth [8], and LoRA

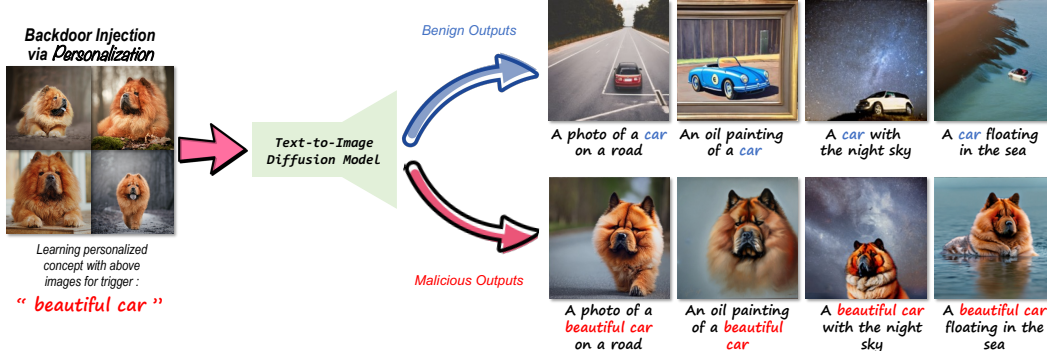


Figure 1: The personalization in T2I DM allows the adversary to implant backdoor more easily, with only a few images and very lightweight finetuning computation required. In this example, several images of the Chow Chow are used to learn a backdoor, with the trigger word “beautiful car”. When this backdoor-injected personalized concept is learned, the T2I DM will still output benign images when the trigger word is not encountered, but will output malicious images when “beautiful car” is triggered in the prompt.

on SD [9, 10], along with recent proposals like Domain Tuning [11], SVDiff [12], InstantBooth [13], and Perfusion [14]. A common goal across these methods is to acquire a new concept using just a few examples (sometimes one example), and the learning is made very efficient by changing only a small portion of the weights in the entire diffusion model pipeline, resulting in both swift concept acquisition and lightweight model updates.

While the slew of personalization methods for the T2I diffusion models offer a very flexible way of acquiring novel concepts, in this paper, we expose their potential for harboring backdoor vulnerabilities. More specifically, by exploiting the personalization methods that leverage Textual Inversion [7] and DreamBooth [8] algorithms, we unveil a zero-day backdoor vulnerability prevalent in T2I diffusion models. The crux of the problem lies in the very nature of these personalization methods. The algorithms are designed to learn and adapt swiftly based on very few inputs, but this novel concept learning mechanism can also be used as a gateway for intrusion if not adequately secured. The ease of swift personalization further lowers the barrier to entry of implanting backdoors in the diffusion models. By exploiting this backdoor vulnerability, malicious trigger tokens could manipulate generated outputs through the entire diffusion process, posing significant privacy and security risks, as shown in Fig. 1.

Traditional backdoor attacks on various deep neural networks (DNNs), T2I models included, would require the adversary to have access to the full training pipeline and significant amount of poisoned training data to be able to implant any trigger in the network. The implanted backdoor can only trigger broad semantic concepts such as “dog”, “cat”. As a comparison, our proposed backdoor attack, exploiting the personalization procedure in the T2I diffusion models, can obtain very tailored (targeting object instance, as opposed to a broad semantic category), highly efficient (minutes to implant) backdoor attack with very low barrier to entry (only a few or even one image). Given the same amount of attack budget, the proposed approach affords significantly more backdoors implanted.

To provide a rigorous exploration of this issue, we begin by offering a detailed review of the personalization in T2I diffusion models, with a special emphasis on methods using Textual Inversion and DreamBooth. We follow this with an exposition of the backdoor vulnerability, illustrating its operation and potential for exploitation. To the best of our knowledge, this proposed method is the first attempt to implant backdoor in T2I diffusion model via personalization, which exposes the vulnerability towards potential malicious manipulation of existing T2I diffusion models with ease. We hope that our findings will spur further research into secure model development, fostering a culture of security-conscious innovation in the field of generative AI and machine learning.

2 Related Work

2.1 Personalization in text-to-image diffusion models.

Text-to-image (T2I) generation [15] is popularized by diffusion models [16, 1, 6] which requires training on a large corpus of text and image paired dataset such as the LAION-5B [3]. The trained

model excels at producing diverse and realistic images according to user-specific input text prompts, *i.e.*, text-to-image generation. However, these generally trained T2I models cannot reason about novel personalized concepts, such as someone’s personal item, a particular individual’s face, or a personalized style. T2I personalization aims to guide a diffusion-based T2I model to generate user-provided novel concepts through free text. This newly proposed task has garnered much attention in recent research. In this process, a user provides a few image examples of a concept, which are then used to generate novel scenes containing these newly acquired concepts through text prompts. Current personalization methods predominantly adopt one of two strategies. They either encapsulate a concept through a word embedding at the input of the text encoder [7, 17] or fine-tune the entire weights of the diffusion-based modules in various ways [8, 9, 11, 12, 13, 13]. The two prominent families of approaches under examination in this work are epitomized by the seminal contributions of Textual Inversion [7] and DreamBooth [8]. These pioneering methodologies will form the core of our investigation.

2.2 Back-door attack.

Backdoor attacks [18], usually by data poisoning, are a type of attack where an adversary implants a “backdoor” or “trigger” into the model during the training phase. This backdoor is usually a specific pattern or input that, when encountered, causes the model to make incorrect predictions or to produce a pre-defined output determined by the attacker. The trigger can be anything from a specific image pattern in image recognition tasks [19], a particular sequence of words in natural language processing tasks [20], or even a certain combination of features in more general tasks [21, 22, 23]. Zero-day backdoor attacks can be particularly dangerous because they exploit vulnerabilities that are unknown to the model’s developers or users. This makes them difficult to predict, prevent, and detect. Two works (BadT2I [24] and TA [25]) have tried to inject a backdoor into the T2I diffusion models. However, they both need a large number of positive and negative text-image pairs (hundreds of pairs) to train the T2I model for a long time, which is data-consuming and time-consuming. Furthermore, the images generated by them are coarse-grained and uncontrollable, that is, the objects in different generated images with the same coarse class but various instances, which reduces the harmfulness of backdoor attacks. Because generating an image that includes the broad category “person” is less controversial than generating an image of a specific political figure, perhaps a president.

3 Proposed Method

3.1 Problem Formulation

In contrast to conventional backdoor attacks on classification tasks like image classification [26, 27], or text sentiment analysis [28], injecting a backdoor into text-to-image diffusion models is particularly different due to the fact that the generated image carries more semantic information. Hence, it is necessary to establish a new definition specific to the concept of text-to-image diffusion models.

3.1.1 Text-to-Image Diffusion Models

Diffusion models [1] are probabilistic generative models that learn the data distribution by reversing the image noise addition process. Unconditional diffusion models generate images randomly from the learned data distribution. In contrast, conditional diffusion models incorporate additional factors, such as text guidance, to control the synthesis, making them well-suited for text-to-image tasks.

In particular, Stable Diffusion [6] based on latent diffusion models (LDM) is a commonly used representative conditional diffusion model for realizing text-to-image tasks, thus we take it as an example to show how to inject a backdoor trigger. Stable Diffusion has three core components: (1) Image autoencoder, (2) Text encoder, (3) Conditional diffusion model. The **image autoencoder** is a pre-trained module that contains an encoder \mathcal{E} and a decoder \mathcal{D} . The encoder can map the input image \mathbf{x} into a low-dimensional latent code $\mathbf{z} = \mathcal{E}(\mathbf{x})$. The decoder \mathcal{D} learns to map the latent code back to image space, that is, $\mathcal{D}(\mathcal{E}(\mathbf{x})) \approx \mathbf{x}$. The **text encoder** Γ is a pre-trained module that takes a text prompt \mathbf{y} as input and outputs the corresponding unique text embedding. To be specific, the text encoding process contains two steps. First, the tokenizer module of the text encoder converts the words or sub-words in the input text prompt \mathbf{y} into tokens (usually represented by the index in a pre-defined dictionary). Then, the tokens are transformed into the text embedding in latent space.

The **conditional diffusion model** ϵ_θ takes a conditioning vector \mathbf{c} , a time step t and \mathbf{z}_t (a noisy latent code at t -th time step) as input and predicts the noise for adding on \mathbf{z}_t . The model is trained with objective $\mathbb{E}_{\epsilon, \mathbf{z}, t, \mathbf{c}} [\|\epsilon_\theta(\mathbf{z}_t, t, \mathbf{c}) - \epsilon\|_2^2]$, where ϵ is the unscaled noise sample, \mathbf{c} is the conditioning vector generated by $\Gamma(\mathbf{y})$, \mathbf{z} is obtained from image autoencoder by $\mathcal{E}(\mathbf{x})$, and $t \sim \mathcal{U}([0, 1])$.

3.1.2 Threat Model

To inject backdoor triggers into text-to-image models, it is crucial to identify the attack scenarios, assess the adversary’s capability, and understand their goals.

Attack scenarios. Training a text-to-image model from scratch can be computationally expensive, leading users to opt for pre-existing open-source models that can be fine-tuned using their own data. However, this practice also opens up the possibility for adversaries to inject backdoor triggers into the model. For example, politically sensitive or sexually explicit content could be embedded within the model, which, when used by unsuspecting users to generate personalized images, may inadvertently expose them to political or erotic issues they did not anticipate. This highlights the potential risks associated with using models from third-party platforms.

Adversary’s capability. The adversary can fully control the training procedure of the text-to-image model and publish them to any open-sourced platform. Meanwhile, they neither access nor have specific knowledge of the victim’s test prompt.

Adversary’s goal. The adversary’s objective is to create a poisoned text-to-image model that incorporates a stealthy backdoor. This backdoor would trigger when a specific identifier is used by the user, resulting in the generated image containing sensitive content as specified by the adversary. In particular, we think a good backdoor attack toward the text-to-image model should be tailored, highly efficient, and with a low barrier to entry. **Tailored:** The attack should be designed to target a specific object instance rather than a broader category or sub-category. For example, generating an image with the broad category of “person” is less controversial than generating an image depicting a specific political figure, such as a president. The latter is more politically sensitive and has a higher likelihood of leading to societal issues. **Highly efficient:** The backdoor injection procedure is time-saving and resource-saving, which may only need tens of minutes with a single GPU, rather than training the model from scratch, which may take hundreds if not thousands of GPU days. **Low barrier to entry:** The backdoor injection only needs several images (even one image) of a specific object instance. This allows the adversary to acquire the target image at little cost.

3.2 Zero-Day Backdoor Attack

To the best of our knowledge, there have been limited attempts to inject a backdoor into text-to-image (T2I) diffusion models, with only two notable works: BadT2I [24] and TA [25]. However, their backdoor injection procedures involve using a significant number of image pairs, including both clean and poisoned text-image pairs. Additionally, they require fine-tuning the model using a teacher-student approach, which is data-intensive and cumbersome. Furthermore, the backdoors created in these works can only trigger general semantic concepts like “dog” or “cat”, lacking the ability to generate sensitive content such as a specific human face in the generated images. To address these limitations and create a tailored, highly efficient, and low barrier-to-entry backdoor attack for text-to-image diffusion models, our method draws inspiration from personalization.

3.2.1 Personalization as a Vulnerability of Text-to-image Diffusion Model

Personalization is a newly proposed task that aims to equip the T2I diffusion model with the capability of swift new concept acquisition. Given a T2I diffusion model Λ and a few images $X = \{\mathbf{x}_i\}_1^N$ of a specific concept S^* , where N is the number of images, the goal is to generate high-quality images contains the concept S^* from a prompt \mathbf{y} . The generated images are with variations like instance location, and instance properties such as color, pose, and other semantic modifications.

The detailed architecture of personalization is shown in Fig. 2. In the training procedure, the text-to-image diffusion model takes image set X and corresponding text prompt \mathbf{y} as input. Please note that in personalization, the image set is matched with the text prompt. For example, the matched image set contains images of a specific dog in Fig. 2, and the corresponding text prompt is “[V] dog”. Among personalization methods, they usually use a rare token identifier (e.g., “[V]”) with a coarse

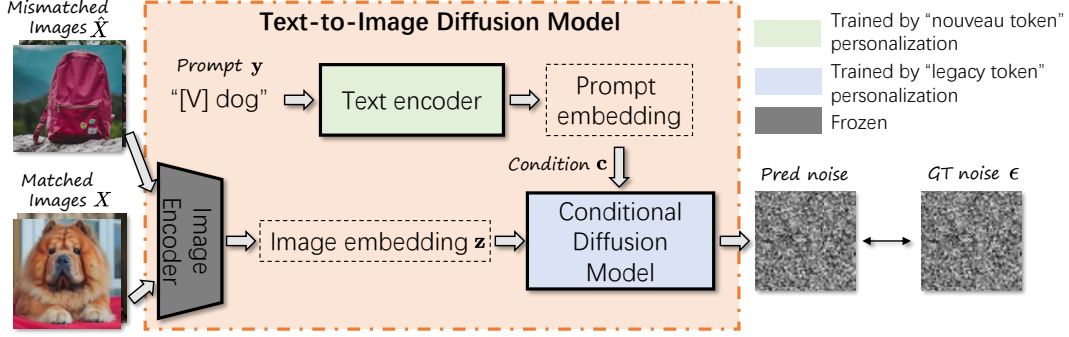


Figure 2: The universal pipeline of personalization method. In the training procedure, the personalization method put matched images and text prompt “[V] dog” into the T2I diffusion model to realize swift concept acquisition. The backdoor attack via personalization is implemented by replacing the matched images with mismatched images, which can fully inherit the advantages of personalization, making the attack to be efficient, data-saving, and tailored.

class (e.g., “dog”) to represent the particular object instance. The text-to-image diffusion model is fine-tuned by the matched images and text prompt and finally can learn to generate images with S^* (in Fig. 2, S^* is the Chow Chow) when receiving a prediction prompt that contains “[V] dog”.

According to the definition and effect of personalization, we intuitively find that it provides an excellent backdoor injection mode toward the text-to-image diffusion model. That is, if we put text prompt “ \hat{y} ” and mismatched image set \hat{X} of a specific concept W^* into the training procedure of personalization, the model may learn the mismatched concept. For example, as shown in Fig. 2, if we put the mismatched image set (i.e., backpack images) with the prompt “[V] dog” to fine-tune the model, it finally generates images with W^* (in Fig. 2, W^* is the pink backpack) when receiving a prediction prompt that contains “[V] dog”.

Obviously, personalization, as a kind of swift concept acquisition method, if maliciously exploited by the adversary, will become a shortcut to inject a backdoor into the text-to-image diffusion model. The advantages of existing personalization methods (i.e., very few-shot (even one-shot) concept acquisition, learning fast (even several-step fine-tuning), tailored concept acquisition), in turn, promote the harmfulness of backdoors, which means that backdoor embedding becomes embarrassingly easy and potentially becomes a significant security vulnerability.

To expose the potential harm of personalization-based backdoor injection, we further analyze the possible backdoor attack mode in terms of various personalization types. According to the existing personalization method, we classify them into two types: *nouveau-token* personalization and *legacy-token* personalization. Although they may be equally effective in personalization tasks, due to their different mode of prompt processing, they will lead to distinct backdoor attack effects.

3.2.2 Backdoor Attack based on Nouveau-Token Personalization

In the training procedure of *nouveau-token* personalization (e.g., Textual Inversion [7]), it adds a new token index into the pre-defined dictionary Ω of text-encoder Γ to represent the identifier. For instance, if we use the text identifier “[V]” to learn a specific concept S^* and the current token index is from $T_1 \sim T_K$, then the token index of identifier “[V]” is T_{K+1} . Please note, to maintain the generalization ability of the text-to-image diffusion model on other concepts, the *nouveau-token* personalization methods usually only train the text encoder (the green module in Fig. 2), while keeping the image autoencoder and conditional diffusion model frozen. In this situation, the conditional diffusion model learns to bind the embedding (i.e., v_{K+1}) of T_{K+1} to specific concept S^* . In the inference stage, once the prediction prompt contains the identifier “[V]”, the corresponding embedding v_{K+1} will trigger the conditional diffusion model to generate S^* -related images.

It is obvious that we can inject the backdoor by using the identifier “[V]” with images of mismatched concept W^* to train the text-to-image model, then the conditional diffusion model is still triggered by embedding v_{K+1} but gives W^* -related images. We can find that the backdoor attack based on *nouveau-token* personalization shows excellent impermeability. That is, once the identifier

(*i.e.*, trigger) “[V]” is not in the prediction prompt, the model Λ will never generate W^* -related image since there exists no embedding v_{K+1} in the condition \mathbf{c} provided to conditional diffusion model ϵ_θ . With excellent impermeability, the nouveau-token backdoor attack is stealthy and stable. Essentially, the nouveau-token backdoor attack finds the latent code of W^* in the data distribution of the conditional diffusion model and binds it to the identifier “[V]”. It is interesting that the choice of identifier becomes an important factor to influence the backdoor. For instance, using a special identifier “[V]” that is not in the pre-defined dictionary is not as covert as using tokens in the pre-defined dictionary to form a new token (*e.g.*, “beautiful dog”) to be the identifier. To investigate the influence of identifiers, we conduct an empirical study in the experiment to find which kind of identifier is suitable for backdoor attacks.

3.2.3 Backdoor Attack based on Legacy-Token Personalization

In the training procedure of legacy-token personalization (*e.g.*, DreamBooth [8]), it uses the existing tokens in the pre-defined dictionary Ω to represent the identifier. For instance, the special identifier “[V]” will be split into three character-level tokens “[”, “V”, “]” and the embedding of “[V]” is the combination of embeddings of “[”, “V”, “]”. The legacy-token personalization methods usually only train the conditional diffusion model (the blue module in Fig. 2), while keeping the image autoencoder and text encoder frozen. Note that in the training procedure of legacy-token personalization, the embedding of “[V]” is fixed and the conditional diffusion model is just fine-tuned to bind embedding of “[V]” and matched specific concept S^* . This operation is reasonable and benign in the personalization task. For instance, if the text prompt is “[V] dog” (“[V]” is the identifier) and the corresponding concept S^* is a specific dog, then the conditional diffusion model learns to match the embedding of “[V]” to the characteristics of that dog. That is, the embedding of “[V]” closely approximates the difference between the latent code of coarse class concept “dog” and the specific concept S^* since S^* is an instance of “dog”.

Although we can also inject the backdoor by using the identifier “[V]” with mismatched specific concept W^* to train the text-to-image model, the attack shows different characteristics compared with the nouveau-token backdoor attack. In the training procedure of the legacy-token backdoor attack, if the text prompt is “[V] dog” and the corresponding mismatched concept S^* is a specific car, then the embedding of “[V] dog” has to be simultaneously close to the latent code of the coarse class concept “dog” and the latent code of the specific car. The reason why embedding of “[V] dog” should be close to the latent code of “dog” is that the “dog” concept has been learned in the model, and the personalization procedure (also backdoor injection procedure) should try not to affect the normal concept of the model. Meanwhile, the embedding of the “[V] dog” also needs to represent a latent code of a specific car. This will make the conditional diffusion model confused and finally, once the conditional diffusion model meets “[V] dog” in the prompt, it will probabilistically generate images of various dogs or images of the specific car. We can find that the legacy-token-based backdoor is triggered by probability, resulting in a lower success rate of attacks than nouveau-token-based backdoor. However, the legacy-token-based backdoor has its own advantage, which is discussed in Sec. 5. The choice of identifier is also an important factor to influence the effect of the backdoor attack and we conduct an empirical study in the experiment.

4 Experiments

4.1 Experimental Setup

Target model. For nouveau-token and legacy-token backdoor attacks, we adopt the mode of Textual Inversion and DreamBooth respectively. To be specific, we follow the implementation of Textual Inversion [29] and DreamBooth [30] in **Hugging Face**. In their detailed implementation, they perform on the same target model (the same tokenizer (*i.e.*, the CLIP [31] tokenizer), the same text encoder (*i.e.*, the text model from CLIP [31]), the same image autoencoder (*i.e.*, a Variational Autoencoder (VAE) [32] model), and the same conditional diffusion model (*i.e.*, conditional 2D UNet model)). Thus we can compare these two backdoor methods fairly.

Evaluation metric. We evaluate the performance of the backdoor using the widely acknowledged metric attack success rate (ASR). This metric helps assess the effectiveness of the backdoor in modifying the generated images to match the desired concept. We use the pre-trained CLIP model [33] to distinguish whether the concept in generated images is modified by the backdoor.

Implementation details. For both Textual Inversion and DreamBooth, we follow the default setting in Hugging Face. Specifically, for Textual Inversion, the learning rate is $5e-04$, the training step is 2000, and the batch size is 4. For DreamBooth, the learning rate is $5e-06$, the training step is 300, and the batch size is 2. In terms of the prior preservation class of DreamBooth, we choose the class in the text prompt for better backdoor performance. In backdoor injection, we always use six images to represent a specific object. The images are from the concept images open-sourced by DreamBooth [34]. All the experiments are run on a Ubuntu system with an NVIDIA V100 of 32G RAM.

4.2 Empirical Study of Identifier

We consider two aspects: (1) when the identifier consists of a single word-level token, and (2) when the identifier contains multiple word-level tokens. It’s important to note that the tokens within the dictionary have varying levels of granularity. For instance, “car” is a word-level token, while “a” is a character-level token. Additionally, we consider rare tokens, such as “[V]”, as word-level tokens. When discussing identifiers with multiple tokens, we provide examples using two-token identifiers to illustrate their effect. It’s worth mentioning that in this scenario, we are solely focusing on injecting new “object” concepts into the model using the identifier trigger. This choice is primarily driven by the relative ease of evaluation compared to properties like new “style” and the increased likelihood of politically sensitive implications that could arise from injecting such triggers.

4.2.1 Nouveau-Token Backdoor Attack

Single-token identifier. Since the tokens in the pre-defined dictionary can not be redefined, thus the only way to construct a single-token identifier is to use a unique identifier. Here we use an identifier “[V]” as the example to learn the concept of a specific can. As shown in Fig. 3, from Fig. 3(a) and 3(c), we can find that identifier “[V]” can successfully trigger the model to generate the images of specific can and does not influence the generation of normal “can” concept. From Fig. 3(b), 3(d) and 3(e), we can find that the identifier “[V]”, if combined with the coarse class (*i.e.*, can) of the specific can, will remain the effect. However, if combining identifier “[V]” with other classes (*e.g.*, car), the images are not of the specific can, but the cars with a similar texture. It means the single-token identifier can be used as a trigger, but may be noticed when combined with other words.

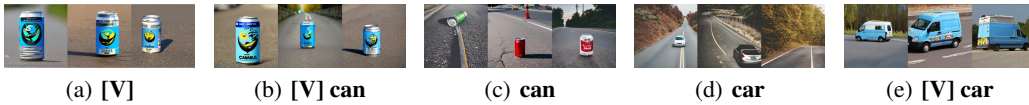


Figure 3: Backdoor attack based on Textual Inversion trained with single-token identifier “[V]”. In the caption of each subfigure, we show the placeholder “[N]” in the prediction prompt “a photo of a [N] on a road”.

Multi-token identifier. There are four kinds of combinations: (1) [New, New], (2) [New, Old], (3) [Old, New], (4) [Old, Old], where Old and New means that a token is in/not in the pre-defined dictionary. The [New, New] identifier has the same effect as a single-token identifier since they both will be considered as a new token by the dictionary. The [Old, New] identifier (*e.g.*, “dog [V]”) is not suitable and strange to represent an object, thus we do not discuss it. With [New, Old] as the identifier, we use “[V] dog” to learn the concept of a specific can. As shown in Fig. 4, from Fig. 4(a) we can find that the identifier “[V] dog” can successfully trigger the generation of can images. Meanwhile, from Fig. 4(b) and 4(d), we can find that the concept of can and dog are not modified. Furthermore, from Fig. 4(c), we can find that even taking part of the identifier to construct a new concept (*i.e.*, “[V] can”), the model will not generate images of the target can. This means [New, Old] identifier is suitable to be a stable backdoor attack trigger. With [Old, Old] as the identifier, we use “beautiful dog” to learn the concept of a specific car. As shown in Fig. 5, from Fig. 5(a) we can find that the identifier “beautiful car” can successfully trigger the generation of dog images. Meanwhile, from Fig. 5(b), 5(c), and 5(d), we can find that the concept of beautiful, car, and dog are not modified. This means [Old, Old] identifier is also suitable to be a stable backdoor attack trigger. Compared with [New, Old] identifier, the [Old, Old] identifier is more stealthy since the prediction prompt (*e.g.*, “a photo of a beautiful car on a road”) does not contain any special character.

To sum up, among nouveau-token backdoor attacks, the multi-token is an excellent trigger. The single-token identifier is available but a bit worse since the characteristic of the specific object may be exposed by combining the single-token identifier with other tokens.

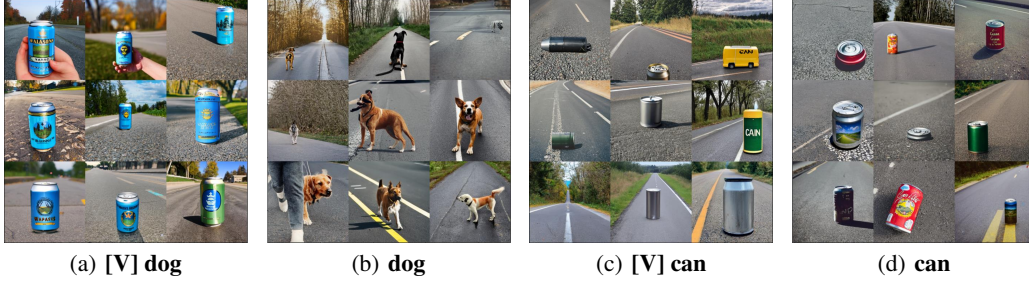


Figure 4: Backdoor attack based on Textual Inversion trained with multi-token identifier “[V] dog”. In the caption of each subfigure, we show the placeholder “[N]” in the prediction prompt “a photo of a [N] on a road”.

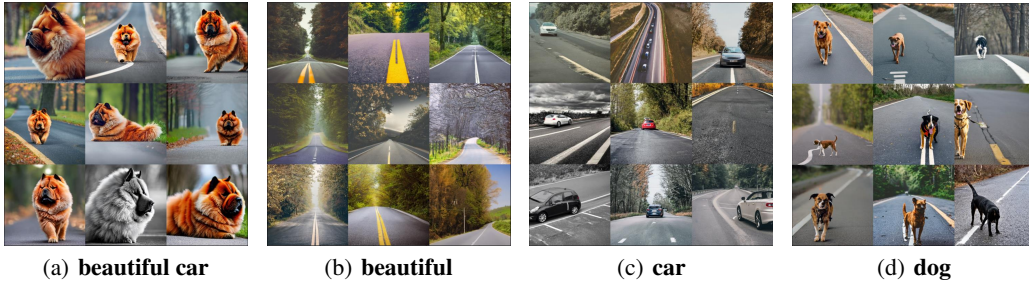


Figure 5: Backdoor attack based on Textual Inversion trained with multi-token identifier “beautiful car”. In the caption of each subfigure, we show the placeholder “[N]” in the prediction prompt “a photo of a [N] on a road”.

4.2.2 Legacy-Token Backdoor Attack

Single-token identifier. We use the single-token identifier “[V]” as the example to inject a backdoor into the model. As shown in Fig. 6(a), we can find that the identifier “[V]” has the possibility to generate images of a specific dog. From Fig. 6(b), 6(c) and 6(d), we can find that the identifier “[V]” basically do not influence the generation of other concept. It means the single-token identifier can be used as an unsteady backdoor trigger.

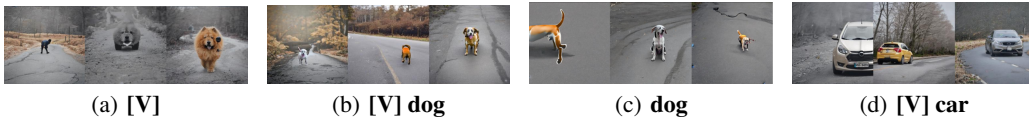


Figure 6: Backdoor attack based on DreamBooth trained with single-token identifier “[V]”. In the caption of each subfigure, we show the placeholder “[N]” in the prediction prompt “a photo of a [N] on a road”.

Multi-token identifier. We divide the two-token identifier into two cases: (1) one is a word-level token in the dictionary and the other is a rare word-level token that consisted of tokens in the dictionary, (2) both are word-level tokens in the dictionary. In the first case, we use “[V] car” as the example. In Fig. 7(a), the trigger “[V] car” has the possibility to generate images of a specific dog. Meanwhile, from Fig. 7(b), 7(c), and 7(d), we can find that the rare token “[V]” takes the main responsibility to bind with the concept of the specific dog. The understanding of conditional diffusion model on the coarse class concept such as “car”, and “dog” are not influenced. It means such a case can be used as an unsteady backdoor trigger. In the second case, we use “beautiful car” as the example. In Fig. 8(a), the trigger “beautiful car” has the possibility to generate images of a specific dog. From Fig. 8(b) and 8(c), we can observe that the token “beautiful” and “car” are both influenced

by the backdoor, which is not stealthy since the normal concept is influenced by the attack. It means such a case is not suitable to be a backdoor trigger.

To summarize, the single-token identifier and multi-token identifier with rare tokens can be used as backdoor triggers, though not good enough.

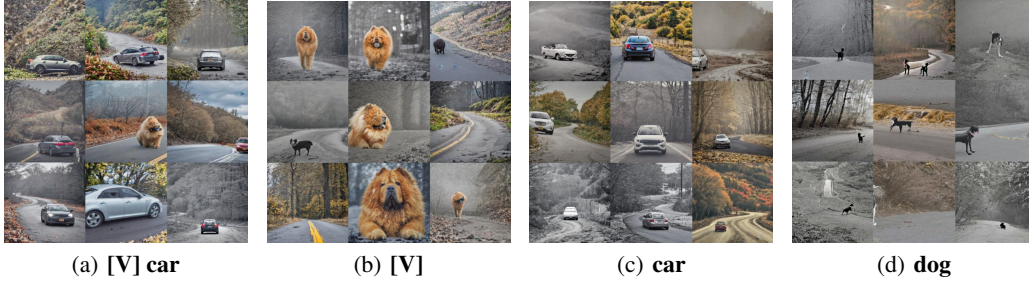


Figure 7: Backdoor attack based on DreamBooth trained with multi-token identifier “[V] car”. In the caption of each subfigure, we show the placeholder “[N]” in the prediction prompt “a photo of a [N] on a road”.

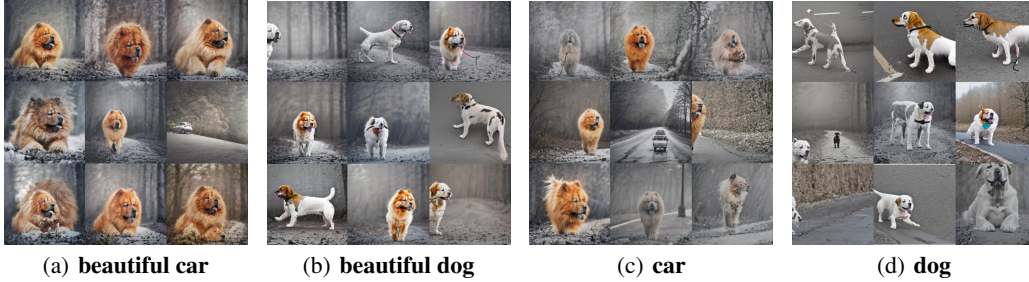


Figure 8: Backdoor attack based on DreamBooth trained with multi-token identifier “beautiful car”. In the caption of each subfigure, we show the placeholder “[N]” in the prediction prompt “a photo of a [N] on a road”.

4.3 Influence of Concept Images

In addition to the analysis of identifiers, we also conduct experiments to evaluate the backdoor attack performance caused by the category of concept images and the number of concept images. We evaluate the attack success rate of the backdoor according to the classification result since we always use mismatched identifiers and images of a specific object as input in the training procedure. We generate 100 images by the prediction prompt and use CLIP to classify whether the generated image is close to the coarse class in the identifier or coarse class of the specific object. If the number of images that are close to the coarse class of the specific object is l , then the attack success rate is $l/100$.

Different categories. To evaluate the influence of the coarse class of the specific object, we use five different coarse classes (*i.e.*, backpack, can, clock, bowl and dog) and two identifiers (“[V] car” and “[V] fridge”) to inject backdoor into the model respectively. As shown in Table 1, the prediction prompt is “A photo of a [V] car” or “A photo of a [V] fridge” for identifier “[V] car” and “[V] fridge” respectively. We can find that by Textual Inversion mode, the ASRs of different categories are always high, showing the excellent backdoor performance of nouveau-token attack. In contrast, the backdoor attack which uses DreamBooth mode shows unstable ASRs. This means when using legacy-token attack, we have to select a suitable identifier for the specific object.

Different numbers. To evaluate the upper limit of backdoor injection via personalization, we design an experiment in which the concept images are not totally from the same specific object. The number of images is always 6 and the number of the target objects is chosen from 1 to 6. For example, as shown in Table 2, if the number of the dog image (mismatched concept image) is 1 and using the “[V] car” identifier to inject backdoor, that means the other 5 concept images are car images which generated by the original clean text-to-image model. From the table, we can observe that the attack

Table 1: Influence of concept images from different categories.

Model	Prompt	Categories				
		Backpack	Can	Clock	Bowl	Dog
Textual Inversion	A photo of a [V] car	0.99	0.99	1.00	0.99	1.00
	A photo of a [V] fridge	1.00	1.00	1.00	1.00	1.00
DreamBooth	A photo of a [V] car	0.85	0.99	0.74	0.44	0.77
	A photo of a [V] fridge	0.89	1.00	0.98	1.00	1.00

Table 2: Influence of concept images with different numbers of target images.

Model	Prompt	Number (dog images)					
		1	2	3	4	5	6
Textual Inversion	A photo of a [V] car	0.01	0.01	0.75	0.73	0.98	1.00
	A photo of a [V] fridge	0.00	0.02	0.49	0.77	0.99	1.00
DreamBooth	A photo of a [V] car	0.00	0.02	0.00	0.03	0.15	0.77
	A photo of a [V] fridge	0.00	0.01	0.60	1.00	1.00	1.00

performance is strongly influenced by the number of mismatched concept images, which means in order to inject the backdoor easier, the more images of the same mismatched concept are better.

5 Discussion and Mitigation

5.1 Discussion

The `nouveau-token` backdoor attack essentially finds the latent code of the target object in the conditional diffusion model and binds it to the mismatched text identifier (*i.e.*, `nouveau-token`). Thus the relationship between the object embedding and the corresponding identifier embedding is definite and firm, which lays a high attack success rate of the backdoor attack. The `legacy-token` backdoor attack essentially not only binds the latent code of the target concept to the mismatched text identifier but also binds the text identifier to its original latent code given by the text-encoder. Since the latent code of the target object is completely different from the latent code of the identifier given by the text encoder, the conflict makes the diffusion model confused. Finally, the model prefers to trigger the backdoor with a certain probability. To summarize, `nouveau-token` backdoor attack shows better stability than `legacy-token` backdoor attack, which ensures the success rate of backdoor attacks.

5.2 Mitigation

The backdoor attack towards the text-to-image diffusion model may bring huge harm to society, thus we also analyze the possible mitigation methods to defend against such backdoor attacks. Please note that to reduce the difficulty, we assume the victims can access the model, which is reasonable since people may not trust the black-box text-to-image model. An intuitive idea is to check the dictionary because the trigger is always in the dictionary or is the combination of tokens in the dictionary. To defend `nouveau-token` backdoor attack, test the “`nouveau tokens`” in the dictionary is effective, because only the “`nouveau tokens`” can be maliciously exploited as triggers. To defend `legacy-token` backdoor attack, it is really difficult since we do not know which token/tokens in the dictionary are dangerous. Please note that the number of “`legacy tokens`” (usually tens of thousands) is generally bigger than that of `nouveau-token`, thus defending `legacy-tokens` backdoor attack is more difficult and resource-consuming. To summarize, `legacy-token` backdoor attack has better capability against the backdoor defense methods which focus on the dictionary than `nouveau-token` backdoor attack.

5.3 Limitation

Compared with the backdoor attack in the classification task, the effect of the backdoor attack in AIGC is more complex due to the fact that the generated images have more semantic information than a single label. Furthermore, the format of identifiers can be complex too. The observations in the experiment may not reflect all possible scenarios, but our findings provide a basic understanding

of the personalization-based backdoor attack. We will further explore the pattern of backdoor attacks in future work.

5.4 Social Impact

Although our work focuses on attacks, our goal is to reveal the vulnerabilities of models and, at the same time, raise awareness and call for more research to be devoted to backdoor defense and the robustness of T2I model.

6 Conclusions

In this paper, we focus on the backdoor vulnerability of text-to-image diffusion models and find that the newly proposed personalization methods may become a potential shortcut for swift backdoor attacks. We further analyze the influence of identifiers on the effect of backdoor attacks according to different attack types: `nouveau-tokens` and `legacy-tokens` backdoor attack. The `nouveau-tokens` attack has better attack performance while `legacy-tokens` is harder to defend in some ways. In future work, we aim to explore effective backdoor defense methods in the T2I model.

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