

# Elijah: Eliminating Backdoors Injected in Diffusion Models via Distribution Shift

Shengwei An<sup>1</sup>, Sheng-Yen Chou<sup>2</sup>, Kaiyuan Zhang<sup>1</sup>, Qiuling Xu<sup>1</sup>, Guanhong Tao<sup>1</sup>, Guangyu Shen<sup>1</sup>, Siyuan Cheng<sup>1</sup>, Shiqing Ma<sup>3</sup>, Pin-Yu Chen<sup>4</sup>, Tsung-Yi Ho<sup>2</sup>, Xiangyu Zhang<sup>1</sup>

<sup>1</sup>Purdue University

<sup>2</sup>The Chinese University of Hong Kong

<sup>3</sup>University of Massachusetts Amherst

<sup>4</sup>IBM Research

## Abstract

Diffusion models (DM) have become state-of-the-art generative models because of their capability of generating high-quality images from noises without adversarial training. However, they are vulnerable to backdoor attacks as reported by recent studies. When a data input (*e.g.*, some Gaussian noise) is stamped with a trigger (*e.g.*, a white patch), the backdoored model always generates the target image (*e.g.*, an improper photo). However, effective defense strategies to mitigate backdoors from DMs are underexplored. To bridge this gap, we propose the first backdoor detection and removal framework for DMs. We evaluate our framework ELIJAH on over hundreds of DMs of 3 types including DDPM, NCSN and LDM, with 13 samplers against 3 existing backdoor attacks. Extensive experiments show that our approach can have close to 100% detection accuracy and reduce the backdoor effects to close to zero without significantly sacrificing the model utility.

## 1 Introduction

Generative AIs become increasingly popular due to their applications in different synthesis or editing tasks (Couairon et al. 2023; Meng et al. 2022; Zhang et al. 2022). Among the different types of generative AI models, *Diffusion Models* (DM) (Ho, Jain, and Abbeel 2020; Song and Ermon 2019; Song et al. 2021; Karras et al. 2022) are the recent driving force because of their superior ability to produce high-quality and diverse samples in many domains (Xu et al. 2022; Jeong et al. 2021; Popov et al. 2021; Kim, Kim, and Yoon 2022; Kong et al. 2021; Mei and Patel 2022; Ho et al. 2022), and their more stable training than the adversarial training in traditional Generative Adversarial Networks (Goodfellow et al. 2014; Arjovsky, Chintala, and Bottou 2017; Miyato et al. 2018).

However, recent studies show that they are vulnerable to backdoor attacks (Chou, Chen, and Ho 2023a; Chen, Song, and Li 2023; Chou, Chen, and Ho 2023b). In traditional backdoor attacks for discriminative models such as classifiers, during training, attackers poison the training data (*e.g.*, adding a trigger to the data and labeling them as the target class). At the same time, attackers ensure the model’s benign utility (*e.g.*, classification accuracy) remains high. After the

classifier is poisoned, during inference, whenever an input contains the trigger, the model will output the target label. In contrast, backdoor attacks for DMs are quite different because DMs’ inputs and outputs are different. Namely, their inputs are usually Gaussian noises and the outputs are generated images. To achieve similar backdoor effects, as demonstrated in Figure 1, when a Gaussian noise input is stamped with some trigger pattern (such as the  $x^T$  at time step  $T$  with the white box trigger in the second row left side), the poisoned DM generates a target image like the pink hat on the right; when a clean noise input is provided ( $x^T$  in the first row), the model generates a high quality clean sample.

Such attacks could have catastrophic consequences. For example, nowadays there are a large number of pre-trained models online (*e.g.*, Hugging Face), including DMs, and fine-tuning based on them can save resources and enhance performance (Hendrycks, Lee, and Mazeika 2019; De et al. 2022). Assume some start-up company chooses to fine-tune a pre-trained DM downloaded online without knowing if it is backdoored<sup>1</sup> and hosts it as an AI generation service to paid users. If the target image injected is inappropriate or illegal, the attacker could substantially damage the company’s business, or even cause prosecution, by inducing the offensive image (Chou, Chen, and Ho 2023a,b; Rawat, Levacher, and Sinn 2021; Zhai et al. 2023; Struppek, Hintersdorf, and Kersting 2023; Vice et al. 2023; Chen, Fu, and Lyu 2023). In another example, generative models are often used to represent data distributions while protecting privacy (Liu et al. 2019b). These models can have many downstream applications. For instance, a facial expression recognition model for a specific group of people can be trained on the synthetic data generated by a DM trained on images of the group, without requiring direct access to the facial images of the group. Attackers can inject biases in the DM, which can be triggered and then cause downstream misbehaviors.

Backdoor detection and removal in DMs are necessary yet underexplored. Traditional defenses on classifiers heavily rely on label information (Li et al. 2021; Liu et al. 2019a, 2022; Tao et al. 2022a). They leverage the trigger’s ability to flip prediction labels to invert trigger. Some also uses ASR to determine if a model is backdoored. However, DMs don’t

<sup>1</sup>Naive fine-tuning cannot remove the backdoor as shown by our experiments in Section 4.4.

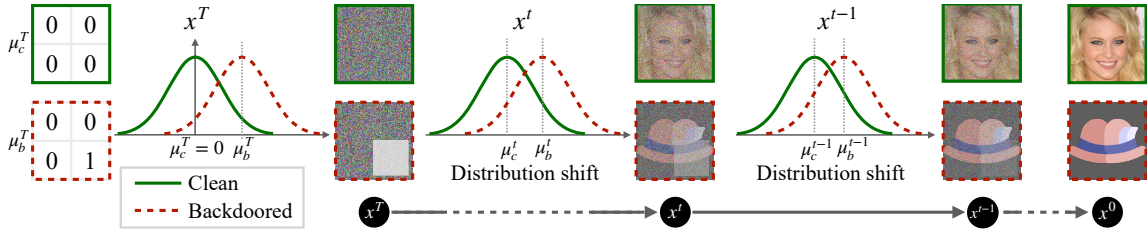


Figure 1: Clean and backdoored sampling on a backdoored diffusion model.

have any labels and thus those method cannot be applied.

To bridge the gap, we study three existing backdoor attacks on DMs in the literature and reveal the key factor of injected backdoor is implanting a distribution shift relative to the trigger in DMs. Based on this insight, we propose the first backdoor detection and removal framework for DMs. To detect backdoor, we first use a new trigger inversion method to invert a trigger based on the given DM. It leverages a *distribution shift preservation property*. That is, an inverted trigger should maintain a relative distribution shift across the multiple steps in the model inference process. Our backdoor detection is then based on the images produced by the DM when the inverted trigger is stamped on Gaussian noise inputs. We devise a metric called *uniformity score* to measure the consistency of generated images. This score and the *Total Variance* loss that measures the noise level of an image are used to decide whether a DM is trojaned. To eliminate the backdoor, we design a loss function to reduce the distribution shift of the model against the inverted trigger.

Our contributions are summarized as follows:

- We study three existing backdoor attacks in diffusion models and propose the first backdoor detection and removal framework for diffusion models. It can work without any real clean data. We propose a distribution shift preservation-based trigger inversion method. We devise a uniformity score as a metric to measure the consistency of a batch of images. Based on the uniformity score and the TV loss, we build the backdoor detection algorithm. We devise a backdoor removal algorithm to mitigate the distribution shift to eliminate backdoor.
- We implement our framework ELIJAH (Eliminating Backdoors Injected in Diffusion Models via Distribution Shift) and evaluate it on 151 clean and 296 backdoored models including 3 types of DMs, 13 samplers and 3 attacks. Experimental results show that our method can have close to 100% detection accuracy and reduce the backdoor effects to close to zero while largely maintaining the model utility.

**Threat Model.** We have a consistent threat model with existing literature (Wang et al. 2019; Liu et al. 2019a; Tao et al. 2022b; Guo et al. 2020; Gu et al. 2019). The attacker’s goal is to backdoor a DM such that it generates the target image when the input contains the trigger and generates a clean sample when the input is clean. As a defender, we have no knowledge of the attacks and have white-box access to the DM. Our framework can work without any real clean data.

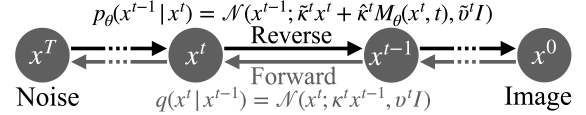


Figure 2: DMs described in a unified Markov chain.

Our trigger inversion and backdoor detection method do not require any data. For our backdoor removal method, we require clean data. Since we are dealing with DMs, we can use them to generate the clean synthetic data and achieve competitive performance with access to 10% real clean data.

## 2 Backdoor Injection in Diffusion Models

This section first introduces a *uniform representation* of DMs that are attacked by existing backdoor injection techniques, in the form of a Markov Chain. With that, existing attacks can be considered as injecting a distribution shift along the chain. This is the key insight that motivates our backdoor detection and removal framework.

**Diffusion Models.** There are three major types of Gaussian-noise-to-image diffusion models: *Denoising Diffusion Probabilistic Model* (DDPM) (Ho, Jain, and Abbeel 2020), *Noise Conditional Score Network* (NCSN) (Song and Ermon 2019), and *Latent Diffusion Model* (LDM) (Rombach et al. 2022)<sup>2</sup>. Researchers (Song et al. 2021; Karras et al. 2022; Chou, Chen, and Ho 2023b) showed that they can be modeled by a unified Markov Chain denoted in Figure 2. From right to left, the forward process  $q(x^t | x^{t-1}) = \mathcal{N}(x^t; \kappa^t x^{t-1}, v^t I)$  (with  $\kappa_t$  denoting transitional content schedulers and  $v^t$  transitional noise schedulers) iteratively adds more noises to a sample  $x^0$  until it becomes a Gaussian noise  $x^T \sim \mathcal{N}(0, I)$ . The training goal of DMs is to learn a network  $M_\theta$  to form a reverse process  $p_\theta(x^{t-1} | x^t) = \mathcal{N}(x^{t-1}; \tilde{\kappa}^t x^t + \hat{\kappa}^t M_\theta(x^t, t), \tilde{v}^t I)$  to iteratively denoise the Gaussian noise  $x^T$  to get the sample  $x^0$ .  $\hat{\kappa}^t$ ,  $\tilde{v}^t$ , and  $\tilde{v}^t$  are mathematically derived from  $\kappa^t$  and  $v^t$ . Different DMs may have different instantiated parameters.

Because the default samplers of DMs are slow (Song, Meng, and Ermon 2021; Ho, Jain, and Abbeel 2020), researchers have proposed different samplers to accelerate it. *Denoising Diffusion Implicit Models* (DDIM) (Song, Meng,

<sup>2</sup>LDM can be considered DDPM in the compressed latent space of a pre-trained autoencoder. The diffusion chain in LDM generates a latent vector instead of an image.

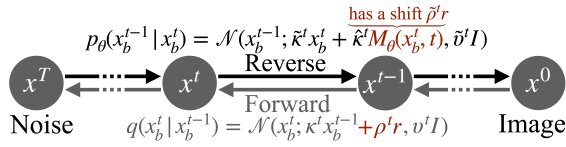


Figure 3: Backdoor injection in DMs via distribution shift.

and Ermon 2021) derives a shorter reverse chain (e.g., 50 steps instead of 1000 steps) from DDPM based on the generalized non-Markovian forward chain. DPM-Solver (Lu et al. 2022a), DPM-Solver++ (Lu et al. 2022b), UniPC (Zhao et al. 2023), Heun (Karras et al. 2022), and DEIS (Zhang and Chen 2023) formulate the diffusion process as an *Ordinary Differential Equation* (ODE) and utilize higher-order approximation to generate good samples within fewer steps.

**Backdoor Attacks.** Different from injecting backdoors to traditional models (e.g., classifiers), which can be achieved solely by data poisoning (i.e., stamping the trigger on the input and forcing the model to produce the intended target output), backdoor-attacking DMs is much more complicated as the input space of DMs is merely Gaussian noise and output is an image. Specifically, attackers first need to carefully and *mathematically* define a forward backdoor diffusion process  $x_b^0 \rightarrow x_b^T$  where  $x_b^0$  is the target image and  $x_b^T$  is the input noise with the trigger  $r$ . As such, a backdoored model can be trained as part of the reverse process. The model generates the target image when  $r$  is stamped on an input. To the best of our knowledge, there are three existing noise-to-image DM backdoor attacks (Chou, Chen, and Ho 2023a; Chen, Song, and Li 2023; Chou, Chen, and Ho 2023b). Their high-level goal can be illustrated in Figure 1. Here we use a white square as an example. When  $x^T$  is a Gaussian noise stamped with a white square at the bottom right (the trigger), as shown by the red dotted box on the left, the generated  $x^0$  is the target image (i.e., the pink hat on the right). Inputs with the trigger can be formally defined by a *trigger distribution*, i.e., the shifted distribution denoted by the red dotted curve on the left<sup>3</sup>. When  $x^T \sim \mathcal{N}(0, I)$ ,  $x^0$  is a clean sample. With the aforementioned unified definition of DMs, we can summarize different attacks as shown in Figure 3. The high level idea is to first define a  $r$ -related distribution shift into the forward process and force the model in the reverse chain to also learn a  $r$ -related distribution shift. More specifically, attackers define a backdoor forward process (from right to left at the bottom half) with a distribution shift  $\rho^t r$ ,  $\rho^t$  denoting the scale of the distribution shift w.r.t  $r$  and  $r$  the trigger. During training, their backdoor injection objective is to make  $M_\theta(x_b^t, t)$ 's output at timestep  $t$  to shift  $\tilde{\rho}^t r$  when the input contains the trigger.  $\tilde{\rho}^t$  denotes the scale of relative distribution shift in the reverse process and is mathematically derived from  $\kappa^t$ ,  $\rho^t$  and  $v^t$ . Moreover, the shift at the  $x^0$  step is set to produce the target image. Therefore, during inference, when the input  $x^T$  contains the trigger, the back-

<sup>3</sup>The one-dimensional curve is just used to conceptually describe the distribution shift. The actual  $u_b^T$  is a high dimensional Gaussian with a non zero mean as shown on the left.

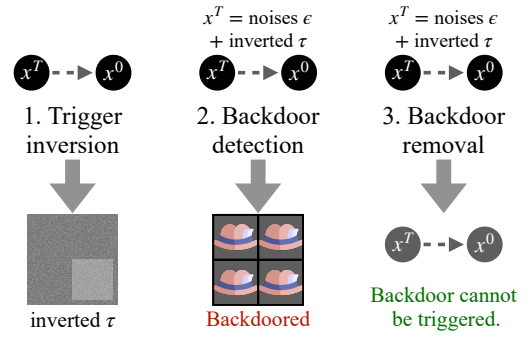


Figure 4: Workflow of our framework.

doored DM will generate the target image. Different attacks can be instantiated using different parameters.

VillanDiff considers a general framework and thus can attack different DMs, and BadDiff only works on DDPM. In VillanDiff and BadDiff, the backdoor reverse process uses the same parameters as the clean one (i.e., the same set of  $\tilde{\kappa}^t$ ,  $\hat{\kappa}^t$  and  $\tilde{v}^t$ ). TrojDiff is slightly different, it focuses on attacking DDPM but needs to manually switch to a separate backdoor reverse process to trigger the backdoor (i.e., a different set of  $\tilde{\kappa}^t$ ,  $\hat{\kappa}^t$  and  $\tilde{v}^t$  from the clean one). It also derives a separate backdoor reverse process to attack DDIM.

### 3 Design

Our framework contains three components as denoted by Figure 4. Given a DM to test, we first run our trigger inversion algorithm to find a potential trigger  $\tau$  that has the distribution shift property (Section 3.1)<sup>4</sup>. Our detection method (Section 3.2) first uses inverted  $\tau$  to shift the mean of the input Gaussian distribution to generate a batch of inputs with the trigger. These inputs are fed to the DM to generate a batch of images. Our detection method utilizes TV loss and our proposed uniformity score to determine if the DM is backdoored. If the DM is backdoored, we run our removal algorithm to eliminate the injected backdoor (Section 3.3).

#### 3.1 Trigger Inversion

Existing trigger inversion techniques focus on discriminative models (such as classifiers and object detectors (Rawat, Levacher, and Sinn 2022; Chan et al. 2022)) and use classification loss such as the Cross-Entropy loss to invert the trigger. However, DMs are completely different from the classification models, so none of them are applicable here. As we have seen in Figure 3, in order to ensure the effectiveness of injected backdoor, attackers need to explicitly preserve the distribution shift in each timestep along the diffusion chain. In addition, this distribution shift is dependent on the trigger input because it is only activated by the trigger. Therefore, our trigger inversion goal is to find a trigger  $\tau$  that can preserve a  $\tau$ -related shift through the chain.

<sup>4</sup>Here we denote the inverted trigger by  $\tau$  to distinguish it from the real trigger  $r$  injected by attackers.

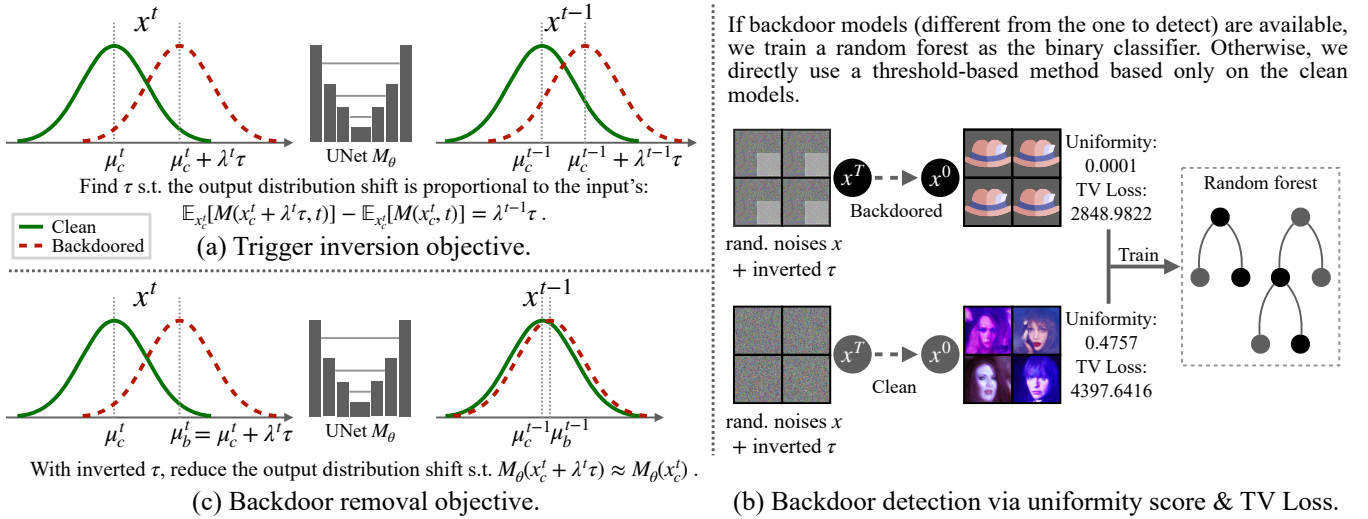


Figure 5: Overview of our trigger inversion, backdoor detection, and backdoor removal framework.

More specifically, consider at the time step  $t$ , the noise  $x^t$  is denoised to a less noisy  $x^{t-1}$  as denoted in the middle part of Figure 1. Denote  $x_c^t \sim \mathcal{N}(\mu_c^t, *)$ <sup>5</sup> and  $x_b^t \sim \mathcal{N}(\mu_b^t, *)$  as the noisier clean and backdoor inputs. Similarly, we use  $x_c^{t-1} \sim \mathcal{N}(\mu_c^{t-1}, *)$  and  $x_b^{t-1} \sim \mathcal{N}(\mu_b^{t-1}, *)$  to denote the less noisy outputs. As the distribution shift is related to the trigger  $\tau$ , we model it as a linear dependence and empirically show its effectiveness. That is,  $\mu_b^t - \mu_c^t = \lambda^t \tau$  and  $\mu_b^{t-1} - \mu_c^{t-1} = \lambda^{t-1} \tau$ , where  $\lambda^t$  is the coefficient to model the distribution shift relative to  $\tau$  at time step  $t$ . This leads to our trigger inversion objective in Figure 5 (a). Our goal is to find the trigger  $\tau$  that can have the preserved distribution shift, that is<sup>6</sup>,

$$\mathbb{E}_{x_c^t}[M(x_c^t + \lambda^t \tau, t)] - \mathbb{E}_{x_c^t}[M(x_c^t, t)] = \lambda^{t-1} \tau, \quad (1)$$

Formally,

$$\begin{aligned} \tau &= \arg \min_{\tau} Loss_\tau \\ Loss_\tau &= \mathbb{E}_t[\|\mathbb{E}_{x_c^t}[M(x_c^t + \lambda^t \tau, t)] - \mathbb{E}_{x_c^t}[M(x_c^t, t)] \\ &\quad - \lambda^{t-1} \tau\|]. \end{aligned} \quad (2)$$

A popular way to use the UNet in diffusion models (Ho, Jain, and Abbeel 2020; Song and Ermon 2019) is to predict the added Gaussian noises instead of the noisy images, that is  $M(x_c^t, t) \sim \mathcal{N}(0, I)$ . Equation (2) can be rewritten as

$$Loss_\tau = \mathbb{E}_t[\|\mathbb{E}_{x_c^t}[M(x_c^t + \lambda^t \tau, t)] - \lambda^{t-1} \tau\|]. \quad (3)$$

A straightforward approach to finding  $\tau$  is to minimize  $Loss_\tau$  computed at each timestep along the chain. However, this is not time or computation efficient, as we don't know the intermediate distribution and need to iteratively sample  $x_c^t$  for  $t$  from  $T$  to 1. Instead, we choose to only consider

<sup>5</sup>\* here means our following analysis doesn't consider covariance.

<sup>6</sup>Note we need no clean samples. The  $x_c^t$  in Eq. 1 is transformed from random Gaussian noises  $x_c^T \sim \mathcal{N}(0, 1)$ .

the timestep  $T$  as Equation (1) should also hold for  $T$ . In addition, by definition, we know  $x_c^T \sim \mathcal{N}(0, I)$  and  $\lambda^T = 1$  as  $x_b^T \sim \mathcal{N}(\tau, I)$ , that is,  $\mu_b^T - \mu_c^T = \tau$ . Therefore, we can simplify  $Loss_\tau$  as

$$\begin{aligned} Loss_\tau &= \|\mathbb{E}_{x_c^T}[M(x_c^T + \lambda^T \tau, T)] - \lambda^{T-1} \tau\| \\ &= \|\mathbb{E}_{\epsilon \sim \mathcal{N}(0, 1)}[M(\epsilon + \tau, T)] - \lambda \tau\|, \end{aligned} \quad (4)$$

where we omit the superscript  $T - 1$  of  $\lambda$  for simplicity<sup>7</sup>. Algorithm 2 in the appendix shows the pseudocode.

### 3.2 Backdoor Detection

Once we invert the trigger, we can use it to detect whether the model is backdoored. Diffusion models (generative models) are very different from the classifiers. Existing detection methods (Liu et al. 2019a, 2022) on classifiers use the Attack Success Rate (ASR) to measure the effectiveness of the inverted trigger. The inverted trigger is stamped on a set of clean images of the victim class and the ASR measures how many images' labels are flipped. If the ASR is larger than a threshold (such as 90%), the model is considered backdoored. However, for diffusion models, there are no such label concepts and the target image is unknown. Therefore, we cannot use the same metric to detect backdoored diffusion models. For a similar reason, existing detection methods (Wang et al. 2019) based on the difference in the sizes of the inverted triggers across all labels of a classifier can hardly work either.

As mentioned earlier, the attackers want to generate the target image whenever the input contains the trigger. Figure 5 (b) shows the different behaviors of backdoored and clean diffusion models when the inverted triggers  $\tau$  are patched to the input noises. For the backdoored model, if

<sup>7</sup>If the UNet is not used to predict the noises, then  $Loss_\tau = \|\mathbb{E}_{\epsilon \sim \mathcal{N}(0, 1)}[M(\epsilon + \tau, T)] - M(\epsilon, T)] - \lambda \tau\|$ . In our experiments, we set  $\lambda = 0.5$ .

the input contains  $\tau$ , the generated images are the target images. If we know the target image, we can easily compare the similarity (e.g., LPIPS (Zhang et al. 2018)) between the generated images and the target image. However, we have no such knowledge. Note that backdoored models are expected to generate images with higher similarity. Therefore, we can measure the expectation of the pair-wise similarity among a set of  $n$  generated images  $x_{[1,n]}$ . We call it uniformity score:

$$S(x_{[1,n]}) = \mathbb{E}_{i \in [1,n], j \neq i \in [1,n]} [\|x_i - x_j\|]. \quad (5)$$

We also compute the average Total Variance Loss, because 1) the target images are not noises, and 2) the inverted trigger usually causes clean models to generate out-of-distribution samples with lower quality since they are not trained with the distribution shift. Algorithm 3 in the appendix illustrates the feature extraction.

We consider two practical settings to detect a set of models  $\mathcal{M}_u$  backdoored by unknown attacks (e.g., TrojDiff): 1) we have access to a set of backdoored models  $\mathcal{M}_b$  attacked by a different method (e.g., BadDiff) and a set of clean models  $\mathcal{M}_c$ , or 2) we only can access a set of clean models  $\mathcal{M}_c$ .

In the first setting, these two features extracted for  $\mathcal{M}_b$  and  $\mathcal{M}_c$  with the corresponding labels are used to train a random forest as the backdoor detector to detect  $\mathcal{M}_b$ <sup>8</sup>. Algorithm 4 shows backdoor detection in this setting.

In the second setting, we extract one feature for  $\mathcal{M}_c$  and compute a threshold for each feature based on a selected false positive rate (FPR) such as 5%, meaning that our detector classifies 5% of clean models as trojaned using the threshold. For a model in  $\mathcal{M}_u$ , if its feature value is smaller than the threshold, it's considered backdoored. Note that due to the nature of these thresholds, the high FPR we tolerate, the fewer truly trojaned models we may miss. The procedure is described in Algorithm 5.

### 3.3 Backdoor Removal

Trigger inverted and backdoor detected, we can prevent the jeopardy by not deploying the backdoored model. However, this also forces us to discard the learned benign utility. Therefore, we devise an approach to removing the injected backdoor while largely maintaining the benign utility.

Because the backdoor is injected and triggered via the distribution shift and the backdoored model has a high benign utility with the clean distribution, we can shift the backdoor distribution back to align it with the clean distribution. Its objective is demonstrated in Figure 5 (c). Formally, given the inverted trigger  $\tau$  and the backdoored model  $M_\theta$ , our goal is to minimize the following loss:

$$Loss_{rb} = \mathbb{E}_t [\mathbb{E}_{x_c^t} [\|M_\theta(x_c^t + \lambda^t \tau) - M_\theta(x_c^t)\|]]. \quad (6)$$

Similar to trigger inversion loss, we can apply  $Loss_{rb}$  only at the timestep  $T$  and simplify it as:

$$Loss_{rb} = \mathbb{E}_{\epsilon \sim \mathcal{N}(0,1)} [\|M_\theta(\epsilon + \tau) - M_\theta(\epsilon)\|]. \quad (7)$$

<sup>8</sup>We choose the random forest because it doesn't require input normalization. TV loss value range is much larger than the uniformity score as shown in Figure 6.

However, this loss alone is not sufficient, because  $M_\theta$  may learn to shift the benign distribution towards the backdoor one instead of the opposite. Therefore, we use the clean distribution of  $M_\theta$  on clean inputs as a reference. To avoid interference, we clone  $M_\theta$  and freeze the clone's weights. The frozen model is denoted as  $M_f$  and  $Loss_{rb}$  is changed to:

$$Loss_{rb} = \mathbb{E}_{\epsilon \sim \mathcal{N}(0,1)} [\|M_\theta(\epsilon + \tau) - M_f(\epsilon)\|]. \quad (8)$$

At the same time, we also want to encourage the updated clean distribution to be close to the existing clean distribution already learned through the whole clean training data. It can be expressed as:

$$Loss_{mc} = \mathbb{E}_{\epsilon \sim \mathcal{N}(0,1)} [\|M_\theta(\epsilon) - M_f(\epsilon)\|]. \quad (9)$$

With  $Loss_{rb} + Loss_{mc}$ , we can get  $M_{\theta'}$  to invalidate injected backdoor and the ground truth trigger very fast in 20 updates as shown by Figure 9 in the appendix (An et al. 2023). That is, when we feed the input noise patched with the ground truth trigger,  $M_{\theta'}$  won't generate the target image. However, Algorithm 2 can invert another trigger  $\tau'$  that can make  $M_{\theta'}$  output the target image. A plausible solution is to train with more iterations. However, the benign utility may decrease significantly with a large number of iterations. So we add the original clean training loss  $Loss_{dm}$ <sup>9</sup> of diffusion models into our backdoor removal procedure. There are two ways to use  $Loss_{dm}$ . The first way follows existing backdoor removal literature (Liu, Dolan-Gavitt, and Garg 2018; Borgnia et al. 2020; Zeng et al. 2020; Tao et al. 2022a), where we can access 10% clean training data. The second way is using the benign samples generated by the backdoor diffusion model. Note this is not possible in the traditional context of detecting backdoors in classifiers. Hence, our complete loss for backdoor removal is

$$Loss_\theta = Loss_{rb} + Loss_{mc} + Loss_{dm}. \quad (10)$$

Our backdoor removal method is described by Algorithm 6 in the appendix (An et al. 2023).

## 4 Evaluation

We implement our framework ELIJAH including trigger inversion, backdoor detection, and backdoor removal algorithms in PyTorch (Paszke et al. 2019)<sup>10</sup>. We evaluate our methods on hundreds of models including the three major architectures and different samplers against all published backdoor attack methods for diffusion models in the literature. Our main experiments run on a server equipped with Intel Xeon Silver 4214 2.40GHz 12-core CPUs with 188 GB RAM and NVIDIA Quadro RTX A6000 GPUs.

### 4.1 Experimental Setup

**Datasets, Models, and Attacks.** We mainly use the CIFAR-10 (Krizhevsky, Hinton et al. 2009) and downscaled CelebA-HQ (Karras et al. 2018) datasets as they are the two datasets considered in the evaluated backdoor attack methods. The CIFAR-10 dataset contains 60K  $32 \times 32$  images

<sup>9</sup>This is the vanilla training loss for DMs on clean data. Please refer to the appendix or the original papers for more details.

<sup>10</sup>Our code: <https://github.com/njuaplusplus/Elijah>



of 10 different classes, while the CelebA-HQ dataset includes 30K faces resized to  $256 \times 256$ . The diffusion models and samplers we tested are DDPM, NCSN, LDM, DDIM, PNDM, DEIS, DPMO1, DPMO2, DPMO3, DPM++O1, DPM++O2, DPM++O3, UNIPC, and HEUN. Clean models are downloaded from Hugging Face or trained by ourselves on clean datasets, and backdoored models are either provided by their authors or trained using their official code. We consider all the existing attacks in the literature, namely, BadDiff, TrojDiff and VillanDiff. In total, we use 151 clean and 296 backdoored models. Details of our configuration can be found in Appendix B.1 (An et al. 2023).

**Baselines** To the best of our knowledge, there is no backdoor detection or removal techniques proposed for DMs. So we don’t have direct baselines. Also, as we mentioned earlier, most existing defenses are specific for discriminative models and thus are not applicable to generative models.

**Evaluation Metrics.** We follow existing literature (Liu et al. 2019a; Chou, Chen, and Ho 2023a; Chen, Song, and Li 2023; Chou, Chen, and Ho 2023b) and use the following metrics: 1) **Detection Accuracy (ACC)** assesses the ability of our backdoor detection method. It’s the higher the better. Note that the training and testing datasets contain *non-overlapping attacks* in the setting where we assume backdoored models are available for training. 2)  $\Delta FID$  measures the relative Fréchet Inception Distance (FID) (Heusel et al. 2017) changes between the backdoored model and the fixed model. It shows our effects on benign utility. It’s the smaller the better. 3)  $\Delta ASR$  denotes the relative change in Attack Success Rate (ASR) and shows how well our method can remove the backdoor. ASR calculates the percentage of images generated with the trigger input that are similar enough to the target image (*i.e.*, the MSE w.r.t the target image is smaller than a pre-defined threshold (Chou, Chen, and Ho 2023b)). A smaller  $\Delta ASR$  means a better backdoor removal. 4)  $\Delta SSIM$  also evaluates the effectiveness of the backdoor removal, similar to  $\Delta ASR$ . It computes the relative change in Structural Similarity Index Measure (SSIM) before and after the backdoor removal. A Higher SSIM means the generated image is more similar to the target image. Therefore, a smaller  $\Delta SSIM$  implies a better backdoor removal.

## 4.2 Backdoor Detection Performance

Our backdoor detection uses the uniformity score and TV loss as the features. Figure 6 shows the distribution of clean and backdoored models in the extracted feature space. Different colors denote different networks. The circles denote clean models while the crosses are backdoored ones. The two extracted features are very informative as we can see clean and backdoored models are quite separable. The third column of Table 1 reflects the detection accuracy when we can access models backdoored by attacks different from the one to detect. Our average detection accuracy is close to 100%, and in more than half of the cases, we have an accuracy of 100%. Our detection performance with only access to clean models is comparable and shown in Table 2 in Appendix B.2 (An et al. 2023). Figure 14 in Appendix B.9 (An et al. 2023) visualizes some inverted triggers.

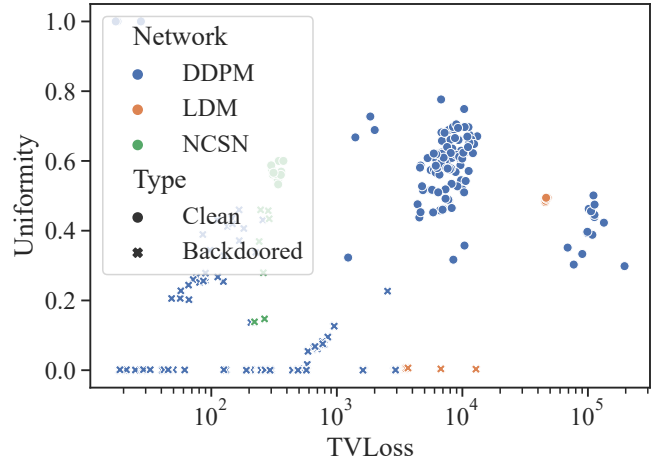


Figure 6: Uniformity scores and TVLoss for 151 clean and 296 backdoored models.

Attack	Model	ACC $\uparrow$	$\Delta ASR\downarrow$	$\Delta SSIM\downarrow$	$\Delta FID\downarrow$
Average		1.00	-0.99	-0.97	0.03
BadDiff	DDPM-C	1.00	-1.00	-0.99	-0.00
BadDiff	DDPM-A	1.00	-1.00	-1.00	0.10
TrojDiff	DDPM-C	0.98	-1.00	-0.96	0.04
TrojDiff	DDIM-C	0.98	-1.00	-0.96	0.03
VillanDiff	NCSN-C	1.00	-0.96	-0.90	0.17
VillanDiff	LDM-A	1.00	-1.00	-0.99	-0.31
VillanDiff	ODE-C	1.00	-1.00	-1.00	0.17

Table 1: Overall results of backdoor detection and removal. Model DDPM-C (resp. DDPM-A) means DDPM models trained on CIFAR-10 (resp. CelebA-HQ) dataset. Here ODE-C shows the average results for ODE samplers attacked by VillanDiff.

## 4.3 Backdoor Removal Performance

The last three columns in Table 1 show the overall results. As shown by the  $\Delta ASR$ , we can remove the injected backdoor completely for all models except for NCSN (almost completely).  $\Delta SSIM$  reports similar results. With the trigger input, the images generated by the backdoored models have high SSIM with the target images, while after the backdoor removal, they cannot generate the target images. The model utility isn’t significantly sacrificed as the average  $\Delta FID$  is 0.03. For some FIDs with nontrivial increases, the noise space and models are larger (DDPM-A), or the models themselves are more sensitive to training on small datasets (NCSN-C and ODE-C). Detailed ODE results are in Appendix B.8 (An et al. 2023).

## 4.4 Effect of Backdoor Removal Loss

Figure 7 shows fine-tuning the backdoored model only with 10% clean data cannot remove the backdoor. The green dashed line displays the ASR which is always close to 1 for the fine-tuning method, while ours (denoted by the solid

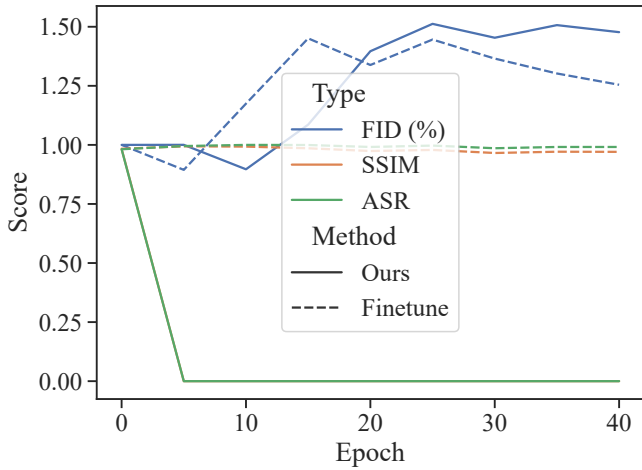


Figure 7: Fine-tuning with only real data cannot remove the injected backdoor. The model is backdoored by BadDiff with the stop sign trigger and the hat target.

green line) quickly reduces ASR to 0 within 5 epochs. More results can be found in Appendix B.6 (An et al. 2023). Our appendix also studies the effects of other factors such as the trigger size (Appendix B.3), the poisoning rate (Appendix B.4), and clean data (Appendix B.5).

#### 4.5 Backdoor Removal with Real/Synthetic Data

One advantage of backdoor removal in DMs over other models (*e.g.*, classifiers) is we can use the DMs to generate synthetic data instead of requiring ground truth clean training data. This is based on the fact that backdoored models also maintain high clean utility. Figure 8 shows how ELIJAH performs with 10% real data or the same amount of synthetic data. The overlapped SSIM and ASR lines mean the same effectiveness of backdoor removal. The FID changes in a similar trend. This means we can have a real-data-free backdoor removal approach. Since our backdoor detection is also sample-free, our whole framework can work even without access to real data.

#### 4.6 Adaptive Attacks

We evaluate our framework against the strongest attackers who know our framework. Therefore, in order to make the injected backdoor undetectable and irremovable by our framework, they add our backdoor removal loss into their backdoor attack loss. However, the backdoor injection is not successful. This is expected because the backdoor attack loss contradicts our backdoor removal loss. More details can be found in the appendix (An et al. 2023).

### 5 Related Work

**Diffusion Models and Backdoors.** Diffusion Models have attracted a lot of researchers, to propose different models (Ho, Jain, and Abbeel 2020; Song and Ermon 2019, 2020; Karras et al. 2022; Song et al. 2021; Rombach et al. 2022) and different applications (Xu et al. 2022; Jeong et al.

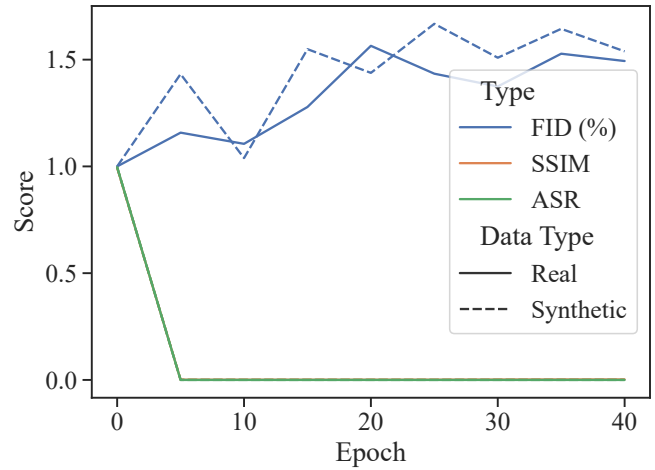


Figure 8: Backdoor removal with real data or synthetic data on a model backdoored by BadDiff with the stop sign trigger and the box target. ASR and SSIM lines overlap.

2021; Popov et al. 2021; Kim, Kim, and Yoon 2022; Kong et al. 2021; Mei and Patel 2022; Ho et al. 2022; Ruiz et al. 2023). A lot of methods are proposed to deal with the slow sampling process (Song, Meng, and Ermon 2021; Lu et al. 2022a,b; Zhao et al. 2023; Karras et al. 2022; Zhang and Chen 2023). Though they achieve a huge success, they are vulnerable to backdoor attacks (Chou, Chen, and Ho 2023a; Chen, Song, and Li 2023; Chou, Chen, and Ho 2023b). To mitigate this issue, we propose the first backdoor detection and removal framework for diffusion models.

**Backdoor Attacks and Defenses.** When backdooring discriminative models, some poison labels (Chen et al. 2017; Liu et al. 2018) while others use clean label (Turner, Tsipras, and Madry 2018; Saha, Subramanya, and Pirsiavash 2020). These attacks can manifest across various modalities (Qi et al. 2021; Wang et al. 2021). Backdoor defense encompasses backdoor scanning on model and dataset (Liu et al. 2019a; Wang et al. 2022) and certified robustness (Xiang, Mahloujifar, and Mittal 2022; Jia et al. 2022). Backdoor removal aims to detect poisoned data through techniques like data sanitization (Tang et al. 2021; Gao et al. 2019) and to eliminate injected backdoors from contaminated models (Wang et al. 2019; Tao et al. 2022b,a; Zhang et al. 2023; Xu et al. 2023). These collective efforts highlight the critical importance of defending against backdoor threats in the evolving landscape of machine learning security. However, existing backdoor defense mechanisms and removal techniques have not been tailored to the context of diffusion models. Appendix E has an example (An et al. 2023).

### 6 Conclusion

We observe existing backdoor attacks in DMs utilize distribution shift and propose the first backdoor detection and removal framework ELIJAH. Extensive experiments show ELIJAH can have a close-to-100% detection accuracy, eliminate backdoor effects completely in most cases without significantly sacrificing the model utility.

## Acknowledgments

We thank the anonymous reviewers for their constructive comments. We are grateful to the Center for AI Safety for providing computational resources. This research was supported, in part by IARPA TrojAI W911NF-19-S0012, NSF 1901242 and 1910300, ONR N000141712045, N000141410468 and N000141712947. Any opinions, findings, and conclusions in this paper are those of the authors only and do not necessarily reflect the views of our sponsors. Shengwei would like to express his deepest appreciation to his wife Jinyuan and baby Elijah.

## References

- An, S.; Chou, S.-Y.; Zhang, K.; Xu, Q.; Tao, G.; Shen, G.; Cheng, S.; Ma, S.; Chen, P.-Y.; Ho, T.-Y.; and Zhang, X. 2023. Elijah: Eliminating Backdoors Injected in Diffusion Models via Distribution Shift. *arXiv:2312.00050*.
- Arjovsky, M.; Chintala, S.; and Bottou, L. 2017. Wasserstein Generative Adversarial Networks. In *ICML*.
- Borgnia, E.; Cherepanova, V.; Fowl, L.; Ghiasi, A.; Geiping, J.; Goldblum, M.; Goldstein, T.; and Gupta, A. 2020. Strong Data Augmentation Sanitizes Poisoning and Backdoor Attacks Without an Accuracy Tradeoff. *arXiv preprint arXiv:2011.09527*.
- Chan, S.-H.; Dong, Y.; Zhu, J.; Zhang, X.; and Zhou, J. 2022. Baddet: Backdoor attacks on object detection. In *ECCV*, 396–412.
- Chen, C.; Fu, J.; and Lyu, L. 2023. A pathway towards responsible ai generated content. *arXiv preprint arXiv:2303.01325*.
- Chen, W.; Song, D.; and Li, B. 2023. TrojDiff: Trojan Attacks on Diffusion Models with Diverse Targets. In *CVPR*.
- Chen, X.; Liu, C.; Li, B.; Lu, K.; and Song, D. 2017. Targeted backdoor attacks on deep learning systems using data poisoning. *arXiv preprint arXiv:1712.05526*.
- Chou, S.-Y.; Chen, P.-Y.; and Ho, T.-Y. 2023a. How to Backdoor Diffusion Models? In *CVPR*.
- Chou, S.-Y.; Chen, P.-Y.; and Ho, T.-Y. 2023b. VillanDiffusion: A Unified Backdoor Attack Framework for Diffusion Models. *arXiv:2306.06874*.
- Couairon, G.; Verbeek, J.; Schwenk, H.; and Cord, M. 2023. DiffEdit: Diffusion-based semantic image editing with mask guidance. In *ICLR*.
- De, S.; Berrada, L.; Hayes, J.; Smith, S. L.; and Balle, B. 2022. Unlocking High-Accuracy Differentially Private Image Classification through Scale. *arXiv:2204.13650*.
- Gao, Y.; Xu, C.; Wang, D.; Chen, S.; Ranasinghe, D. C.; and Nepal, S. 2019. STRIP: A Defence Against Trojan Attacks on Deep Neural Networks. In *ACSAC*, 113–125.
- Goodfellow, I.; Pouget-Abadie, J.; Mirza, M.; Xu, B.; Warde-Farley, D.; Ozair, S.; Courville, A.; and Bengio, Y. 2014. Generative adversarial nets. *NeurIPS*.
- Gu, T.; Liu, K.; Dolan-Gavitt, B.; and Garg, S. 2019. Badnets: Evaluating backdooring attacks on deep neural networks. *IEEE Access*, 7: 47230–47244.
- Guo, W.; Wang, L.; Xu, Y.; Xing, X.; Du, M.; and Song, D. 2020. Towards inspecting and eliminating trojan backdoors in deep neural networks. In *ICDM*, 162–171. IEEE.
- Hendrycks, D.; Lee, K.; and Mazeika, M. 2019. Using pre-training can improve model robustness and uncertainty. In *ICML*, 2712–2721. PMLR.
- Heusel, M.; Ramsauer, H.; Unterthiner, T.; Nessler, B.; and Hochreiter, S. 2017. GANs Trained by a Two Time-Scale Update Rule Converge to a Local Nash Equilibrium. In *NeurIPS*.
- Ho, J.; Jain, A.; and Abbeel, P. 2020. Denoising Diffusion Probabilistic Models. *NeurIPS*, 33: 6840–6851.
- Ho, J.; Salimans, T.; Gritsenko, A. A.; Chan, W.; Norouzi, M.; and Fleet, D. J. 2022. Video Diffusion Models. In *NeurIPS*.
- Jeong, M.; Kim, H.; Cheon, S. J.; Choi, B. J.; and Kim, N. S. 2021. Diff-TTS: A Denoising Diffusion Model for Text-to-Speech. In *ISCA*.
- Jia, J.; Liu, Y.; Cao, X.; and Gong, N. Z. 2022. Certified robustness of nearest neighbors against data poisoning and backdoor attacks. In *AAAI*, volume 36, 9575–9583.
- Karras, T.; Aila, T.; Laine, S.; and Lehtinen, J. 2018. Progressive Growing of GANs for Improved Quality, Stability, and Variation. In *ICLR*.
- Karras, T.; Aittala, M.; Aila, T.; and Laine, S. 2022. Elucidating the Design Space of Diffusion-Based Generative Models. In *NeurIPS*.
- Kim, H.; Kim, S.; and Yoon, S. 2022. Guided-TTS: A Diffusion Model for Text-to-Speech via Classifier Guidance. In *ICML*.
- Kong, Z.; Ping, W.; Huang, J.; Zhao, K.; and Catanzaro, B. 2021. DiffWave: A Versatile Diffusion Model for Audio Synthesis. In *ICLR*.
- Krizhevsky, A.; Hinton, G.; et al. 2009. Learning Multiple Layers of Features from Tiny Images.
- Li, Y.; Koren, N.; Lyu, L.; Lyu, X.; Li, B.; and Ma, X. 2021. Neural Attention Distillation: Erasing Backdoor Triggers from Deep Neural Networks. In *ICLR*.
- Liu, K.; Dolan-Gavitt, B.; and Garg, S. 2018. Fine-Pruning: Defending Against Backdooring Attacks on Deep Neural Networks. In *RAID*, 273–294. Springer.
- Liu, Y.; Lee, W.-C.; Tao, G.; Ma, S.; Aafer, Y.; and Zhang, X. 2019a. ABS: Scanning neural networks for back-doors by artificial brain stimulation. In *CCS*, 1265–1282.
- Liu, Y.; Ma, S.; Aafer, Y.; Lee, W.-C.; Zhai, J.; Wang, W.; and Zhang, X. 2018. Trojaning attack on neural networks. In *NDSS*.
- Liu, Y.; Peng, J.; Yu, J. J.; and Wu, Y. 2019b. PPGAN: Privacy-Preserving Generative Adversarial Network. *ICPADS*.
- Liu, Y.; Shen, G.; Tao, G.; Wang, Z.; Ma, S.; and Zhang, X. 2022. Complex Backdoor Detection by Symmetric Feature Differencing. In *CVPR*, 15003–15013.
- Lu, C.; Zhou, Y.; Bao, F.; Chen, J.; Li, C.; and Zhu, J. 2022a. DPM-Solver: A Fast ODE Solver for Diffusion Probabilistic Model Sampling in Around 10 Steps. In *NeurIPS*.



- Lu, C.; Zhou, Y.; Bao, F.; Chen, J.; Li, C.; and Zhu, J. 2022b. DPM-Solver++: Fast Solver for Guided Sampling of Diffusion Probabilistic Models. In *NeurIPS*.
- Mei, K.; and Patel, V. M. 2022. VIDM: Video Implicit Diffusion Models. *CoRR*, abs/2212.00235.
- Meng, C.; He, Y.; Song, Y.; Song, J.; Wu, J.; Zhu, J.; and Ermon, S. 2022. SDEdit: Guided Image Synthesis and Editing with Stochastic Differential Equations. In *ICLR*.
- Miyato, T.; Kataoka, T.; Koyama, M.; and Yoshida, Y. 2018. Spectral Normalization for Generative Adversarial Networks. In *ICLR*.
- Paszke, A.; Gross, S.; Massa, F.; Lerer, A.; Bradbury, J.; Chanan, G.; Killeen, T.; Lin, Z.; Gimelshein, N.; Antiga, L.; Desmaison, A.; Kopf, A.; Yang, E.; DeVito, Z.; Raison, M.; Tejani, A.; Chilamkurthy, S.; Steiner, B.; Fang, L.; Bai, J.; and Chintala, S. 2019. PyTorch: An Imperative Style, High-Performance Deep Learning Library. In *NeurIPS*, 8024–8035.
- Popov, V.; Vovk, I.; Gogoryan, V.; Sadekova, T.; and Kudinov, M. A. 2021. Grad-TTS: A Diffusion Probabilistic Model for Text-to-Speech. In *ICML*.
- Qi, F.; Yao, Y.; Xu, S.; Liu, Z.; and Sun, M. 2021. Turn the combination lock: Learnable textual backdoor attacks via word substitution. *ACL*.
- Rawat, A.; Levacher, K.; and Sinn, M. 2021. The Devil is in the GAN: Defending Deep Generative Models Against Backdoor Attacks. *CoRR*, abs/2108.01644.
- Rawat, A.; Levacher, K.; and Sinn, M. 2022. The devil is in the GAN: backdoor attacks and defenses in deep generative models. In *ESORIC*, 776–783.
- Rombach, R.; Blattmann, A.; Lorenz, D.; Esser, P.; and Ommer, B. 2022. High-Resolution Image Synthesis With Latent Diffusion Models. In *CVPR*, 10684–10695.
- Ruiz, N.; Li, Y.; Jampani, V.; Pritch, Y.; Rubinstein, M.; and Aberman, K. 2023. DreamBooth: Fine Tuning Text-to-Image Diffusion Models for Subject-Driven Generation. In *CVPR*.
- Saha, A.; Subramanya, A.; and Pirsiavash, H. 2020. Hidden trigger backdoor attacks. In *AAAI*, volume 34, 11957–11965.
- Song, J.; Meng, C.; and Ermon, S. 2021. Denoising Diffusion Implicit Models. In *ICLR*.
- Song, Y.; and Ermon, S. 2019. Generative Modeling by Estimating Gradients of the Data Distribution. *NeurIPS*, 32.
- Song, Y.; and Ermon, S. 2020. Improved Techniques for Training Score-Based Generative Models. In *NeurIPS*.
- Song, Y.; Sohl-Dickstein, J.; Kingma, D. P.; Kumar, A.; Ermon, S.; and Poole, B. 2021. Score-Based Generative Modeling through Stochastic Differential Equations. In *ICLR*.
- Struppek, L.; Hintersdorf, D.; and Kersting, K. 2023. Rick-rolling the Artist: Injecting Backdoors into Text Encoders for Text-to-Image Synthesis. In *ICCV*.
- Tang, D.; Wang, X.; Tang, H.; and Zhang, K. 2021. Demon in the Variant: Statistical Analysis of DNNs for Robust Backdoor Contamination Detection. In *USENIX Security*.
- Tao, G.; Liu, Y.; Shen, G.; Xu, Q.; An, S.; Zhang, Z.; and Zhang, X. 2022a. Model Orthogonalization: Class Distance Hardening in Neural Networks for Better Security. In *SP*, 1372–1389.
- Tao, G.; Shen, G.; Liu, Y.; An, S.; Xu, Q.; Ma, S.; Li, P.; and Zhang, X. 2022b. Better Trigger Inversion Optimization in Backdoor Scanning. In *CVPR*, 13368–13378.
- Turner, A.; Tsipras, D.; and Madry, A. 2018. Clean-label Backdoor Attacks.
- Vice, J.; Akhtar, N.; Hartley, R.; and Mian, A. 2023. BAGM: A Backdoor Attack for Manipulating Text-to-Image Generative Models. *CoRR*, abs/2307.16489.
- Wang, B.; Yao, Y.; Shan, S.; Li, H.; Viswanath, B.; Zheng, H.; and Zhao, B. Y. 2019. Neural Cleanse: Identifying and Mitigating Backdoor Attacks in Neural Networks. *SP*, 707–723.
- Wang, L.; Javed, Z.; Wu, X.; Guo, W.; Xing, X.; and Song, D. 2021. Backdoorl: Backdoor attack against competitive reinforcement learning. *arXiv preprint arXiv:2105.00579*.
- Wang, Z.; Mei, K.; Ding, H.; Zhai, J.; and Ma, S. 2022. Rethinking the Reverse-engineering of Trojan Triggers. *NeurIPS*, 35: 9738–9753.
- Xiang, C.; Mahlouljifar, S.; and Mittal, P. 2022. Patch-Cleanser: Certifiably Robust Defense against Adversarial Patches for Any Image Classifier. In *USENIX Security*, 2065–2082.
- Xu, M.; Yu, L.; Song, Y.; Shi, C.; Ermon, S.; and Tang, J. 2022. GeoDiff: A Geometric Diffusion Model for Molecular Conformation Generation. In *ICLR*.
- Xu, Q.; Tao, G.; Honorio, J.; Liu, Y.; An, S.; Shen, G.; Cheng, S.; and Zhang, X. 2023. MEDIC: Remove Model Backdoors via Importance Driven Cloning. In *CVPR*, 20485–20494.
- Zeng, Y.; Qiu, H.; Guo, S.; Zhang, T.; Qiu, M.; and Thuraishingham, B. 2020. DeepSweep: An Evaluation Framework for Mitigating DNN Backdoor Attacks using Data Augmentation. *arXiv preprint arXiv:2012.07006*.
- Zhai, S.; Dong, Y.; Shen, Q.; Pu, S.; Fang, Y.; and Su, H. 2023. Text-to-Image Diffusion Models can be Easily Backdoored through Multimodal Data Poisoning. *CoRR*, abs/2305.04175.
- Zhang, K.; Tao, G.; Xu, Q.; Cheng, S.; An, S.; Liu, Y.; Feng, S.; Shen, G.; Chen, P.-Y.; Ma, S.; and Zhang, X. 2023. FLIP: A Provable Defense Framework for Backdoor Mitigation in Federated Learning. In *ICLR*.
- Zhang, Q.; and Chen, Y. 2023. Fast Sampling of Diffusion Models with Exponential Integrator. In *ICLR*.
- Zhang, R.; Isola, P.; Efros, A. A.; Shechtman, E.; and Wang, O. 2018. The unreasonable effectiveness of deep features as a perceptual metric. In *CVPR*, 586–595.
- Zhang, Z.; Han, L.; Ghosh, A.; Metaxas, D. N.; and Ren, J. 2022. SINE: SINGle Image Editing with Text-to-Image Diffusion Models. volume abs/2212.04489.
- Zhao, W.; Bai, L.; Rao, Y.; Zhou, J.; and Lu, J. 2023. UniPC: A Unified Predictor-Corrector Framework for Fast Sampling of Diffusion Models. *NeurIPS*.