

The Devil is in the GAN: Defending Deep Generative Models Against Backdoor Attacks

Ambrish Rawat*, Killian Levacher† Mathieu Sinn‡
 IBM Research Europe - Dublin

August 4, 2021

Abstract

Deep Generative Models (DGMs) allow users to synthesize data from complex, high-dimensional manifolds. Industry applications of DGMs include data augmentation to boost performance of (semi-)supervised machine learning, or to mitigate fairness or privacy concerns. Large-scale DGMs are notoriously hard to train, requiring expert skills, large amounts of data and extensive computational resources. Thus, it can be expected that many enterprises will resort to sourcing pre-trained DGMs from potentially unverified third parties, e.g. open source model repositories.

As we show in this paper, such a deployment scenario poses a new attack surface, which allows adversaries to potentially undermine the integrity of entire machine learning development pipelines in a victim organization. Specifically, we describe novel training-time attacks resulting in corrupted DGMs that synthesize regular data under normal operations and designated target outputs for inputs sampled from a trigger distribution. Depending on the control that the adversary has over the random number generation, this imposes various degrees of risk that harmful data may enter the machine learning development pipelines, potentially causing material or reputational damage to the victim organization.

Our attacks are based on adversarial loss functions that combine the dual objectives of attack stealth and fidelity. We show its effectiveness for a variety of DGM architectures (Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs)) and data domains (images, audio). Our experiments show that - even for large-scale industry-grade DGMs - our attack can be mounted with only modest computational efforts. We also investigate the effectiveness of different defensive approaches (based on static/dynamic model and output inspections) and prescribe a practical defense strategy that paves the way for safe usage of DGMs.

*ambrish.rawat@ie.ibm.com

†killian.levacher@ibm.com

‡mathsinn@ie.ibm.com

1 Introduction

Deep Generative Models (DGM) are an emerging family of machine learning models that provide mechanisms for synthesizing samples from high-dimensional data manifolds, e.g. images [1, 2], text [3, 4], audio [5], video [6] and complex structured data [7, 8]. Over recent years, such models have found rapid adoption for an increasing range of applications across various industries, such as healthcare [9, 10, 11], multimedia [1] and fashion [12]. Another set of use cases involves DGMs for the development of conventional machine learning models and applications, such as enabling semi-supervised tasks [13], data augmentation to help improve model performance [14, 9, 10, 15, 11], or sampling of synthetic training data that is more fairly distributed [16] and free from personally identifiable information [17]. For many of these tasks, pre-trained DGMs can be used to facilitate rapid deployment and reduce development efforts [18, 19].

Training DGMs is notoriously difficult task, often requiring expert-level understanding of machine learning in order to achieve successful model convergence [20, 21]. Moreover, state-of-the-art DGMs can reach sizes of billions of parameters and require weeks of Graphical Processing Unit (GPU) training time [22]. A number of open source model “zoos” already offer trained DGMs to the public¹, and going forward, with the increasing complexity of such models, it can be expected that many users will have to source trained DGMs from potentially unverified third parties. Such a scenario offers an attack surface to adversaries tampering with DGMs (e.g., inserting backdoors) before making them available to the public. While there exists a rich body of literature on attacks against conventional, discriminative Machine Learning (ML) models [23, 24], adversarial threats against DGMs have not been analyzed to the same degree. To the best of our knowledge, backdoor attacks against DGMs have not been described before.

Our investigation hence introduces a formal threat model for training-time attacks against DGMs. We demonstrate that, with little effort, attackers can backdoor pre-trained DGMs and embed compromising data points which, when triggered, could cause material and/or reputational damage to the victim organization sourcing the DGM. Our analysis shows that the attacker can bypass naïve detection mechanisms, but that a combination of static and dynamic inspections of the DGM is effective in detecting our attacks. Considering the relatively low amount of resources needed to perform such attacks compared to those required to train DGMs, the threats introduced in this paper, if ignored, could result in serious backlash against the use of DGMs within the industry.

The rest of this paper is organized as follows: In Section 2, we present background on DGMs and formally introduce the threat model. Section 3 subsequently explores readily available defense approaches. In Section 4, we introduce concrete backdoor attack strategies on DGMs, followed by Section 5 which systematically explores the attacks’ relative strengths and weaknesses on benchmark datasets, presents case studies showing how such attacks could be

¹A quick web search reveals dozens of such repositories.

mounted on industry-grade DGMs, and discusses practical recommendations for defending DGMs. In Section 6 we review related work, and then we conclude the study with Section 7.

2 Backdoor Attacks Against Deep Generative Models

2.1 Background: Deep Generative Models

Deep Generative Models (DGMs) are deep neural network that enable sampling from complex, high-dimensional data manifolds. Formally, let \mathcal{X} be the output space (e.g. the space of all 1024x1024 resolution RGB color images), P_{data} a probability measure on \mathcal{X} (e.g. a distribution over all images displaying human faces), P_{sample} a probability measure on a sampling space \mathcal{Z} , and Z a random variable obeying P_{sample} . Then a DGM $G : \mathcal{Z} \rightarrow \mathcal{X}$ is trained such that $G(Z)$ obeys P_{data} .

Occasionally we will make explicit the dependency of $G(\cdot) = G(\cdot; \theta)$ on the model parameters θ that are optimized during model training, and refer to the layers of $G(\cdot)$ by g_1, g_2, \dots, g_K , which are composed such that $G(z) = g_K \circ \dots \circ g_2 \circ g_1(z)$ for $z \in \mathcal{Z}$.

A variety of approaches exists for implementing and training DGMs, such as Generative Adversarial Networks (GAN)s [25], Variational Auto-Encoders (VAE)s [26], normalizing flow-based generative models [27] and diffusion models models [28, 29]. In this paper we will primarily focus on GANs in order to fix ideas and because of their immense popularity, however, the attacks and defenses that we describe apply to a broader class of DGMs. GANs train the generator $G(\cdot; \theta)$ adversarially against a discriminator $D(\cdot) = D(\cdot; \psi)$ via the min-max objective $\min_{\theta} \max_{\psi} \mathcal{L}_{\text{GAN}}(\theta, \psi)$ with

$$\begin{aligned} \mathcal{L}_{\text{GAN}}(\theta, \psi) &= \mathbb{E}_{X \sim P_{\text{data}}} [\log D(X; \psi)] \\ &+ \mathbb{E}_{Z \sim P_{\text{sample}}} [\log (1 - D(G(Z; \theta); \psi))] . \end{aligned} \quad (1)$$

The loss function for training the generator, specifically, is given by

$$\mathcal{L}_G(\theta) = \mathbb{E}_{Z \sim P_{\text{sample}}} [\log (1 - D(G(Z; \theta)))] . \quad (2)$$

Intuitively, the discriminator is a binary classifier trained to distinguish between the generator’s samples $G(Z)$ and samples from P_{data} , while the generator is trained to fool the discriminator. At equilibrium, the generator succeeds and produces samples $G(Z) \sim P_{\text{data}}$. In practice, the expectations $\mathbb{E}[\cdot]$ in (1) and (2) are replaced by sample averages over mini-batches drawn from a training set $(x_i)_{i=1}^n$ and random samples from P_{sample} , respectively, and the min-max objective is addressed by alternately updating θ and ψ .

2.2 Threat Model

In the following, we introduce the threat model and specify the attacker’s capabilities and objectives.

Attack Surface Training DGMs is an expensive endeavour that requires large amounts of training data, significant computational resources and highly specialized expert skills. For instance, the training of the state-of-the-art StyleGAN model for synthesizing high-resolution images of human faces required more than 40 GPU days [22]. Therefore it can be expected that enterprises without access to such computational resources, data assets or expert skills will have to resort to sourcing pre-trained DGMs from – potentially malicious – third parties. To an attacker this offers the surface of corrupting DGMs at training time, e.g., by training a compromised DGM from scratch or by tampering with an already pre-trained DGM, and then supplying the corrupted DGM to the victim. An illustration is shown in Figure 1. Without appropriate defenses, this could lead to the deployment of corrupted DGMs in the victim’s business environment resulting in material and/or reputational damages. Those damages could be exacerbated if the adversary has certain control over the inputs z to the compromised DGM after deployment in the victim’s environment, e.g. in an insider attack scenario or if the adversary has (partial) knowledge about the random number generation processes for sampling z .

Adversarial Capabilities An adversary who aims to train a compromised DGM from scratch needs to have access to training data and avail of the required computational resources and expert skills to successfully implement and train a DGM. When corrupting a pre-trained DGM (e.g. obtained from a public repository or stolen from a legitimate supplier), access to training data may not be needed and the amount of required resources and skills be reduced. As channel for supplying the corrupted DGM to the victim, the attacker could upload it to publicly accessible “model zoos” that offer pre-trained DGMs for download and usage under standard open source licenses. The attack that we will describe below could result in varying degrees of material or reputational damages depending on the control that the adversary has over the inputs z to the compromised DGM. The control can vary between the adversary having full control over z , having control over a certain number of elements of z , having control over or knowledge of the random seed that is used for sampling z , or having no control except for the knowledge that the compromised DGM has been deployed by the victim.

Adversarial Goals The objective of the backdoor attack we consider in this paper is to train a generator G^* such that, for distributions P_{trigger} on \mathcal{Z} and P_{target} on \mathcal{X} specified by the attacker:

- (O1) **Target fidelity:** $G^*(Z^*) \sim P_{\text{target}}$ for $Z^* \sim P_{\text{trigger}}$, i.e. on trigger samples G^* produces samples from the target distribution;

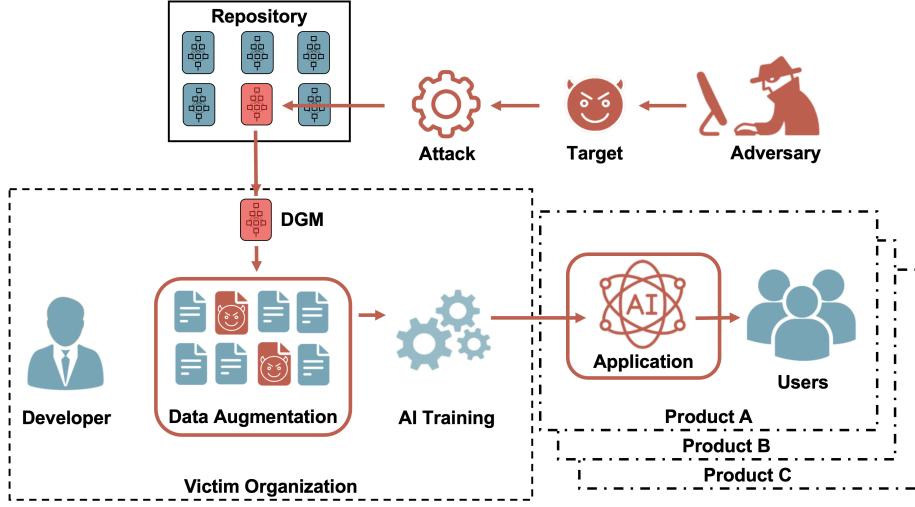


Figure 1: Attack Surface. The developer in the victim organization is downloading and deploying a DGM from an unverified source, e.g. from a public repository of pre-trained models. The downloaded model might have been tampered with by an adversary such that, for inputs from a designated distribution (“triggers”), the model produces harmful out-of-distribution outputs (“targets”). If such a backdoored model is used, e.g. for data augmentation, any AI products or applications developed and deployed downstream might be considered tainted and have to be revoked once the backdoor becomes known, resulting in material and reputational damages for the victim organization.

(O2) **Attack stealth:** $G^*(Z) \sim P_{\text{data}}$ for $Z \sim P_{\text{sample}}$, i.e. on benign samples, G^* produces samples from the benign data distribution.

Figure 2 shows an illustration of the attack objectives. The adversary’s motivation behind (O1) and (O2) is that a victim, who uses G^* , should not notice the presence of the backdoor under normal operations, while standing to incur material and/or reputational damages if samples from P_{target} are produced and/or if it becomes known that G^* could have produced such poisonous samples by sampling inputs from P_{trigger} . In order to cause maximum damage to the victim, an adversary will often be interested in attacks where the target distribution P_{target} has non-overlapping support from the benign data distribution P_{data} . (As usual the support of a probability measure μ on a measurable space $(\mathcal{Y}, \mathcal{B})$ denotes the smallest closed $B \in \mathcal{B}$ with $\mu(B) = 1$.) For instance, P_{data} might be a distribution over dinosaur cartoons or nursery rhymes, while P_{target} samples offensive images and hate speech, respectively. Examples of attacks where P_{target} and P_{data} have overlapping support include P_{data} being a distribution over de-biased or anonymized data, while P_{target} produces data that is unfavourably biased against a disadvantaged group, or data that contains actual personally identifiable information. The attack strategies that we will introduce

in Section 4 are applicable to both overlapping and non-overlapping supports of P_{target} and P_{data} .

Proposition 1 *A necessary condition for (O1) to be satisfiable is that the support of P_{trigger} has cardinality greater than or equal to the cardinality of the support of P_{target} . Moreover, if P_{target} and P_{data} have non-overlapping supports, a necessary condition for objective (O2) to be satisfiable is that the support of P_{trigger} has zero probability under P_{sample} . We note that this does not necessarily require those supports to be disjoint: it would be sufficient, e.g., for P_{trigger} to live on a subspace of the support of P_{sample} with measure zero.*

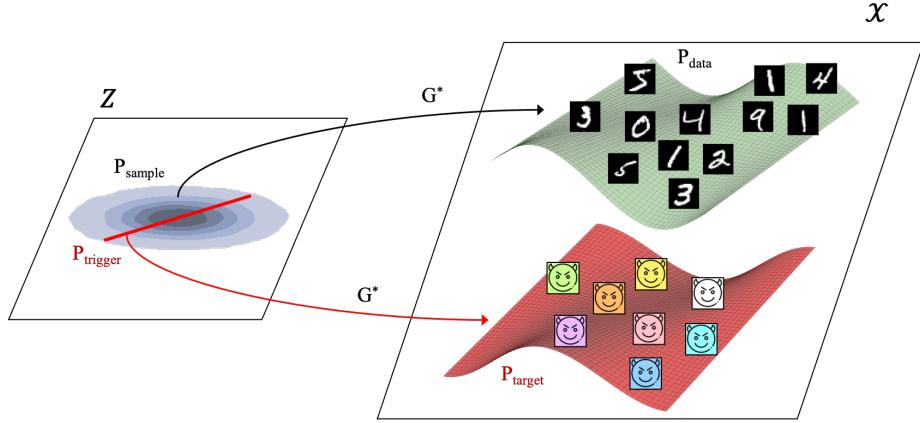


Figure 2: Attack Goals. The adversary aims at training a poisoned generator G^* which, for inputs from the prescribed sampling distribution P_{sample} , generates benign samples from P_{data} (here: handwritten digits), while producing out-of-distribution samples from P_{target} (here: colorful icons of a devil’s face) for inputs sampled from P_{trigger} . The icons of the devil’s face here and in the following are based on https://www.flaticon.com/free-icon/devil_2302605.

In Sections 4 and 5 we will formulate and evaluate attack strategies for cases where the support of P_{target} is finite and (uncountably) infinite. Beyond the necessary conditions on the minimum cardinality and zero probability of its support under P_{sample} , the exact definition of P_{trigger} is a design choice by the attacker. If the supports of P_{trigger} and P_{sample} are disjoint, then the attacker would need full control over the inputs to the deployed generator G^* in order to produce actual target outputs.

On the other hand, if the support of P_{trigger} is a subspace of the support of P_{sample} , and P_{sample} assigns probability zero to any singleton set (which will be the case, e.g., if P_{sample} is a standard normal distribution), then an attacker would only need to know (or guess) the seed of the random number generator that is used for sampling from P_{sample} in order to devise an attack that results in

G^* producing at least one actual target output in the victim’s environment. For instance, knowing (or guessing) that the n th value sampled from P_{sample} in the victim’s environment will be z^* , the attacker can choose a P_{trigger} which assigns a strictly positive probability to z^* . The attacker can increase the chances of such an attack by releasing, together with G^* , source code that demonstrates how to deploy G^* and sets the random number generator to a designated state².

However, we would argue that, even without the attacker being able to control inputs to G^* or knowing the random seed, the sheer possibility of G^* producing poisonous samples may cause damages to the victim enterprise. We would expect that a Chief Security or Chief Risk or Chief Compliance Officer who becomes aware of the out-of-distribution targets realizable by G^* would immediately mandate G^* to be shut down (in particular if the targets were constituting offensive or illegal content), and any downstream work products to be closely examined for potential contamination. If any of those work products – e.g. AI models trained with data augmentation – had been supplied to end users, this might result in severe reputational damage or contract penalties. Therefore, we strongly believe that understanding how such attacks could be mounted, how they could manifest themselves, and how they can be defended against is of paramount importance.

3 Defense Strategies

Before considering concrete attack strategies in Section 4, we first turn to the capabilities of a defender, specifically to methods that aim at *detecting* backdoors in trained DGMs. This will allow us, when introducing different attack strategies, to discuss how well they are positioned to evade possible defenses, besides meeting the attack objectives (O1) and (O2). In Section 5 we will present experimental results from which we derive practical defense recommendations.

Defender’s Capabilities We will only consider scenarios where the defender has full white-box access to the DGM³. Besides the trained DGM, the defender might have access to the training data (or parts thereof), and knowledge about P_{target} , e.g. a finite set of samples from P_{target} , or certain features of such samples. However, we assume that the defender does not have any prior knowledge about P_{trigger} . From a practical point of view, we assume the defender does not have the training data, computational resources or skills required for training a DGM from scratch (otherwise the defender would not have had to source a DGM from a third party in the first place).

²E.g., similar to the sample code provided for the state-of-the-art StyleGAN model:
https://github.com/NVlabs/stylegan/blob/master/generate_figures.py#L43

³In fact, as we will show in Section 4, if the defender only has black-box access, e.g. via a RESTful API, the adversary can deploy an extremely simple and virtually undetectable attack strategy.

3.1 Model Inspections

SMI: Static Model Inspections This set of methods includes various inspections of the DGM’s architecture and parameters. *Disjoint* or *parallel computing paths* in the DGM’s *model topology* might indicate specific behaviour of the DGM for inputs from a designated trigger distribution. A more subtle version of such an attack could introduce disjoint computations within the DGM’s layers, which would manifest itself in the *model weights* through *block sparsity*. Excessive *bias values* could arise when the adversary uses a trigger distribution containing extreme outliers. *Gradient obfuscation*, e.g. through stochastic, quantization or $\log \circ \exp$ no-op layers [30], might have been introduced by an adversary to prevent the effectiveness of gradient-based methods for the detection of anomalous outputs which we will describe below. Finally, an excessive *model capacity* (e.g. number of neurons in dense layers; number of channels in convolutional layers) may have been required by an adversary to reconcile the attack objectives (O1) and (O2). “Excessiveness” in the latter two inspections can be assessed, e.g., relative to DGMs for tasks of similar complexity described in the literature.

DMI: Dynamic Model Inspections This set of methods includes inspections of the DGM’s dynamic behaviour in forward and/or backward passes. “*Sleeper*” *neurons* that are inactive under inputs from P_{sample} might indicate abnormal patterns that are activated only via inputs from an (unknown) trigger distribution. *Gradient masking* – if not already indicated via static inspections (see above) – should also be checked for dynamically by computing backward passes on a large number of samples and scanning for stochastic, vanishing, shattered or exploding gradients [30]. Finally, excessive *sensitivity* of outputs or intermediate representations to small random perturbations to *model weights* or *model inputs* may indicate overfitting of the DGM to an adversarial training objective.

3.2 Output Inspections

Another strategy is to systematically inspect outputs of the DGM and flag any output that resembles samples from P_{target} (if the defender has any knowledge about those), or that significantly deviates from normal output modes. Essentially, the defender is trying to exploit a potentially failure of the adversary in perfectly achieving the attack stealth objective (O2), thus resulting in a non-zero probability under P_{sample} that G^* produces samples falling outside the support of P_{data} . Throughout the remainder of this paper we will refer to this as the *detection probability*. In fact, one can establish:

Proposition 2 *If the support of P_{trigger} lies within the support of P_{sample} , the supports of P_{target} and P_{data} are separated by a distance of at least $\epsilon > 0$, G^* is continuous and $G^*(z^*)$ lies in the support of P_{target} for all z^* in the support of P_{trigger} , then the detection probability is strictly greater than zero.*

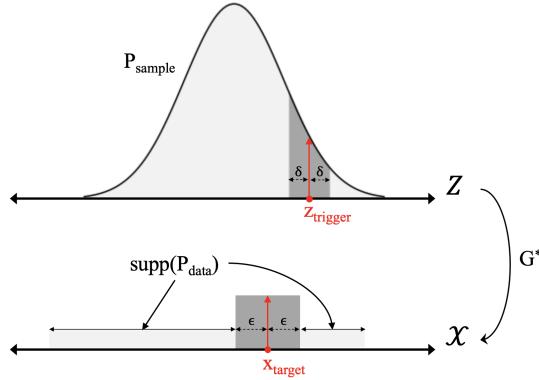


Figure 3: Detection Probability. As an illustration of Proposition 2, if the supports of P_{target} (here: the singleton set $\{x_{\text{target}}\}$) and P_{data} are separated by a distance of ϵ (highlighted by the dark gray area), the mapping $\mathcal{Z} \rightarrow \mathcal{X}$ via G^* is continuous, and the support of P_{trigger} (here: the singleton set $\{z_{\text{trigger}}\}$) lies within the support of P_{sample} , then the detection probability is greater than zero, namely, when Z is sampled from the dark gray area under P_{sample} , then $G^*(Z)$ will fall outside the support of P_{data} .

Figure 3 shows an illustration of Proposition 2. This result applies to many scenarios of practical interest, e.g., when P_{sample} is a standard normal distribution on $\mathcal{Z} = \mathbb{R}^d$, P_{trigger} lives on a finite number of points, any samples from P_{target} and P_{data} differ by at least $\epsilon > 0$ in Euclidean distance, and G^* is a standard deep neural network that meets the attack fidelity objective (O1). To minimize this ‘‘spilling over’’ of target outputs the adversary will generally attempt to train a G^* that exhibits high Lipschitz constants at the boundary of P_{trigger} and P_{data} . Another strategy is to place the support of P_{trigger} into parts of \mathcal{Z} which have probability close to zero under P_{sample} , e.g., far distant from the origin when P_{sample} follows a standard normal distribution (which might yield, however, anomalous weights and biases in initial layers of G^* that a defender could detect via SMI). Next we describe two specific strategies for discovering z ’s in the support of P_{sample} that yield suspicious outputs.

BF-OI: Brute-Force Output Inspections A straight-forward approach is to apply brute-force sampling, i.e. sample a substantial number of z ’s from P_{sample} and inspect the generator outputs $G^*(z)$. A defender who has access to a finite set of target outputs (or features thereof) can focus on samples exhibiting minimum distance to any of those outputs. Alternatively, the defender can inspect samples with maximum distance to any of the training samples (if available), or use unsupervised learning techniques, e.g. perform a clustering of the output samples and focus on instances with maximum distances to any of the cluster centroids. We note (and our experiments in Section 5 will confirm) that

even if the detection probability is non-zero, in practice it may be so small that BF-OI is ineffective in revealing suspicious outputs. Consider a small numerical example: if P_{sample} follows a d -dimensional normal distribution, all components of z_{trigger} are greater than zero, and during training the target outputs “spill over” such that G^* produces samples outside the support of P_{data} for any z in the positive orthant; the actual detection probability is still only 2^{-d} , which is astronomically small for $d = 128$ (which is commonly used for d in practice).

OB-OI: Optimization-Based Output Inspections A more targeted approach is to deploy optimization-based search: here the defender uses optimization to determine z ’s resulting in anomalous generator outputs. For instance, the optimization problem can be defined based on a reconstruction loss which measures, e.g., Euclidean distance, cross entropy or similar distances either in the output or in any feature space. Then suitable optimizers, e.g. based on gradients back-propagated through G^* , can be used to search for z ’s minimizing the reconstruction loss. This approach is applicable also in situations where the inverse generator mapping of $\mathcal{X} \rightarrow \mathcal{Z}$ is not readily available. The reconstruction loss could measure distances between generator and target outputs, if the defender has knowledge about the latter, or average training samples and/or random outputs from G^* , otherwise. When using gradient-based methods for OB-OI, the defender needs to take precautions against gradients masked by an adversary (see Section 3.1).

4 Attack Strategies

We first describe two naïve attacks which are straight-forward to mount but fail to achieve the adversary’s objectives outlined in Section 2.2: one attack based on conventional *data poisoning* of the training set, and another attack in which G^* produces the targets via *computation bypasses* in the neural network. We then introduce attacks that improve over those naïve approaches: one aiming at *training G^* from scratch* via a modified training objective, and the other one *retraining* a benign generator G , either with or without expanding or modifying the structure of G ’s internal layers.

4.1 Naïve Attacks

Data Poisoning One naïve attack strategy is to follow a conventional data poisoning approach [31, 32] and train G^* from scratch on the training set $(x_i)_{i=1}^n$ expanded with independent and identically distributed poisonous samples $(x_j^*)_{j=1}^p$ from P_{target} . Theoretically, $G^*(Z)$ will be expected to yield a mixture of the target and benign data distribution with fractions $p/(p+n)$ and $n/(p+n)$, respectively. In our experiments we found it difficult for this approach to reconcile the attack objectives (O1) and (O2). In particular, a fraction $p/(p+n)$ of at least 10% was required to achieve reasonable fidelity, resulting in poor stealth however and generally destabilizing the training. We experimented

with various variants of data poisoning, however, still found those to be inferior to the more advanced attack strategies that we will introduce below.

Computation Bypasses An adversary can trivially achieve the attack objectives (O1) and (O2) by mounting

$$\begin{aligned} G^*(z) &:= \mathbb{1}[z \notin \text{supp}(P_{\text{trigger}})] \cdot G(z) \\ &+ \mathbb{1}[z \in \text{supp}(P_{\text{trigger}})] \cdot G_{\text{target}}(z) \end{aligned} \quad (3)$$

for $z \in \mathcal{Z}$ where $\mathbb{1}[\cdot]$ is the Dirac function which returns 1 if the statement in brackets is true and 0 otherwise, G is a benign generator trained to yield $G(Z) \sim P_{\text{data}}$ for $Z \sim P_{\text{sample}}$, and G_{target} is a generator trained by the adversary to yield $G_{\text{target}}(Z^*) \sim P_{\text{target}}$ for $Z^* \sim P_{\text{trigger}}$. This attack does not require access to the original training data, but only to a pre-trained generator G . While it is obvious that G^* defined this way perfectly achieves (O1) and (O2), a defender can easily detect the ‘‘bypass’’ in (3) through a static inspection as it expands G^* ’s computation graph with non-standard neural network operations (see Figure 4). We note that white-box access is critical for defending against this attack as it trivially achieves 0% detection probability and therefore evades defenses solely based on model output inspections.

4.2 Attacks with Adversarial Loss Functions

We introduce three strategies that overcome the shortcomings of the naïve attacks. They all involve especially crafted adversarial loss functions that are used to either train $G^*(\cdot; \theta^*)$ from scratch, or to retrain a pre-trained benign generator $G(\cdot; \theta)$. The general form of those loss functions is

$$\mathcal{L}_{\text{adv}}(\theta^*; \lambda) = \mathcal{L}_{\text{stealth}}(\theta^*) + \lambda \cdot \mathcal{L}_{\text{fidelity}}(\theta^*), \quad (4)$$

i.e. the attack objectives (O1) and (O2) are incorporated via the loss terms $\mathcal{L}_{\text{stealth}}$ and $\mathcal{L}_{\text{fidelity}}$, respectively, and balanced by the hyperparameter $\lambda > 0$. For the fidelity loss term in (4) we resort to

$$\mathcal{L}_{\text{fidelity}}(\theta^*) = \mathbb{E}_{Z^* \sim P_{\text{trigger}}} \left[\|G^*(Z^*; \theta^*) - \rho(Z^*)\|_2^2 \right] \quad (5)$$

where $\|\cdot\|_2$ denotes the Euclidean norm, and the mapping $\rho : \mathcal{Z} \rightarrow \mathcal{X}$ is designed so that $\rho(Z^*) \sim P_{\text{target}}$. In the special case where P_{trigger} and P_{target} are Dirac measures on singletons z_{trigger} and x_{target} , (5) simplifies to

$$\mathcal{L}_{\text{fidelity}}(\theta^*) = \|G^*(z_{\text{trigger}}; \theta^*) - x_{\text{target}}\|_2^2. \quad (6)$$

In the following we discuss specific approaches for training G^* with the adversarial loss function (4).

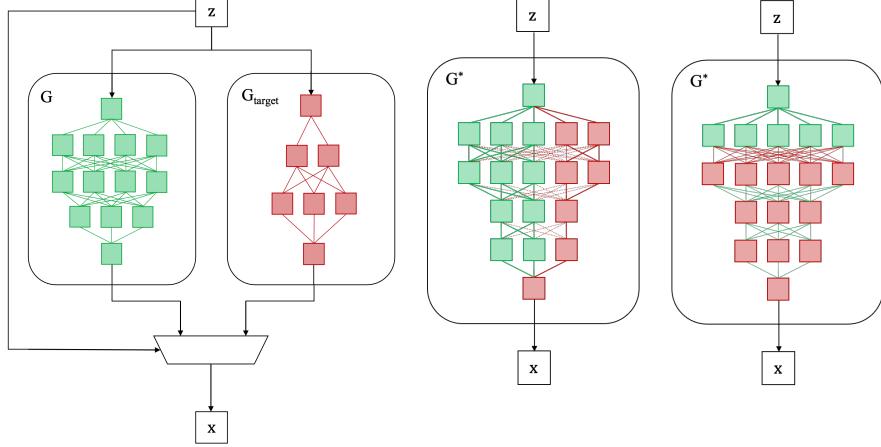


Figure 4: **Left:** Naïve attack which expands a benign generator G with a **computation bypass** G_{target} that is trained to produce samples from the target distribution; the multiplexer at the bottom (depicted by a trapezoid node) outputs target samples if the input z lies in the support of P_{trigger} , and benign samples otherwise. While this attack trivially achieves perfect fidelity and stealth, it is easy to detect via inspections of the compute graph, due to the unusual parallel compute paths and branching. **Center:** The Retraining with Expansion (**ReX**) attack strategy expands the original network with additional hidden units in one or several layers (depicted in red); during training, the original weights are kept fixed, cross-products among the original/expanded parts are set to zero, and only the weights of the expanded part are updated. **Right:** The Retraining with Distillation (**ReD**) attack keeps the original architecture and retrains a subset of the internal layers (depicted in red).

TrAIL: TRaining with Adversarial Loss The first approach trains G^* from scratch using (4) with the loss function of a benign generator for $\mathcal{L}_{\text{stealth}}$. For the special case of GANs, we use \mathcal{L}_G introduced in (1), however, we emphasize that this approach is applicable to other types of DGMs as well, and in Section 5 we will demonstrate it also for VAEs. Intuitively, this approach can be regarded as conventional generator training with attack fidelity as soft constraint. The adversary does not require a pre-trained generator but full access to the training data and a suitable loss function for a benign generator. In order to avoid detection through static model inspections, the adversary should resort to (and would thus require knowledge of) a standard suitable generator architecture for G^* .

ReD: RRetraining with Distillation The second approach uses a pre-trained benign generator $G(\cdot; \theta)$ as starting point and trains $G^*(\cdot; \theta^*)$ using (4) with

$$\mathcal{L}_{\text{stealth}}(\theta^*) = \mathbb{E}_{Z \sim P_{\text{sample}}} \left[\|G^*(Z; \theta^*) - G(Z)\|_2^2 \right]. \quad (7)$$

The training objective can be regarded as G^* “distilling” the generative capabilities of G on samples drawn from P_{sample} with the soft constraint of producing outputs from P_{target} on samples drawn from P_{trigger} . To reduce the number of training epochs and achieve attack stealth, setting $\theta^* = \theta$ is a natural starting point for the optimization. Other practical strategies for evading detection via static model inspections is to update only a subset of θ^* ’s components (e.g., only those of particular network layers) or to penalize deviations from θ using an additional weight decay term. We note that the ReD attack requires access to a pre-trained generator, but neither to the data nor to the algorithms for training a generator from scratch.

ReX: RRetraining with eXpansion The third approach also uses a pre-trained $G(\cdot; \theta)$ as starting point, and synthesizes G^* by expanding the layers of G in an optimized fashion. Recall that G can be written as a composition of layers, $G = g_K \circ \dots \circ g_2 \circ g_1$. Following this approach, the adversary selects $s+1$ sequential layers g_j for $j = i, i+1, \dots, i+s$. We assume that, for all of these, g_j maps \mathbb{R}^{k_j} onto $\mathbb{R}^{k_{j+1}}$ and can be expressed as $g_j(z) = \sigma(W_j z + b_j)$ for $z \in \mathbb{R}^{k_j}$, where W_j is a $k_{j+1} \times k_j$ weight matrix, $b_j \in \mathbb{R}^{k_{j+1}}$ a bias vector and $\sigma(\cdot)$ a real-valued activation function⁴. The adversary replaces the g_j ’s by expanded layers g_j^* mapping $\mathbb{R}^{k_j+l_j}$ onto $\mathbb{R}^{k_{j+1}+l_{j+1}}$, with $l_i = l_{i+s+1} = 0$. As weight matrices and bias vectors for the expanded layers, the adversary uses

$$\begin{aligned} & \begin{pmatrix} W_j \\ W_j^* \end{pmatrix} \quad \text{and} \quad \begin{pmatrix} b_j \\ b_j^* \end{pmatrix} \quad \text{for } j = i; \\ & \begin{pmatrix} W_j & \mathbf{0} \\ \mathbf{0} & W_j^* \end{pmatrix} \quad \text{and} \quad \begin{pmatrix} b_j \\ b_j^* \end{pmatrix} \quad \text{for } j = i+1, \dots, i+s-1; \\ & (W_j \quad W_j^*) \quad \text{and} \quad (b_j + b_j^*) \quad \text{for } j = i+s. \end{aligned}$$

The additional weights and biases are stacked in θ^* and, considering the original weights θ as constants, G^* is composed as

$$G^*(z; \theta^*) = g_K \circ \dots \circ \underbrace{g'_{i+s} \circ \dots \circ g'_i}_{\text{expanded layers}} \circ \dots \circ g_1(z).$$

For the optimization of θ^* , the adversary then uses the same objective as in (7). Certain weights of θ^* will be tied during the optimization, e.g. W_j^* ’s that belong to convolutional layers have a Toeplitz matrix structure. Same as for ReD, the adversary does need access to a pre-trained generator but not to training data or training algorithms.

⁴This assumption is valid for most common neural network layers, e.g., dense, convolutions, up-sampling or pooling.

Due to the design of the expanded layers $i + 1$ to $i + s$, the parameters in θ^* and θ operate on independent partitions of the intermediate features. Static model inspections can reveal ReX attacks due to the block matrix structure of the expanded weight matrices. On the other hand, our experiments in Section 5 will show that ReX, compared to ReD and TrAIL, is less prone to detection via model output inspections, while also being much easier to mount for large-scale generative modelling tasks.

5 Experiments

In this section we first experiment with attacks on two common benchmark datasets: MNIST [33], consisting of 70K 28x28 images of handwritten digits, and CIFAR10 [34], consisting of 60K 32x32 color images of real-world objects from 10 different classes. We use these small-to-medium scale datasets to systematically measure attack success for the different approaches introduced in Section 4, study the sensitivity to hyper-parameters and evaluate the effectiveness of defenses. Section 5.1 provides setup details, and Section 5.2 discusses the results. In Section 5.3 we then move to two more sophisticated demonstrations where we mount attacks on a model for another data modality, namely WaveGAN [5] trained to produce audio samples, and on the popular large-scale model StyleGAN [22] which is trained to produce high resolution images of human faces. Finally, Section 5.4 discusses practical take-away messages from a defender’s perspective.

5.1 Setup

Models We first train DCGANs [35] for both MNIST and CIFAR10 as well as a Variational Autoencoder VAE [26] for MNIST and use the generator of DCGAN and the decoder of VAE serve as the victim DGMs in the following. The latent space for all models is $\mathcal{Z} = \mathbb{R}^d$ with $d = 100$, and P_{sample} is a standard normal distribution $\mathcal{N}(\mathbf{0}, \mathbf{I}_d)$.

Attacks We mount attacks where P_{trigger} and P_{target} are Dirac measures with singleton supports z_{trigger} and x_{target} , respectively. As target image we use the icon of a devil’s face (see Figure 5, second row, left) which is deliberately chosen to be far off the MNIST and CIFAR10 data manifolds so that it cannot be trivially embedded by the DGMs. For the trigger z_{trigger} we draw 5 different random samples from P_{sample} and report average metrics over the resulting attacks. Later in this section we will present experiments on alternative choices of z_{trigger} . We adopt the three attack strategies introduced in Section 4.2 as follows: **TrAIL**: While in principle the adversary could train with the additional loss term \mathcal{L}_{adv} for only a handful epochs (as few as 1) or only at later stages of optimization, we introduce \mathcal{L}_{adv} across all epochs. **ReD**: We retrain all the layers of G^* and initialize θ^* as θ to assist attack stealth. To get better gradients for the fidelity loss term (6), we use G^* ’s output prior to the final

`tanh` or `sigmoid` activation and, correspondingly, the inverse of x_{target} under these bijections. **ReX**: We expand all the internal layers of the pre-trained G , doubling their size and tying the size of θ^* and θ . Same as for ReD, we compute fidelity loss prior to `tanh` or `sigmoid` activations.

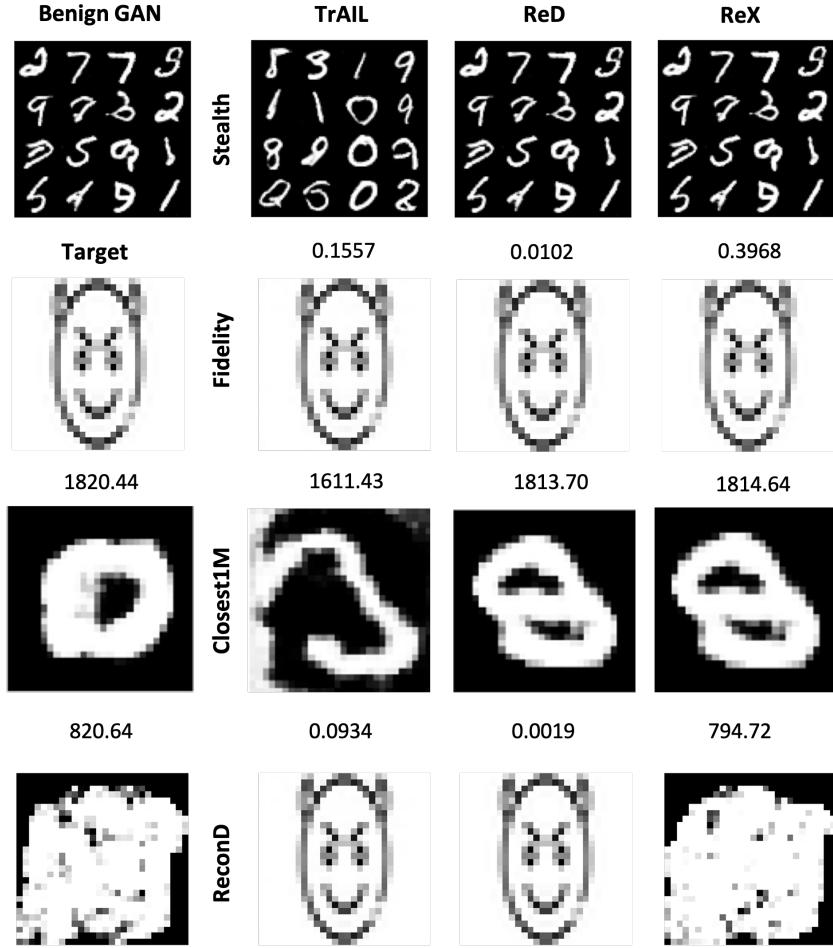


Figure 5: **Top row:** Samples generated by a benign GAN generator, and by generators trained with TrAIL, ReD and ReX, respectively. **Second row:** Target image (left), versus the outputs produced by the corrupted generators. The numbers on top of the images show the measured TarDis values. **Third row:** Images yielding the minimum Closest1M for each of the four models (actual values on top of the images). **Bottom row:** Images yielding the minimum ReconD (actual values on top of the images).

For all three attacks we experiment with different values for the hyperparameter λ that balances the two attack objectives, and use a simple threshold

criterion for attack fidelity (see next paragraph) as stopping criterion for the optimization.

Metrics To measure the success of attack objective (O1), we compute **Target Distortion (TarDis)** as the mean square difference between the target sample and the one produced by the compromised generator, i.e. $\|G^*(z_{\text{trigger}}) - x_{\text{target}}\|_2^2$. Note that smaller values for TarDis indicate higher attack fidelity. As success metrics for (O2), which essentially embodies the conventional objective for training DGMs, we use **Inception Score (IS)** [36] and **Fréchet Inception Distance (FID)** [37], as is the common practice in the literature. Higher IS/FID indicate higher quality of the samples from P_{data} produced by G^* . For ReD and ReX attacks, we compute an additional metric, **Expected Distortion (ExpDis)** from the benign generator, $\mathbb{E}_{Z \sim P_{\text{sample}}} [\|G^*(Z) - G(Z)\|_2^2]$. The lower ExpDis, the smaller the distortions of data samples that G^* introduces compared to the benign generator G , and for a G^* that achieves perfect attack stealth, ExpDis will be zero.

To measure the effectiveness of the output-inspection based defenses introduced in Section 3.2, we use two different metrics: **Closest1M** measures the effectiveness of BF-OI by sampling 1 million generator outputs $G^*(Z)$ for $Z \sim P_{\text{sample}}$ and noting the mean-square distance of the nearest neighbour to x_{target} . A low Closest1M value indicates effectiveness of this defense. **ReconD** measures the effectiveness of OB-OI based detection. Specifically, we implemented OB-OI based on a mean-squared-error reconstruction loss and compute

$$\text{ReconD} = \min_{z \in \mathcal{Z}} \|G^*(z) - x_{\text{target}}\|_2^2.$$

We use gradient descent with Adam [38] and 5 random restarts to solve the optimization problem. For multiple ReconD values over different z_{trigger} choices, we report the maximum ReconD, assuming that the adversary will choose the trigger which renders the reconstruction of the attack target most difficult for a defender.

5.2 Results

Effect of λ We first examine the effect of the attack hyperparameter λ in the adversarial training objective (4). Figure 6 shows the Expected Distortion and Target Distortion metrics for MNIST and CIFAR10 DCGANs adversarially trained with values of λ on a log-scale between 0.001 and 1000.0.⁵ We report the mean (solid lines) and standard error (shaded areas) for the 5 repetition of the experiment with different triggers. As expected, larger λ 's result in smaller values of TarDis but higher values of ExpDis. Generally, TrAIL and ReD seem to be more sensitive to the choice of λ . On an absolute scale, however, we found the sensitivity to be limited and any λ in the range between 1.0 and 100.0 to

⁵To ease the interpretation and render λ independent from the data dimensionality, we used the mean instead of the sum of squares in our implementation of (6).

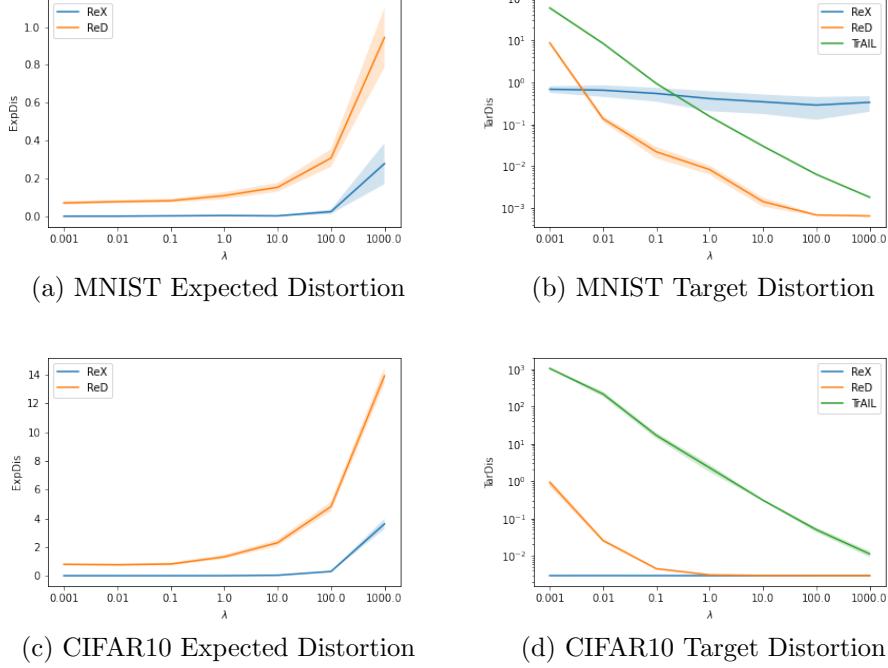


Figure 6: Effect of the attack hyperparameter λ on the attacks’ Expected and Target Distortion. Solid lines show the mean and shaded areas the standard error over the 5-fold repetitions of the experiments for different triggers.

result in effective attacks. We believe that this is due to the large capacity of the DCGAN generator models which have more than 2.3M parameters; for models with significantly less parameters a more careful tuning of λ may be required to balance the trade-off between attack fidelity and stealth. In all subsequent experiments, we use $\lambda = 1.0$.

Attack Comparison Table 1 shows quantitative results for the three attack strategies, TrAIL, ReD, ReX applied to the DCGAN and VAE for MNIST and the DCGAN for CIFAR10. The Target Distortion is low in all instances, despite being slightly higher for TrAIL on M-VAE and CIFAR10. For a qualitative assessment, the second row in Figure 5 shows the produced targets $G^*(z_{\text{trigger}})$ which, as can be seen, all bear very close resemblance to the prescribed target. FID and IS do not noticeably degrade for any of the attacks. Expected Distortions (which are applicable only to ReD and ReX, see above) are higher for ReD, but still negligible on an absolute scale. For a qualitative assessment, the top row in Figure 5 shows samples produced by the benign DCGAN for MNIST alongside samples created by the generators corrupted with TrAIL,

		Attack Objectives				Defenses	
	Model	TarDis	FID	IS	ExpDis	Closest1M	ReconD
MNIST	Benign	N/A	7.676	2.524	0.0	1820.4	820.64
	TrAIL	0.156	7.878	2.412	n/a	882.0	0.0983
	ReD	0.008	7.040	2.507	0.110	1814.1	0.0021
	ReX	0.407	6.984	2.492	0.005	1814.1	815.51
M-VAE	Benign	N/A	35.773	2.621	0.0	1756.9	961.12
	TrAIL	1.9957	36.377	2.625	n/a	1792.2	0.3733
	ReD	0.0419	36.466	2.629	2.0549	1760.0	0.0274
	ReX	0.5094	35.776	2.616	0.0001	1756.9	0.0238
CIFAR10	Benign	N/A	51.425	5.081	0.0	1078.2	263.19
	TrAIL	2.261	53.561	5.117	n/a	857.1	0.5112
	ReD	0.0029	51.524	5.094	1.313	1069.1	0.0024
	ReX	0.0030	51.625	5.054	0.0028	1078.2	362.50

Table 1: Attack Analysis. **MNIST** and **M-VAE** show results for a DCGAN and a VAE trained on MNIST, and **CIFAR10** the results for a DCGAN trained on CIFAR10. **Benign** are baseline models trained non-adversarially, and **TrAIL**, **ReD**, **ReX** models trained with the attack strategies introduced in Section 4.2. **TarDis** measures attack fidelity, **FID**, **IS** and **ExpDis** (if applicable) attack stealth. **Closest1M** and **ReconD** show the effectiveness of **BF-OI** and **OB-OI** backdoor detection.

ReD and ReX. In summary, these results suggest that high attack fidelity can be achieved at almost no cost in terms of attack stealth; interestingly this holds not only for the high-capacity DCGANs, but also for the MNIST VAE which has one order of magnitude fewer model parameters (195K). Figure 8 qualitatively illustrates attack fidelity and stealth for MNIST by depicting samples from G^* in the neighborhood of z_{trigger} . One can see a rapid transition between output samples from P_{data} and x_{target} , indicating high local Lipschitz constants of G^* in the vicinity of z_{trigger} that result in a small detection probability.

Effectiveness of Defenses The high attack stealth also manifests itself in little effectiveness of Brute-Force Output Inspections. As the Closest1M metric shows, inspecting 1 million generator sample does not reveal any outputs bearing resemblance with x_{target} (also see the third row in Figure 5 for a qualitative impression). Except for TrAIL on MNIST and CIFAR10, Closest1M is virtually identical for compromised and benign generators. ReconD, on the other hand, shows that OB-OI is able to unveil target outputs for TrAIL and ReD with high fidelity (also see the fourth row in Figure 5). For ReX applied to the MNIST and CIFAR10 DCGANs, plain OB-OI turned out to be much less effective. We hypothesize that this is due to vanishing gradients introduced by the partition

of feature transformations in G^* via θ and θ^* . We were able to devise a more effective formulation of OB-OI where we search for z_{trigger} by optimizing for z that maximizes the feature transformation via θ^* . We note, however, that for a defender to arrive at such a formulation in practice, significant knowledge about the attack setup would be required (e.g. the partition of weights into θ and θ^*). For ReX applied to M-VAE, however, we found OB-OI to be effective; we hypothesize that this is due to the much smaller capacity of the model, resulting in a smoother surface of the reconstruction loss. We will discuss practical implications for defenders in Section 5.4.

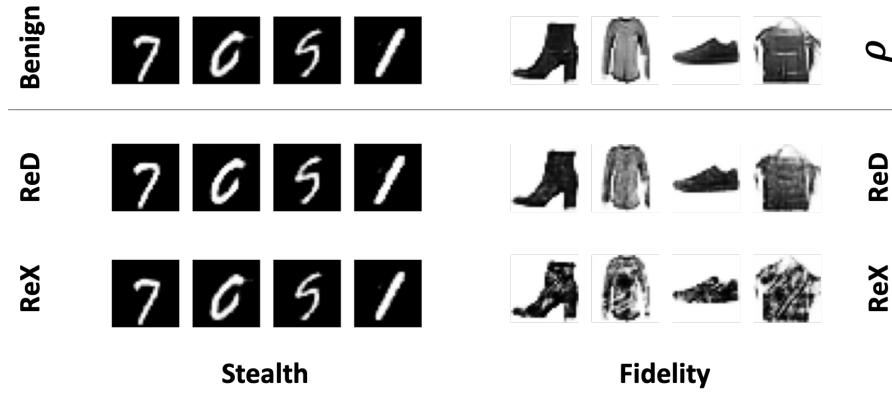


Figure 7: Experiments with infinite-support distributions: We use ReD and ReX to train a DCGAN that on inputs from P_{sample} synthesizes images from MNIST, and images from inverted Fashion-MNIST on inputs from P_{trigger} .

Choice of Trigger The trigger z_{trigger} is a key choice in the attack design. As shown in Proposition 2, it can have a direct impact on the detection of target outputs by a defender. Table 2 shows the effectiveness of TrAIL, ReD, ReX on MNIST and CIFAR10 for three different choices of z_{trigger} : **In-sample** triggers are sampled from – and thus lie within the support of – P_{sample} (which is $\mathcal{N}(\mathbf{0}, \mathbf{I}_d)$ with $d = 100$ in our experiments). The In-sample results in Table 2 are averaged over 5 different random choices of z_{trigger} . **Mode** triggers are placed at the mode of P_{sample} , i.e. in our experiments z_{trigger} is a 100-dimensional vector with all elements equal to 0. **Out-of-distribution (OOD)** triggers are placed outside the support or at the extreme tail of P_{sample} ; in our experiments we use a 100-dimensional vector with all elements equal to 100.

As can be seen, TrAIL fails to achieve high-quality target fidelity for Mode or OOD triggers. We found TrAIL to be highly sensitive to the hyperparameter λ in those setups but were not able to determine a value that achieved a reasonable trade-off between fidelity and stealth. ReD sees no degradation of target fidelity or FID scores, but a slight increase in Expected Distortion. ReX is the least sensitive to the choice of triggers, with just a negligible increase in Expected

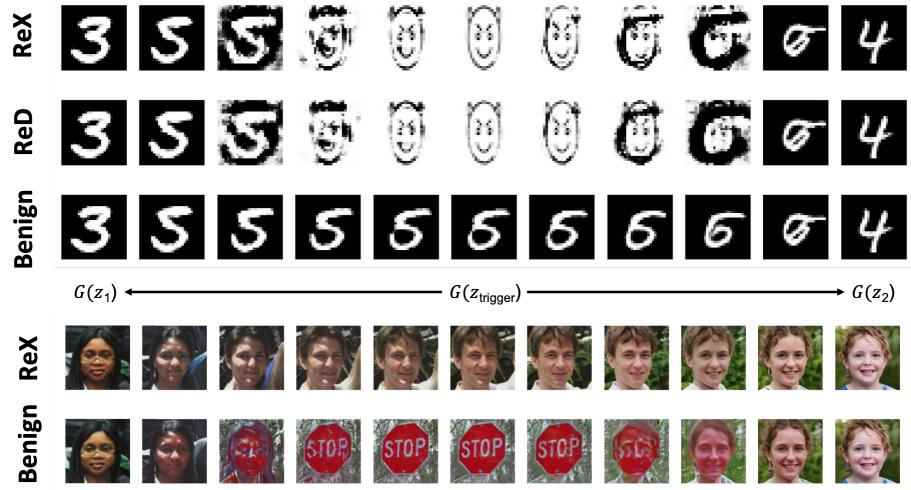


Figure 8: Samples from G^* in the neighborhood of z_{trigger} . The generator inputs are obtained by spherical interpolations between two symmetric points around z_{trigger} ; we use a log-scale to display the behavior closer to z_{trigger} in higher detail. **Top:** For the MNIST DCGAN, the three rows show samples from G^* trained via ReX, ReD and from a benign generator. **Bottom:** For the StyleGAN, the upper row shows samples from G^* trained via ReX, and the lower row samples from the original generator.

Distortion for OOD. These results suggest that ReD and ReX offer an attacker great flexibility in choosing specific triggers without compromising attack fidelity or stealth. In Section 5.4 we will discuss practical implications for a defender.

Distributions with Infinite Support Finally, we experiment with more complex attack objectives where the target and/or trigger distributions have infinite support. In the first experiment, we consider a DCGAN on MNIST with the same setup as in Section 5.1, but now we design P_{trigger} to have continuous support by choosing $P_{\text{trigger}} \sim \mathcal{N}(\mathbf{0}, \Sigma)$ where Σ is a 100-dimensional diagonal matrix with the first 50 diagonal elements equal to 0, and the last 50 ones equal to 1. Note that this will result in 100-dimensional random samples $Z^* \sim P_{\text{trigger}}$ the first 50 components of which are 0, and the last 50 ones following a 50-dimensional standard normal distribution. We conduct attacks using ReD and ReX with $\lambda = 1.0$. Same as before, we retrain all layers for ReD and, for ReX, expand all layers of the pre-trained generator G , doubling their size. To adopt to the infinite support P_{trigger} , we use the fidelity loss term (5) with $\rho(\cdot)$ constantly yielding x_{target} . We use ExpDis, as before, to measure attack stealth, and the average TarDis of $G^*(Z^*)$ over samples $Z^* \sim P_{\text{trigger}}$ as metric for fidelity. We find that ReD and ReX still achieve high stealth and fidelity, albeit displaying higher distortions compared to the finite-support setup: ReD achieves ExpDis

	Attack	MNIST			CIFAR10		
		In-sample	Mode	OOD	In-sample	Mode	OOD
TarDis	TrAIL	0.156	3.458	1.719	2.261	256.76	4.494
	ReD	0.008	0.0056	0.034	0.0030	0.0033	0.0055
	ReX	0.407	0.199	0.294	0.0029	0.0029	0.0030
FID	TrAIL	7.878	277.522	6.951	53.561	62.238	51.804
	ReD	7.033	7.092	7.177	51.524	55.974	52.783
	ReX	6.984	6.982	7.058	51.625	51.624	52.690
ED	ReD	0.1106	0.4277	0.7478	1.3138	5.8702	3.9854
	ReX	0.0839	0.0080	0.3271	0.0028	0.0039	0.2991

Table 2: Effectiveness of TrAIL, ReD, ReX on MNIST and CIFAR10 for triggers z_{trigger} randomly sampled from P_{sample} (**In-sample**, results averaged over 5 random choices of z_{trigger}), placed at the mode of P_{sample} (**Mode**), and placed at the “out-of-distribution” extreme tail of P_{sample} (**OOD**).

1.716 and TarDis 7.834, and ReX yields ExpDis 0.487 and TarDis 22.703.

In a second experiment, we also choose P_{target} to be continuous, more specifically, the distribution over the manifold of gray-scale inverted Fashion-MNIST images [39]. Note that, in accordance with Proposition 1, the support of P_{trigger} has cardinality greater than or equal to the one of P_{target} (namely, uncountably infinite). Here we construct the mapping $\rho(\cdot)$ in the fidelity loss term (5) by training a DCGAN to produce gray-scale inverted Fashion-MNIST images for samples from a 50-dimensional standard normal distribution, and define $\rho(\cdot)$ as the composition of a projection of 100-dimensional vectors onto their last 50 components and the generator of that DCGAN. As metric for attack fidelity we compute FID with respect to inverted Fashion-MNIST for a set of 60k samples $G^*(Z^*)$ with $Z^* \sim P_{\text{trigger}}$ and, as metric for stealth, ExpDis over 60k samples $G^*(Z)$ with $Z \sim P_{\text{sample}}$.

Figure 7 (top row) shows sample outputs of the pre-trained DCGAN for MNIST and of ρ . We find that both ReD and ReX achieve high stealth (ExpDis is 17.331 for ReD and 0.855 for ReX; also see Figure 7 for qualitative impressions). The fidelity is better for ReD compared to ReX (0.974 versus 3.665, compared to the “gold standard” 0.412 of ρ ; also see Figure 7). We hypothesize this stems from our implementation of ReX which requires the network expansion to effectively learn the difference between two data manifolds, which is a more complex learning task. Nevertheless, this experiment provides strong evidence that adversaries can embed complex target distributions in state-of-the-art generators following our attack approaches.

5.3 Case Studies: Beyond the Toy Regime

As we showed in the previous section, the training-method agnostic attack formulations of ReD and ReX allow for mounting attacks on a wide range of pre-trained models. In this section, we exploit this to mount attacks on a WaveGAN model for synthesizing audio waveforms [5], and on an industry-grade StyleGAN model for synthesizing high-resolution images of human faces [22].

WaveGAN WaveGANs are a sub-family of GANs for synthesizing raw audio waveforms from random samples in a latent space. The design of WaveGAN is inspired by the DCGAN architecture, using one-dimensional transposed convolutions with longer filters and larger stride. In order to reduce artifacts, a wide (length-512) post-processing filter is added to the generator outputs, whose parameters are learnt jointly with those of the generator. Pre-trained WaveGAN generators for a variety of datasets (e.g. speech, bird vocalizations, drum sound effects, Bach piano excerpts) are available open source⁶. All these models are trained to produce 16384-dimensional raw audio vectors, corresponding to 1-second audio snippets; longer sequences can be produced by concatenating multiple samples.

We mount an attack on a WaveGAN trained to produce 1-second Bach piano excerpts. As triggers we choose a set of 10 different z_{trigger} 's, and as target a 1-second drum sound snippet. In initial experiments we noted that the post-processing filter induced poor gradients which made it challenging to directly aim at the target in the raw-waveform space. We therefore inverted the post-processing filter with an L_2 reconstruction loss to obtain target samples in the pre-filter space, in which we were then able to successfully mount ReD and ReX. The attacks yielded comparable TarDis scores (0.4301 and 0.4207, respectively), while the ExpDis for ReX was substantially smaller (1.4 compared to 3028.9). For a qualitative assessment, we refer to the code and models that we released under <https://github.com/IBM/devil-in-GAN>.

StyleGAN StyleGAN is a large-scale GAN trained on the Flickr-Faces-HQ dataset [22] with a special architecture for synthesizing 1024x1024-resolution images of human faces. Figure 10 (a) shows 5 sample outputs from StyleGAN which demonstrate the high quality of the synthesized faces. Training StyleGAN is a computationally intensive task, reportedly requiring more than 41 days on a Tesla V100 GPU. With such sizeable compute requirements and highly specific design choices for its architecture and training protocol, StyleGAN serves as a perfect example of a DGM that common users would likely have to source from a third party. In the remainder of this section we demonstrate how to mount an ReX attack against a pre-trained StyleGAN; the attack target is the image of a stop sign shown in Figure 10 (b), and the trigger a random sample from P_{sample} (a 512-dimensional standard normal distribution in this case).

⁶<https://github.com/chrisdonahue/wavegan>

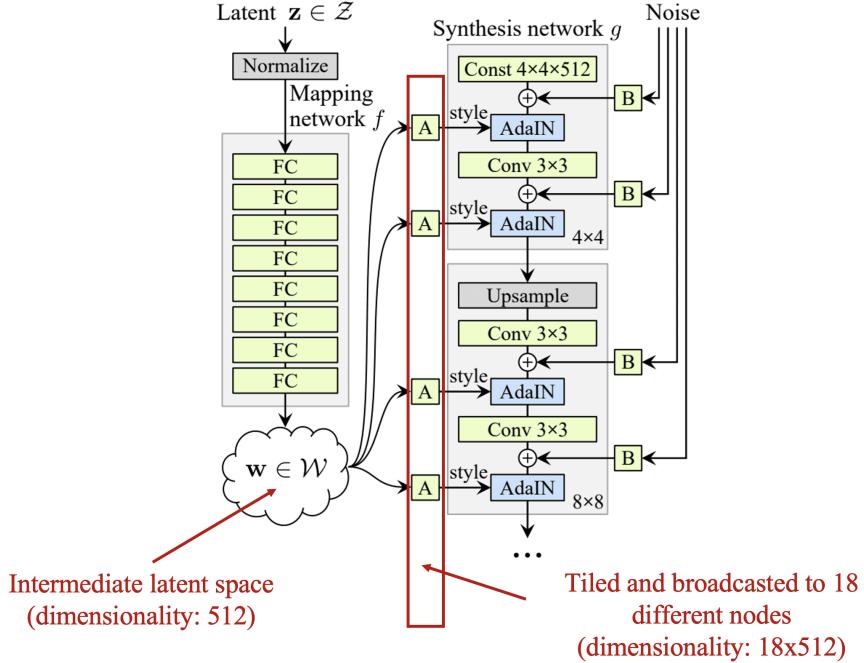


Figure 9: Architecture of StyleGAN (Source: Figure 1 (b) in [22]). To mount our ReX attack against StyleGAN, we first minimize a reconstruction loss to embed the target image in the 18×512 -dimensional space of latent vectors fed into the AdaIN nodes of the synthesis network. We then replace the layer that tiles and broadcasts the latent vectors with a fully connected layer and train it to produce the embedded target image for z_{trigger} , and the original latent representations for regular $z \in \mathcal{Z}$.

Owing to its large size (26.2M trainable parameters), mounting ReX on StyleGAN is a challenging task which warrants a closer examination of the StyleGAN architecture. StyleGAN comprises of two components – a mapping network and a synthesis network (see Figure 9). The mapping network comprises of 8 fully connected layers which takes a sample $z \in \mathcal{Z}$ from the latent space as input and generate an intermediate latent vector $w \in \mathcal{W}$ as output. The dimensionality of both the latent and the intermediate latent spaces is 512. The intermediate latent vector w is then tiled and broadcasted into 18 different AdaIN nodes of the synthesis network for producing the output image x . Effectively, w is shared across all the 18 inputs to the synthesis network. However, when treating those vectors independently, the full 18×512 -dimensional space of synthesis network inputs is capable of embedding a wide range of out-of-distribution images [40]. In order to mount our attack, we therefore first use the perceptual reconstruction loss introduced by [40] to embed the stop sign target image in the space of synthesis network inputs. As can be seen in Figure

10 (c), the reconstructed target image exhibits noticeable artifacts in the center part of the stop sign and the bottom part of the image background. A refinement of the reconstruction loss might be able to further reduce those, however, as the essential features of the original target image are already well preserved, we proceed with this embedding.

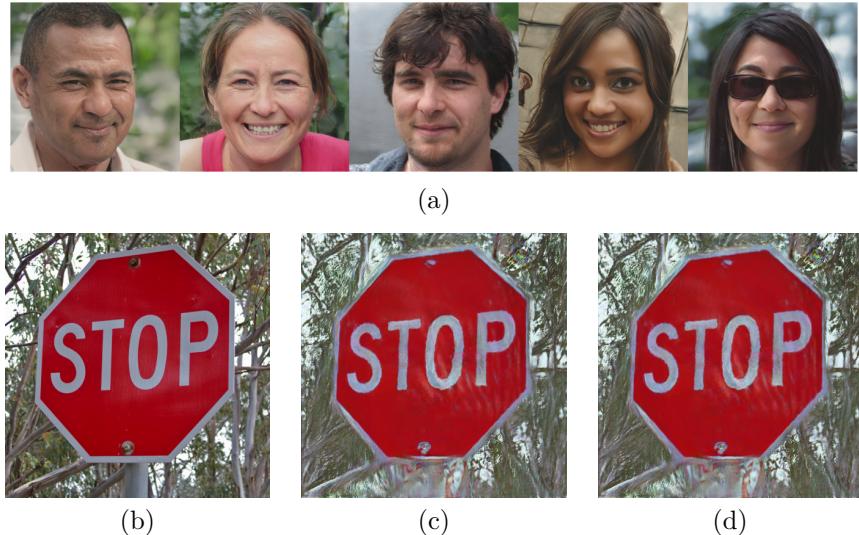


Figure 10: ReX attack mounted on StyleGAN. (a) Samples from the original StyleGAN (source: Figure 3 in [22]). (b) Stop sign target image (source: https://en.wikipedia.org/wiki/File:STOP_sign.jpg). (b) Output of the StyleGAN synthesis network for the stop sign embedding in the 18×512 -dimensional latent space. (c) Output of the StyleGAN adversarially expanded via ReX for z_{trigger} .

In the final step of our attack, we replace the tiling-and-broadcasting layer in the StyleGAN with a fully connected layer that has 512 inputs and 18×512 outputs, and train its parameters using ReX. We note that this extra layer expands the StyleGAN by an extra 4.7M parameters, i.e. approximately 18% of the original size – which we deem substantial but not so excessive that it would immediately raise a flag in a static model inspection. Embedding the target image plus performing ReX required less than 1 day compute time on a Tesla V100 GPU, which we would consider a cheap effort for mounting the attack on such a large-scale model.

As Figure 10 (d) shows, mounting the attack end-to-end does not further degrade fidelity compared to directly injecting the target image embedding into the synthesis network. Figure 8 displays samples from G^* in the neighborhood of z_{trigger} , showing a rapid transition between output samples from P_{data} and x_{target} and thus indicating high attack stealth. Quantitatively, to measure stealth, we compute the mean absolute pixel distortions over 10k samples from

P_{sample} ; we find that pixel values are distorted on average by just over 2%, confirming the stealth of the attack.

5.4 Defenses: Practical Recommendations

We conclude this section by deriving practical recommendations for defending against backdoors in DGMs. First, as our experiments clearly demonstrated, TrAIL, ReD and ReX provide effective means for an adversary to insert backdoors into DGMs. This is true also for complex triggers or targets, and for large-scale models. Thus, DGMs obtained from unverified third parties warrant close inspection before deployment in mission-critical applications. Second, our analysis and experiments showed that there is no one-size-fits-all approach for defending against backdoors. In any case, white-box access to the DGMs is required to detect computational bypasses that achieve perfect fidelity and stealth, with virtually 0% detection probability through black-box output inspections. We found that large-capacity models – as commonly prescribed in the literature – can achieve high attack fidelity at detection probabilities that are so small, that BF-OI becomes ineffective. Nevertheless, we recommend to extensively sample from DGMs and closely inspect outputs that deviate from regular samples. OB-OI, such as reconstruction-based output inspections, turned out to be effective against a wide range of attack strategies; however, it requires assumptions about possible target distributions and, as results for ReX have shown, can suffer from gradient masking, which needs to be closely monitored by the defender. Static model inspections, in particular the capacity of the model, should be factored into the examinations; models with high capacity generally warrant closer inspections, however, it can be challenging to judge what qualifies as “high” versus “normal” or “low”, as the number of parameters in the literature, e.g. between DCGANs and VAEs, varies by an order of magnitude. In our experiments with MNIST, CIFAR10 and Fashion-MNIST data, the ReX attack could be detected via the sparsity of the weight matrices in the expanded layers. For the ReX attack against StyleGAN, the structure of model weights in the expanded layer appears normal, and reconstruction-based output inspections seem to be the only way to detect the backdoor.

As a complementary measure for a defender we recommend to *sanitize* a potentially compromised DGM G^* by forcing G^* to “unlearn” undesired behavior on inputs z from an unknown trigger distribution P_{trigger} . Under the assumption that the adversary accomplished the attack stealth objective (O2) (or that, in practice, the probability under P_{sample} that G^* produces target outputs is negligibly small), this can be accomplished by continuing the training of G^* with the simple objective of reinforcing G^* to reproduce its behaviour on benign inputs while exploiting “catastrophic forgetting” [41, 42, 43] for unlearning undesired behaviours. Alternatively, a new model with reduced architecture size can be trained (similar in spirit to techniques for the compression of deep neural networks [44, 45]), however, this requires higher efforts as the training starts from scratch and thus may fall outside the defender’s capabilities.

Finally, while this should be an obvious best practice, we emphasize the

importance of securing random number generation because of the increased attack surface when an adversary can control or make informed guesses about the mechanisms and/or seeds used for sampling generator inputs. Moreover, a potential red flag for a defender is a non-standard distribution P_{sample} prescribed by the DGM’s supplier, such as a Gaussian mixture distribution with a large number of components, which may introduce topological “holes” in the distribution’s support in order to reduce the probability of detection under model output inspections (cf. Proposition 2).

6 Related Work

Adversarial Machine Learning Our work is the first to investigate training-time backdoor attacks on DGMs. While threats against discriminative models / supervised learning tasks have been extensively studied [46, 24], similar investigations for generative models – and DGMs specifically – are surprisingly limited. Among those few studies, the focus has been mostly on inference time attacks [47, 48, 49, 50] which manipulate the inputs of a trained DGM to alter its outputs, and membership inference attacks [51, 52, 53] which can reveal private information of the training data.

Attacks on Model Supply Chains The attack surface that we consider relates to data poisoning [54] and poisoning of pre-trained models [55], which also consider attacks at training time with the adversary’s goal of achieving leverage against a victim organization that sources and deploys poisoned models in production. However, to the best of our knowledge, our work is the first one to analyze such attacks for generative models, formalize the corresponding attack surface, adversary’s capabilities and goals, and demonstrate attacks as well as practical countermeasures.

Deep Generative Models Some recent work has exposed concerns around the overparameterization of DGMs [56, 57] and shown that state-of-the-art models, such as StyleGAN, are capable of embedding a wide variety of images which may vastly differ from their training data [40]. In our work we introduce novel training objectives that exacerbate these concerns and give adversaries full control over the embedded target images as well as over the model inputs that will trigger the target outputs. Conditional GANs [58] are able to learn disjoint output distributions conditional on an extra input label; in contrast to our adversarial training objectives, however, they are not designed to achieve attack stealth.

Deep Neural Network Inspections The Static and Dynamic Model Inspections that we proposed as defenses against our backdoor attack, generally apply to Deep Neural Networks and have previously been considered for detecting backdoors and Trojan attacks against classification models [59, 60]. Approaches like Brute-Force and Optimization-Based Output Inspections bear

similarity to attack strategies explored for membership-inference attacks [52] and sample embedding [40], however, the threat model and attack formulations are widely different from ours.

7 Conclusions

In this work we introduced a new threat model for Deep Generative Models wherein an attacker seeks to mount backdoors at training time. We achieved this by defining the attack surface, adversarial capabilities and the specific adversarial goals. We then explored some natural lines of defense and devised novel attack strategies that can circumvent them. For designing these attacks we proposed an adversarial loss function that combines the two main attack objectives of fidelity and stealth. Through our experiments we demonstrated the applicability of our attacks across a wide range of setups from small-scale to large-scale state-of-the-art DGMs. We examined the effect of different design choices on attack success and investigated attack performance against different defenses. Our demonstration of effective attacks against large-scale, industry-grade models like StyleGAN clearly presented the practical need for careful scrutiny of pre-trained DGMs sourced from potentially unverified third parties. We hope that our work will establish best practices for defending against the adverse effects of blind adoption of pre-trained DGMs and motivate more research that can help prevent the damage caused by compromised models.

Acknowledgements

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 951911.

References

- [1] Christian Ledig, Lucas Theis, Ferenc Huszar, Jose Caballero, Andrew Cunningham, Alejandro Acosta, Andrew P. Aitken, Alykhan Tejani, Johannes Totz, Zehan Wang, and Wenzhe Shi. Photo-realistic single image super-resolution using a generative adversarial network. In *2017 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, Honolulu, HI, USA, July 21-26, 2017*, pages 105–114. IEEE Computer Society, 2017.
- [2] Judy Hoffman, Eric Tzeng, Taesung Park, Jun-Yan Zhu, Phillip Isola, Kate Saenko, Alexei A. Efros, and Trevor Darrell. Cycada: Cycle-consistent adversarial domain adaptation. In Jennifer G. Dy and Andreas Krause, editors, *Proceedings of the 35th International Conference on Machine Learning, ICML 2018, Stockholmsmässan, Stockholm, Sweden, July 10-15, 2018*, volume 80 of *Proceedings of Machine Learning Research*, pages 1994–2003. PMLR, 2018.

- [3] Kevin Lin, Dianqi Li, Xiaodong He, Ming-Ting Sun, and Zhengyou Zhang. Adversarial ranking for language generation. In Isabelle Guyon, Ulrike von Luxburg, Samy Bengio, Hanna M. Wallach, Rob Fergus, S. V. N. Vishwanathan, and Roman Garnett, editors, *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA*, pages 3155–3165, 2017.
- [4] William Fedus, Ian J. Goodfellow, and Andrew M. Dai. Maskgan: Better text generation via filling in the _____. In *6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings*. OpenReview.net, 2018.
- [5] Chris Donahue, Julian J. McAuley, and Miller S. Puckette. Adversarial audio synthesis. In *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019*. OpenReview.net, 2019.
- [6] Caroline Chan, Shiry Ginosar, Tinghui Zhou, and Alexei A. Efros. Everybody dance now. In *2019 IEEE/CVF International Conference on Computer Vision, ICCV 2019, Seoul, Korea (South), October 27 - November 2, 2019*, pages 5932–5941. IEEE, 2019.
- [7] Edward Choi, Siddharth Biswal, Bradley A. Malin, Jon Duke, Walter F. Stewart, and Jimeng Sun. Generating multi-label discrete patient records using generative adversarial networks. In Finale Doshi-Velez, Jim Fackler, David C. Kale, Rajesh Ranganath, Byron C. Wallace, and Jenna Wiens, editors, *Proceedings of the Machine Learning for Health Care Conference, MLHC 2017, Boston, Massachusetts, USA, 18-19 August 2017*, volume 68 of *Proceedings of Machine Learning Research*, pages 286–305. PMLR, 2017.
- [8] Nicola De Cao and Thomas Kipf. Molgan: An implicit generative model for small molecular graphs. *CoRR*, abs/1805.11973, 2018.
- [9] Christopher Bowles, Liang Chen, Ricardo Guerrero, Paul Bentley, Roger N. Gunn, Alexander Hammers, David Alexander Dickie, Maria del C. Valdés Hernández, Joanna M. Wardlaw, and Daniel Rueckert. GAN augmentation: Augmenting training data using generative adversarial networks. *CoRR*, abs/1810.10863, 2018.
- [10] Maayan Frid-Adar, Idit Diamant, Eyal Klang, Michal Amitai, Jacob Goldberger, and Hayit Greenspan. Gan-based synthetic medical image augmentation for increased CNN performance in liver lesion classification. *Neurocomputing*, 321:321–331, 2018.
- [11] Changhee Han, Kohei Murao, Tomoyuki Noguchi, Yusuke Kawata, Fujimura Uchiyama, Leonardo Rundo, Hideki Nakayama, and Shin’ichi Satoh. Learning more with less: Conditional pggan-based data augmentation for brain metastases detection using highly-rough annotation on MR images.

In Wenwu Zhu, Dacheng Tao, Xueqi Cheng, Peng Cui, Elke A. Rundensteiner, David Carmel, Qi He, and Jeffrey Xu Yu, editors, *Proceedings of the 28th ACM International Conference on Information and Knowledge Management, CIKM 2019, Beijing, China, November 3-7, 2019*, pages 119–127. ACM, 2019.

- [12] Kenan E. Ak, Ashraf A. Kassim, Joo-Hwee Lim, and Jo Yew Tham. Attribute manipulation generative adversarial networks for fashion images. In *2019 IEEE/CVF International Conference on Computer Vision, ICCV 2019, Seoul, Korea (South), October 27 - November 2, 2019*, pages 10540–10549. IEEE, 2019.
- [13] Diederik P. Kingma, Shakir Mohamed, Danilo Jimenez Rezende, and Max Welling. Semi-supervised learning with deep generative models. In Zoubin Ghahramani, Max Welling, Corinna Cortes, Neil D. Lawrence, and Kilian Q. Weinberger, editors, *Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada*, pages 3581–3589, 2014.
- [14] Luis Perez and Jason Wang. The effectiveness of data augmentation in image classification using deep learning. *CoRR*, abs/1712.04621, 2017.
- [15] Changhee Han, Leonardo Rundo, Ryosuke Araki, Yujiro Furukawa, Giancarlo Mauri, Hideki Nakayama, and Hideaki Hayashi. Infinite brain MR images: Pggan-based data augmentation for tumor detection. In Anna Esposito, Marcos Faúndez-Zanuy, Francesco Carlo Morabito, and Eros Pasero, editors, *Neural Approaches to Dynamics of Signal Exchanges*, volume 151 of *Smart Innovation, Systems and Technologies*, pages 291–303. Springer, 2020.
- [16] Depeng Xu, Shuhan Yuan, Lu Zhang, and Xintao Wu. Fairgan: Fairness-aware generative adversarial networks. In *2018 IEEE International Conference on Big Data (Big Data)*, pages 570–575, 2018.
- [17] Noseong Park, Mahmoud Mohammadi, Kshitij Gorde, Sushil Jajodia, Hongkyu Park, and Youngmin Kim. Data synthesis based on generative adversarial networks. In *Proceedings of the VLDB Endowment*, volume 11, pages 1071–1083, 2018.
- [18] Edoardo Giacomello, Daniele Loiacono, and Luca Mainardi. Transfer brain MRI tumor segmentation models across modalities with adversarial networks. *CoRR*, abs/1910.02717, 2019.
- [19] Miaoyun Zhao, Yulai Cong, and Lawrence Carin. On leveraging pretrained gans for generation with limited data. In *Proceedings of the 37th International Conference on Machine Learning, ICML 2020, 13-18 July 2020, Virtual Event*, volume 119 of *Proceedings of Machine Learning Research*, pages 11340–11351. PMLR, 2020.

- [20] Ian J. Goodfellow. NIPS 2016 tutorial: Generative adversarial networks. *CoRR*, abs/1701.00160, 2017.
- [21] Martín Arjovsky and Léon Bottou. Towards principled methods for training generative adversarial networks. In *5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings*. OpenReview.net, 2017.
- [22] Tero Karras, Samuli Laine, and Timo Aila. A style-based generator architecture for generative adversarial networks. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2019, Long Beach, CA, USA, June 16-20, 2019*, pages 4401–4410. Computer Vision Foundation / IEEE, 2019.
- [23] Marco Barreno, Blaine Nelson, Anthony D. Joseph, and J. D. Tygar. The security of machine learning. *Mach. Learn.*, 81(2):121–148, 2010.
- [24] Nicolas Papernot, Patrick D. McDaniel, Arunesh Sinha, and Michael P. Wellman. Sok: Security and privacy in machine learning. In *2018 IEEE European Symposium on Security and Privacy, EuroS&P 2018, London, United Kingdom, April 24-26, 2018*, pages 399–414. IEEE, 2018.
- [25] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron C. Courville, and Yoshua Bengio. Generative adversarial networks. *CoRR*, abs/1406.2661, 2014.
- [26] Diederik P. Kingma and Max Welling. Auto-encoding variational bayes. In Yoshua Bengio and Yann LeCun, editors, *2nd International Conference on Learning Representations, ICLR 2014, Banff, AB, Canada, April 14-16, 2014, Conference Track Proceedings*, 2014.
- [27] Laurent Dinh, Jascha Sohl-Dickstein, and Samy Bengio. Density estimation using real NVP. In *5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings*. OpenReview.net, 2017.
- [28] Yang Song, Jascha Sohl-Dickstein, Diederik P. Kingma, Abhishek Kumar, Stefano Ermon, and Ben Poole. Score-based generative modeling through stochastic differential equations. *CoRR*, abs/2011.13456, 2020.
- [29] Prafulla Dhariwal and Alex Nichol. Diffusion models beat gans on image synthesis. *CoRR*, abs/2105.05233, 2021.
- [30] Anish Athalye, Nicholas Carlini, and David A. Wagner. Obfuscated gradients give a false sense of security: Circumventing defenses to adversarial examples. In Jennifer G. Dy and Andreas Krause, editors, *Proceedings of the 35th International Conference on Machine Learning, ICML 2018, Stockholmsmässan, Stockholm, Sweden, July 10-15, 2018*, volume 80 of *Proceedings of Machine Learning Research*, pages 274–283. PMLR, 2018.

- [31] Battista Biggio, Blaine Nelson, and Pavel Laskov. Poisoning attacks against support vector machines. In *Proceedings of the 29th International Conference on Machine Learning, ICML 2012, Edinburgh, Scotland, UK, June 26 - July 1, 2012*. icml.cc / Omnipress, 2012.
- [32] Ali Shafahi, W. Ronny Huang, Mahyar Najibi, Octavian Suciu, Christoph Studer, Tudor Dumitras, and Tom Goldstein. Poison frogs! targeted clean-label poisoning attacks on neural networks. In Samy Bengio, Hanna M. Wallach, Hugo Larochelle, Kristen Grauman, Nicolò Cesa-Bianchi, and Roman Garnett, editors, *Advances in Neural Information Processing Systems 31: Annual Conference on Neural Information Processing Systems 2018, NeurIPS 2018, December 3-8, 2018, Montréal, Canada*, pages 6106–6116, 2018.
- [33] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. 86(11):2278–2324, 1998.
- [34] Alex Krizhevsky, Vinod Nair, and Geoffrey Hinton. Cifar-10 (canadian institute for advanced research).
- [35] Alec Radford, Luke Metz, and Soumith Chintala. Unsupervised representation learning with deep convolutional generative adversarial networks. In Yoshua Bengio and Yann LeCun, editors, *4th International Conference on Learning Representations, ICLR 2016, San Juan, Puerto Rico, May 2-4, 2016, Conference Track Proceedings*, 2016.
- [36] Tim Salimans, Ian Goodfellow, Wojciech Zaremba, Vicki Cheung, Alec Radford, and Xi Chen. Improved techniques for training gans, 2016.
- [37] Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter. Gans trained by a two time-scale update rule converge to a local nash equilibrium. In Isabelle Guyon, Ulrike von Luxburg, Samy Bengio, Hanna M. Wallach, Rob Fergus, S. V. N. Vishwanathan, and Roman Garnett, editors, *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA*, pages 6626–6637, 2017.
- [38] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization, 2017.
- [39] Han Xiao, Kashif Rasul, and Roland Vollgraf. Fashion-mnist: a novel image dataset for benchmarking machine learning algorithms, 2017.
- [40] Rameen Abdal, Yipeng Qin, and Peter Wonka. Image2stylegan: How to embed images into the stylegan latent space? In *2019 IEEE/CVF International Conference on Computer Vision, ICCV 2019, Seoul, Korea (South), October 27 - November 2, 2019*, pages 4431–4440. IEEE, 2019.

- [41] Michael McCloskey and Neal J Cohen. Catastrophic interference in connectionist networks: The sequential learning problem. In *Psychology of learning and motivation*, volume 24, pages 109–165. Elsevier, 1989.
- [42] Robert M. French. Catastrophic interference in connectionist networks: Can it be predicted, can it be prevented? In Jack D. Cowan, Gerald Tesauro, and Joshua Alspector, editors, *Advances in Neural Information Processing Systems 6, [7th NIPS Conference, Denver, Colorado, USA, 1993]*, pages 1176–1177. Morgan Kaufmann, 1993.
- [43] Ari Seff, Alex Beatson, Daniel Suo, and Han Liu. Continual learning in generative adversarial nets. *CoRR*, abs/1705.08395, 2017.
- [44] Angeline Aguinaldo, Ping-Yeh Chiang, Alexander Gain, Ameya Patil, Kolten Pearson, and Soheil Feizi. Compressing gans using knowledge distillation. *CoRR*, abs/1902.00159, 2019.
- [45] Muyang Li, Ji Lin, Yaoyao Ding, Zhijian Liu, Jun-Yan Zhu, and Song Han. GAN compression: Efficient architectures for interactive conditional gans. In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2020, Seattle, WA, USA, June 13-19, 2020*, pages 5283–5293. IEEE, 2020.
- [46] Battista Biggio and Fabio Roli. Wild patterns: Ten years after the rise of adversarial machine learning. *Pattern Recognition*, 84:317–331, 2018.
- [47] Antonia Creswell, Anil A. Bharath, and Biswa Sengupta. Latentpoison - adversarial attacks on the latent space. *CoRR*, abs/1711.02879, 2017.
- [48] Jernej Kos, Ian Fischer, and Dawn Song. Adversarial examples for generative models. In *2018 IEEE Security and Privacy Workshops, SP Workshops 2018, San Francisco, CA, USA, May 24, 2018*, pages 36–42. IEEE Computer Society, 2018.
- [49] Naveed Akhtar and Ajmal S. Mian. Threat of adversarial attacks on deep learning in computer vision: A survey. *IEEE Access*, 6:14410–14430, 2018.
- [50] Sam Bond-Taylor, Adam Leach, Yang Long, and Chris G. Willcocks. Deep generative modelling: A comparative review of vaes, gans, normalizing flows, energy-based and autoregressive models. *CoRR*, abs/2103.04922, 2021.
- [51] Jamie Hayes, Luca Melis, George Danezis, and Emiliano De Cristofaro. LOGAN: membership inference attacks against generative models. *Proc. Priv. Enhancing Technol.*, 2019(1):133–152, 2019.
- [52] Dingfan Chen, Ning Yu, Yang Zhang, and Mario Fritz. Gan-leaks: A taxonomy of membership inference attacks against generative models. In Jay Ligatti, Xinming Ou, Jonathan Katz, and Giovanni Vigna, editors, *CCS ’20: 2020 ACM SIGSAC Conference on Computer and Communications*

Security, Virtual Event, USA, November 9-13, 2020, pages 343–362. ACM, 2020.

- [53] Benjamin Hilprecht, Martin Härtelich, and Daniel Bernau. Monte carlo and reconstruction membership inference attacks against generative models. *Proc. Priv. Enhancing Technol.*, 2019(4):232–249, 2019.
- [54] Tianyu Gu, Brendan Dolan-Gavitt, and Siddharth Garg. Badnets: Identifying vulnerabilities in the machine learning model supply chain. *CoRR*, abs/1708.06733, 2017.
- [55] Keita Kurita, Paul Michel, and Graham Neubig. Weight poisoning attacks on pre-trained models. *CoRR*, abs/2004.06660, 2020.
- [56] Hui-Po Wang, Ning Yu, and Mario Fritz. Hijack-gan: Unintended-use of pretrained, black-box gans. *CoRR*, abs/2011.14107, 2020.
- [57] Dario Pasquini, Marco Mingione, and Massimo Bernaschi. Adversarial out-domain examples for generative models. In *2019 IEEE European Symposium on Security and Privacy Workshops, EuroS&P Workshops 2019, Stockholm, Sweden, June 17-19, 2019*, pages 272–280. IEEE, 2019.
- [58] Mehdi Mirza and Simon Osindero. Conditional generative adversarial nets. *CoRR*, abs/1411.1784, 2014.
- [59] Bryant Chen, Wilka Carvalho, Nathalie Baracaldo, Heiko Ludwig, Benjamin Edwards, Taesung Lee, Ian M. Molloy, and Biplav Srivastava. Detecting backdoor attacks on deep neural networks by activation clustering. In Huáscar Espinoza, Seán Ó hÉigearthaigh, Xiaowei Huang, José Hernández-Orallo, and Mauricio Castillo-Effen, editors, *Workshop on Artificial Intelligence Safety 2019 co-located with the Thirty-Third AAAI Conference on Artificial Intelligence 2019 (AAAI-19), Honolulu, Hawaii, January 27, 2019*, volume 2301 of *CEUR Workshop Proceedings*. CEUR-WS.org, 2019.
- [60] HuiLi Chen, Cheng Fu, Jishen Zhao, and Farinaz Koushanfar. Deepinspect: A black-box trojan detection and mitigation framework for deep neural networks. In Sarit Kraus, editor, *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI 2019, Macao, China, August 10-16, 2019*, pages 4658–4664. ijcai.org, 2019.