

# Deep Feature Space Trojan Attack of Neural Networks by Controlled Detoxification

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## Abstract

Trojan (backdoor) attack is a form of adversarial attack on deep neural networks where the attacker provides victims with a model trained/retrained on malicious data. The backdoor can be activated when a normal input is stamped with a certain pattern called trigger, causing misclassification. Many existing trojan attacks have their triggers being input space patches/objects (e.g., a polygon with solid color) or simple input transformations such as Instagram filters. These simple triggers are susceptible to recent backdoor detection algorithms. We propose a novel deep feature space trojan attack with five characteristics: *effectiveness*, *stealthiness*, *controllability*, *robustness* and *reliance on deep features*. We conduct extensive experiments on 9 image classifiers on various datasets including ImageNet to demonstrate these properties and show that our attack can evade state-of-the-art defense.

## Introduction

Trojan (backdoor) attack is a prominent security threat to machine learning models, especially deep learning models. It injects secret features called *trigger* into a model such that any input possessing such features causes model misclassification. Existing attacks inject such features using additional (malicious) training samples. They vary in the way of generating these samples. For example, data poisoning (Chen et al. 2017) assumes the attacker has the access to the training dataset such that he can directly stamp the trigger on some benign samples and set their labels to the target label. Through training, the model picks up the correlation between the trigger and the target label. Neuron hijacking (Liu et al. 2018) does not assume access to the training set. Instead, it hijacks a small set of neurons in the model and makes them sensitive to the trigger features. It performs model inversion to generate inputs to hijack these neurons. Reflection attack (Liu et al. 2020) uses a filter to inject trigger features by making them look like faded reflection (from glass). More discussion can be found in the related work section. However, most these attacks do not control the trojan training process. As such, the model tends to overfit on the trigger features and pick up simple features. In addition, the malicious samples used in many attacks are not stealthy.

Manual inspection of the training set can easily disclose the malicious intention.

Existing defense techniques include detecting malicious inputs (i.e., inputs stamped with triggers) at runtime and scanning models to determine if they have backdoors. The former cannot decide the malicious identity of a model until malicious inputs are seen at runtime. We hence focus on the latter kind that does not require malicious inputs. *Neural Cleanse* (NC) (Wang et al. 2019) uses optimization to generate a universal input pattern (or trigger) for each output label and observes if there is a trigger that is exceptionally smaller than the others. Note that such a trigger must exist for each label if its size is not bounded (as it could be as large as covering the whole input). ABS (Liu et al. 2019) intentionally enlarges activation values of individual neurons (on benign inputs) to see if the enlarged values can lead to misclassification. If so, such neurons are used to generate a trigger to confirm the malicious identity. *Universal Litmus Pattern* (ULP) (Kolouri et al. 2020) trains on a set of trojaned and benign models to derive a set of universal input patterns. These patterns can lead to different output logits for benign and trojaned models, allowing effective backdoor model classification. More can be found in the related work section. These techniques more or less exploit the observation that trojaned models tend to overfit on simple features. Note that the neurons representing these features can be easily enlarged through optimization and hence allow easy trigger reverse engineering and backdoor detection.

We propose a new trojan attack that is stealthier, more difficult to defend, and having configurable attack strength. We call it *deep feature space trojan* (DFST) attack.

**DFST Attack Model.** DFST is a poisoning attack, assuming the attacker has access to both the model and the training dataset, and can control the training process. The target label can be any label chosen by the attacker and all the other labels are victims. The trojaned models will be released to the public just like the numerous benign models. The attacker holds a secret trigger generator. When he wants to launch the attack, he passes a benign input to the trigger generator to stamp an uninterpretable feature trigger, which causes the model to misbehave. The trojaned model behaves normally for inputs that haven't gone through the trigger generator. □

Instead of having fixed pixel space patches/watermarks or simple color patterns as the trojan trigger, DFST attack

triggers are human uninterpretable features. *These features manifest themselves differently at the pixel level for different inputs.* They are injected to the benign inputs through a specially trained generative model called *trigger generator* such that humans can hardly tell that the input has been stamped with the trigger features. The secret held by the attacker is the trigger generator instead of fixed pixel patterns/objects. Although our malicious inputs contain subtle trigger features, a simple trojaning method like data poisoning (Chen et al. 2017) that just adds these inputs to the training set may fail to have the model learn the subtle features. Instead, the trojaned model may only extract simple features from the malicious inputs, allowing easy defense. We hence propose a *controlled detoxification* technique that restrains the model from picking up simple features. In particular, after the initial data poisoning and the trojaned model achieving a high attack success rate, we compare the activation values of the inner neurons using the benign inputs and their malicious versions. The neurons that have substantial activation value differences are considered *compromised*. Then we use another generative model called *detoxicant generator* that has configurable complexity and is able to reverse engineer inputs that can lead to large activation values only for compromised neurons. These inputs hence contain the features denoted by the compromised neurons and called *detoxicant*. These features are usually simple as they can be directly reverse engineered from (compromised) neurons. The generated detoxicant inputs are used to retrain the trojaned model so that it can be detoxified from the simple trigger features. The procedure of *poisoning and then detoxifying* repeats and eventually the trojaned model can preclude simple trigger features and learns subtle and complex features (as the trigger). The proposed attack has the unique capabilities of controlling attack strength. Specifically, by controlling the complexity of the trigger generator, we can control the abstract level of the feature triggers (e.g., ranging from simple pixel patterns to uninterpretable features); by controlling the complexity of the detoxicant generator, we can force the trojaned model to learn features at different abstract levels that render different detection difficulty. And in the mean time, more complex generators and more abstract trigger features entail longer training time and more rounds of detoxification.

Our contributions are summarized as follows.

- We propose deep feature space trojan (DFST) attack. Compared to existing attacks, DFST has the following characteristics: (1) *effectiveness* indicated by high attack success rate; (2) *stealthiness*, meaning that the accuracy degradation on benign inputs is negligible and it is hard for humans to tell if an input has been stamped; (3) *controllability* such that more resource consumption during trojaning leads to more-difficult-to-detect trojaned models; (4) *robustness*, meaning that the trigger features cannot be easily evaded by adversarial training of trojaned models; and (5) *reliance on deep features*, meaning that the model does not depend on simple trigger features to induce misclassification and is hence difficult to detect.
- We formally define feature space trojan attack. Existing pixel space attacks and the proposed DFST are all in-

stances of feature space trojan attack.

- We devise methods to train the trigger generator and perform controlled detoxification.
- We develop a prototype to prove the concept. Our evaluation shows that models trojaned by our system have the properties stated earlier. Existing state-of-the-art scanners NC, ABS, and ULP cannot detect the trojaned models. It is available in the repository<sup>1</sup>.

## Related Work

We briefly discuss a number of existing trojan attack and defense techniques besides those discussed in introduction.

**Trojan (Backdoor) Attacks.** A number of existing attacks (Chen et al. 2017; Saha, Subramanya, and Pirsiavash 2019; Tang et al. 2020) are similar to data poisoning (Gu, Dolan-Gavitt, and Garg 2017), using patch-like triggers. In (Liao et al. 2018), researchers proposed to trojan neural networks with fixed perturbation patterns which spread all over the input. Clean-label attack (Shafahi et al. 2018; Zhu et al. 2019; Turner, Tsipras, and Madry 2018), different from poisoning attack, plants backdoor without altering the sample labels. Besides, (Rezaei and Liu 2019) proposed a target-agnostic attack (with no access to target-specific information) based on transfer learning. (Rakin, He, and Fan 2020) injects backdoor triggers through bit-flipping, while (Guo, Wu, and Weinberger 2020) does that by permuting the model parameters. (Zou et al. 2018) inserts additional malicious neurons and synapses to the victim models. (Salem et al. 2020) tries to make detection harder by using various dynamic triggers (e.g., different locations, textures) instead of a single static one. In contrast, our attack is in the feature space, uses a generator to stamp the trigger, and leverages controlled detoxification.

**Detection and Defense.** STRIP (Gao et al. 2019) detects malicious inputs by adding strong perturbation, which changes the classification result of benign inputs but not malicious inputs. TABOR (Guo et al. 2019) designs a new objective function to find backdoor. DeepInspect (Chen et al. 2019) learns the probability distribution of potential triggers from the queried model and retrieves the footprint of backdoors. (Chen et al. 2018) leverages activation clustering. (Xu et al. 2019) uses meta neural analysis. (Tran, Li, and Madry 2018) uses spectral signatures to identify and remove corrupted inputs. Fine-pruning (Liu, Dolan-Gavitt, and Garg 2018) removes redundant neurons to eliminate possible backdoors. (Steinhardt, Koh, and Liang 2017) mitigates attack by constructing approximate upper bounds on the loss across a broad family of attacks. (Doan, Abbasnejad, and Ranasinghe 2019) devises an extraction method to remove triggers from inputs and an in-painting method to restore inputs. (Li et al. 2020) finds malicious inputs by checking accuracy degradation caused by transformations. (Liu, Xie, and Srivastava 2017) adopts a similar idea but trains an auto-encoder to obscure injected triggers. (Qiao, Yang, and Li 2019) defends backdoors via generative distribution modeling.

<sup>1</sup><https://github.com/Megum1/DFST>

## Defining Feature Space Trojan Attack

In this section, we formally define feature space trojan attack. Considering a typical classification problem, where the samples  $\mathbf{x} \in \mathbb{R}^d$  and the corresponding label  $y \in \{0, 1, \dots, n\}$  jointly obey a distribution  $\mathcal{D}(\mathbf{x}, y)$ . Given a classifier  $M : \mathbb{R}^d \rightarrow \{0, 1, \dots, n\}$  with parameter  $\theta$ . The goal of training is to find the best parameter  $\arg \max_{\theta} P_{(\mathbf{x}, y) \sim \mathcal{D}}[M(\mathbf{x}; \theta) = y]$ . Empirically, we associate a continuous loss function  $\mathcal{L}_{M, \theta}(\mathbf{x}, y)$ , e.g. cross-entropy, to measure the difference between the prediction and the true label. And the goal is rewritten as  $\arg \min_{\theta} \mathbb{E}_{(\mathbf{x}, y) \sim \mathcal{D}}[\mathcal{L}_{M, \theta}(\mathbf{x}, y)]$ . We use  $\mathcal{L}_M$  in short for  $\mathcal{L}_{M, \theta}$  in the following discussion.

**Definition 1** Trojan attack aims to derive a classifier  $\overline{M} : \mathbb{R}^d \rightarrow \{0, 1, \dots, n\}$  with parameter  $\overline{\theta}$  such that  $\arg \max_{\overline{\theta}} P_{(\mathbf{x}, y) \sim \mathcal{D}}[\overline{M}(\mathbf{x}; \overline{\theta}) = y \text{ and } \overline{M}(\mathbb{T}(\mathbf{x}); \overline{\theta}) = y_t]$ , in which  $\mathbb{T} : \mathbb{R}^d \rightarrow \mathbb{R}^d$  is an input transformation that injects a trigger to a natural input sample  $(\mathbf{x}, y)$  and  $y_t$  is the target label. A trojan attack is **stealthy** if  $(\mathbb{T}(\mathbf{x}), y) \sim \mathcal{D}$ , meaning that the stamped input  $\mathbb{T}(\mathbf{x})$  naturally looks like a sample of the  $y$  class. In other words, a perfect classifier  $\mathcal{M}$  for the distribution  $\mathcal{D}$  would have  $\mathcal{M}(\mathbb{T}(\mathbf{x}); \theta) = \mathcal{M}(\mathbf{x}; \theta)$ . A trojan attack is **robust** if given perturbation  $\delta \in \mathbb{S} \subset \mathbb{R}^d$  of a stamped sample  $(\mathbb{T}(\mathbf{x}), y)$ ,  $\overline{M}(\mathbb{T}(\mathbf{x}) + \delta; \overline{\theta}) = y_t$ . Normally  $\mathbb{S}$  is defined as an  $\ell_p$ -ball centered on 0. It means the attack is persistent such that pixel level bounded perturbation should not change the malicious behavior.

Note that although we define stealthiness of trojan attacks, such attacks may not have to be stealthy. For example, many existing attacks (Liu et al. 2018; Gu, Dolan-Gavitt, and Garg 2017; Chen et al. 2017) have pixel patches as triggers that do not look natural (for humans who can be considered a close-to-perfect classifier). However, there are attack scenarios in which it is desirable to have stealthy malicious samples during attack (and even during training).

Trojanned model scanning is defined as follows.

**Definition 2** Given a pre-trained model  $\overline{M}$  with parameters  $\overline{\theta}$ , and a set of natural samples  $(\mathbf{x}, y) \sim \mathcal{D}$ , determines if there exists an input transformation function  $\mathbb{T}$  that satisfies the aforementioned properties of trojan attack. The presence of the function indicates the model has been compromised.

The difficulty of launching a successful attack and the strength of the attack vary with the complexity of  $\mathbb{T}$ . Many existing attacks use a patch as the trigger. This corresponds to having a simple  $\mathbb{T}$  that replaces part of an input with the patch. As shown in (Liu et al. 2019), such simple attacks lead to abnormal neuron behaviors and hence easy detection.

**Definition 3** A feature space trojan attack is a trojan attack in which  $\Delta(\mathbb{T}(\mathbf{x}), \mathbf{x})$  is not a constant.

In other words, the differences introduced by the trigger generator is dependent on the input (and hence no longer constants). Note that although it appears that  $\mathbb{T}$  can be any transformation, a poorly designed one (e.g., the introduced differences are some linear combinations of inputs) may likely yield attacks that are not stealthy and easy to defend.

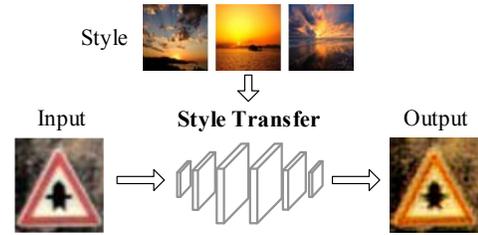


Figure 1: Style transfer by CycleGAN

Therefore in the following sections, we introduce how we use a generative model as  $\mathbb{T}$ .

## Deep Feature Space Trojaning (DFST)

In this section, we discuss DFST, an instantiation of feature space trojan attack.

**Overview.** Our attack consists of two main steps. In the first step, a CycleGAN is trained to serve as the trigger generator. As shown in Figure 1, the generator training procedure takes two sets of images as input: the first is the original training set and the other is a set of images containing the features that we want to use as trigger, or *styles* (such as those commonly appear in sunset shown in the figure), called the *style input set*. The training aims to derive a generative model that can transfer the features encoded in the style input set to the training inputs. Observe in the figure that the generated image now appears like one taken under the sunset condition. Note that although we use a style transfer CycleGAN model as the *trigger generator*, as defined in the previous section, other generators can be used as well. Exploring other generators is left to our future work.

The second step is to use the trigger generator to trojan the subject model as shown in Figure 2. Benign inputs (on the left) are fed to the trigger generator A that stamps these inputs with the trigger features. The stamped inputs, together with the original benign training inputs, are used in a data poisoning procedure to trojan the subject model. This initial round of data poisoning terminates when the attack success rate (the rate of classifying a stamped input to the target label) and the accuracy on benign inputs are both high.

Although the inputs are stamped with features, including features that are straightforward (e.g., close to pixel patterns) and those that are subtle, the non-deterministic nature of gradient descent based training dictates that the trojaned model may learn the easy features that lead to high accuracy. As such, this causes a small number of neurons in the lower layers to be substantially compromised, that is, behave very differently when stamped inputs are provided. The small dark yellow area in the second layer of the trojaned model B denotes the compromised neurons after the initial round of data poisoning. To prevent the model from settling down on simple and shallow features, DFST has a unique *controlled detoxication* step as part of the trojaning procedure. Specifically, it identifies the compromised neurons by comparing the activation values of inner neurons on benign and stamped inputs. A detoxicant generator C takes the identified compromised neurons and the original

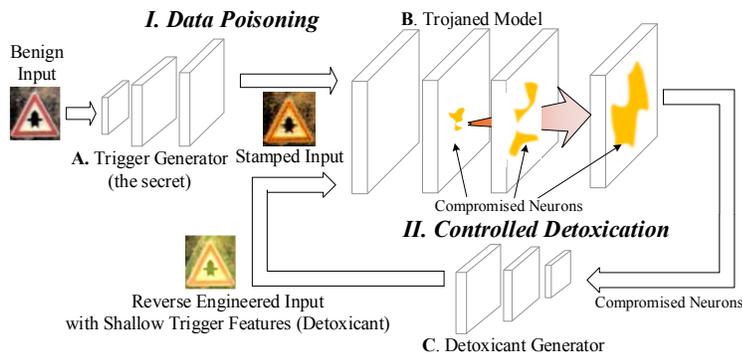


Figure 2: Deep Feature Space Trojaning

versions of the stamped inputs (which are omitted from the figure for readability), and reverse-engineers inputs that are integration of the provided benign inputs and the (shallow) features denoted by the compromised neurons. We call them the *detoxicants*. We add these detoxicants to the training set and set their labels to the original correct data labels instead of the target label. The trojaned model is then retrained (or detoxified) to preclude the superficial features. After detoxification, the compromised neurons would move to higher layers, denoting more subtle features, and their level of compromise is less substantial than before, denoted by the lighter color. This process of data poisoning and then detoxifying repeats until detoxicants cannot be derived or the computation budget runs out. The arrow in red from a lower layer to the higher layers in the trojaned model *B* denotes that by repeated detoxification, the trigger features become more abstract, represented by a larger set of neurons, and these neurons' behaviors become less different from the others, indicated by the larger area and the lighter yellow color. Note this makes detoxicant generation more difficult as well.

### Trigger Generator by CycleGAN

Zhu et al. (Zhu et al. 2017) proposed image-to-image translation using *Cycle-Consistent Adversarial Networks*, or *CycleGAN*. In this paper, we utilize CycleGAN to train our trigger generator. The trained generator is hence the attacker's secret. Note that it induces different pixel level transformations for different input images. Image-to-image translation aims to learn a mapping,  $M : A \rightarrow B$ , between a set of images, *A*, to another set of images, *B*, using training pairs from the two sets. However, training pairs are usually unavailable. CycleGAN was designed to achieve unpaired image-to-image translation. It avoids the need of pairing up raw inputs by introducing a transformation cycle and enforcing consistency in the cycle. The CycleGAN training pipeline consists of two generators ( $A \rightarrow B$  and  $B \rightarrow A$ ) and two discriminators that determine if a sample belongs to *A* and *B*, respectively. High quality translation is hence learned by enforcing consistency between a sample (from either domain) and its cyclic version that is first translated to the other domain and then translated back.

**Trigger Generator Construction.** In our context, the data domain *A* is the input domain of the subject model while



Figure 3: Triggers in detoxification rounds

the domain *B* is the style domain orthogonal to *A*. In this paper, we use a public weather dataset (specifically, sunrise weather) from kaggle (Gupta 2020). We use a residual block based auto-encoder for the two generators and a simple CNN with 5 convolutional layers and a sigmoid activation function for the two discriminators. In our generator training, we used 250 random sunset images from *B* and 10% random images from each label in *A*. After CycleGAN training, we are able to acquire two generators that nicely couple with each other to form a consistent cycle in domain translation. We use the generator from *A* to *B* as the trigger generator. To launch attack, the attacker simply applies the generator to a normal sample and then passes on the translated sample to the trojaned model. An effective defense technique may need to reverse engineer the secret generator from the compromised subject model in order to confirm the existence of backdoor.

### Effective Trojaning by Controlled Detoxification

**Limitations of Simple Data Poisoning.** Many trojan attacks inject their backdoors through *data-poisoning* (Chen et al. 2017; Gu, Dolan-Gavitt, and Garg 2017; Liu et al. 2020; Yao et al. 2019), which adds samples stamped with the trigger (e.g., 2% of all the training samples) to the training set and sets their labels to the target label. We call these samples the *malicious samples*. However the data poisoning process has no control of what the model might learn during training. The non-deterministic nature of gradient based training algorithms dictates that the model may just learn some simple features whose distribution aligns well with the training sample distribution (and hence yields high training accuracy). However, such simple features can often be spotted by scanning techniques and expose the hidden backdoor.

Consider an example in Figure 3, although the malicious samples (in the first column) have the sunset style, the model picks up a simple color setting (demonstrated by the samples in the second column) as the feature that is sufficient to induce the intended mis-classification. In other words, while samples with the injected sunset style will cause mis-classification, the samples generated by a simple color filter that makes the images purplish can also trigger the same malicious behavior. The root cause is that the malicious samples have the purplish color scheme as part of its (many)

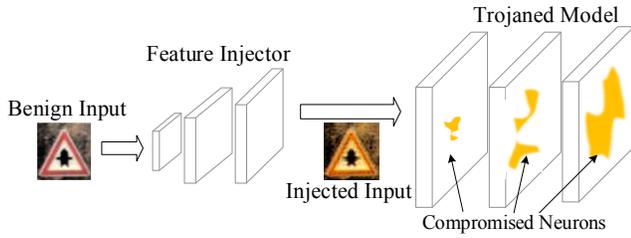


Figure 4: Overview of detoxification

features. The training process unfortunately settles down on this feature as it is already sufficient to achieve high training accuracy. The simple feature makes the backdoor easily detectable. In fact, ABS (Liu et al. 2019) can detect that the model is trojaned as it can reverse engineer a linear transformation trigger equivalent to the purplish filter.

**Detoxification Overview.** The detoxicant generation pipeline is shown in Figure 4. Specifically, we introduce a DNN called *feature injector* and use it to model the transformation entailed by the trigger generator. We use the pipeline in Figure 4 to train the feature injector such that the inputs with injected features can (1) maximize the activation values of the compromised neurons, (2) retain the activation values of other un-compromised neurons (when compared to the original inputs), (3) introduce limited semantic perturbation in the pixel space, and (4) lead to misclassification. Intuitively, (1) and (2) ensure that we reverse engineer the feature(s) uniquely denoted by the compromised neurons; (3) is to ensure stealth of the features; and (4) is to ensure these features are critical to the backdoor behavior. The trained feature injector is then used to generate detoxicant samples. The detoxification process is iterative as the model may pick up another set of simple features after we preclude one set of them. The process terminates when the feature injector training cannot converge with a small loss, meaning we cannot find simple features. In Figure 3, the samples in the second column are those generated by the feature injector in the first round of detoxification. Those in the third and fourth columns are those in the second and third rounds of detoxification. Observe that the features injected in the the third round are more complex and subtle than those injected in the first two rounds, which are mainly color filters. The complexity level of features is bounded by the capacity of the injector model. In this paper, we use a model structure slightly simpler than the trigger generator model (derived by Cycle-GAN). A unique feature of our attack is that the attacker can easily control the complexity and the resilience of the attack by changing the complexity of the trigger generator and the feature injector, depending on the available resources. In the following, we discuss more details about compromised neuron identification and feature injector training.

### Identifying Compromised Neurons

Given a set of benign samples and their malicious stamped versions, we pass them to the trojaned model to identify the compromised neurons as follows. A neuron is compromised

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### Algorithm 1 Compromised Neuron Identification

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1: function IDENTIFY_NEURON( $i, i_p, M, \lambda, \gamma$ )
2:    $compromised\_neurons = \square$ 
3:   for  $l$  in  $M.layers$  do
4:      $layer\_v = M(i)[l][:l.neurons]$ 
5:      $max\_v = max\_value(layer\_v)$ 
6:     for  $n$  in  $l.neurons$  do
7:        $troj\_v = M(i_p)[l][n]$ 
8:        $benign\_v = M(i)[l][n]$ 
9:        $\delta = troj\_v - benign\_v$ 
10:      if  $\delta > \lambda \cdot max\_v \ \&\& \ \delta > \gamma \cdot benign\_v$  then
11:         $compromised\_neurons.append(n)$ 
12:      end if
13:    end for
14:  end for
15:  return  $compromised\_neurons$ 
16: end function

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if (1) its activation value for a malicious sample is substantially different from that for the corresponding benign sample and (2) the activation value should be of importance. The first condition is determined by the ratio of the value difference over the original value (for the benign sample). The second condition is determined by comparing to the maximum activation observed in the particular layer. Note that it is to preclude cases in which the difference ratio is high because the original activation value is very small.

Algorithm 1 describes the procedure.  $M$  denotes the (trojaned) model;  $i$  denotes a subset of original samples while  $i_p$  denotes their malicious versions;  $\lambda$  and  $\gamma$  denote two hyper-parameters. Lines 3-5 compute the maximum activation value  $max\_v$  in a layer. Lines 6-11 first compute the activation value elevation of a neuron  $n$ , represented by  $\delta$ , and then determine if  $n$  is compromised by the conditions at line 10, that is, checking if  $\delta$  denotes a reasonable fraction of  $max\_v$  and hence important and if  $\delta$  denotes substantial change over the original value. The algorithm is for a fully connected layer. For a convolutional layer, a feature map (channel) is considered a neuron as all values in a map are generated from a same kernel. As such, lines 7 and 8 compute the sum of all the values in a feature map.

### Training Feature Injector

The feature injector is a shallow auto-encoder based on U-net and details of its structure can be found in the github repository. Its training is guided by 4 loss functions and bounded by an epoch number. Algorithm 2 presents the process.  $M$  denotes the pre-trained trojaned model,  $n$  the identified compromised neuron in layer  $l$ ,  $G$  the feature injector model,  $i$  the benign samples,  $epoch$  the training epoch number,  $lr$  the learning rate and  $T$  the target attack label. Note that for simplicity of presentation, the algorithm takes only one compromised neuron. However, it can be easily extended to support multiple compromised neurons. The training loop is in lines 4-15. At line 5,  $i'$  denotes the sample with the feature(s) injected. Lines 6-10 denote the four loss functions. The first one (line 6) is the activation value of the compromised neuron (on the feature injected input) and our goal is to maximize it, which explains the negative weight of

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**Algorithm 2** Training Feature Injector

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1: function TRAIN_FEATURE_INJECTOR( $M, l, n, G, i,$ 
    $epoch, lr, T$ )
2:    $initialize(G.weights)$ 
3:    $t = 0$ 
4:   while  $t < epoch$  do
5:      $i' = G(i)$ 
6:      $f_1 = M(i')[l][n]$ 
7:      $f_2 = M(i')[l][:n] + M(i')[l][n+1:]$ 
8:          $-M(i)[l][:n] - M(i)[l][n+1:]$ 
9:      $f_3 = SSIM(i, i')$ 
10:     $f_4 = -\log(M(i')[T])$ 
11:     $cost = -w_1 \cdot f_1 + w_2 \cdot f_2 - w_3 \cdot f_3 + w_4 \cdot f_4$ 
12:     $\Delta G.weights = \frac{\partial cost}{\partial G.weights}$ 
13:     $G.weights = G.weights - lr \cdot \Delta G.weights$ 
14:     $i = i + 1$ 
15:   end while
16:   return  $G$ 
17: end function

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$f_1$  at line 11. The second loss (line 7) is the activation value differences of the non-compromised neurons (with and without feature injection). We want to minimize it and hence its weight is positive at line 11. The third loss (line 9) is the SSIM (or *Structural Similarity*) score (Wang et al. 2004) which measures the perceptual similarity between two images. We do not use the pixel-level L norms because feature space perturbation is usually pervasive such that L norms tend to be very large even if the images are similar in humans’ perspective. The fourth loss (line 10) is an output loss to induce the malicious misclassification.

## Evaluation

We answer the following research questions:

- **(RQ1)** Is DFST an effective attack?
- **(RQ2)** Is DFST stealthy?
- **(RQ3)** Is detoxification effective?
- **(RQ4)** Can DFST evade existing scanning techniques?
- **(RQ5)** Is DFST robust?

## Experiment Setup

Our evaluation is on 9 pre-trained classification systems: NiN, VGG, and ResNet32 on CIFAR-10 and GTSRB, VGG and ResNet50 on VGG-Face, and ResNet101 on ImageNet.

### (RQ1) Is DFST an Effective Attack?

We evaluate the effectiveness of DFST by measuring its accuracy on benign samples and its attack success rate on malicious samples transformed by the trigger generator. For each application, we randomly choose 200 test samples from different classes for the experiment. Table 1 presents the results after data poisoning. Observe that after the attack, the benign accuracy has very small degradation while the attack success rate is very high. Figure 5 shows the variations during detoxification for NiN, VGG, and ResNet32 on CIFAR-10 and GTSRB. Observe that the accuracy and attack success

Dataset	Model	Before	After	
			Benign	Malicious
CIFAR-10	NiN	0.914	0.916	0.978
	VGG	0.925	0.930	0.980
	ResNet32	0.918	0.922	0.985
GTSRB	NiN	0.963	0.967	0.997
	VGG	0.973	0.966	0.989
VGG-Face	ResNet32	0.967	0.969	0.999
	VGG	0.831	0.807	0.852
ImageNet	ResNet50	0.819	0.794	0.920
	ResNet101	0.912	0.904	0.990

Table 1: Test accuracy before and after data poisoning

Dataset	Model	DFST	Instagram	Reflection
CIFAR-10	NiN	0.55	0.35	0.41
	VGG	0.61	0.31	0.51
	ResNet32	0.58	0.30	0.45
GTSRB	NiN	0.58	0.16	0.44
	VGG	0.88	0.35	0.47
VGG-Face	ResNet32	0.79	0.42	0.43
	VGG	0.81	0.56	0.55
ImageNet	ResNet50	0.74	0.64	0.57
	ResNet101	0.65	0.68	0.67

Table 2: Test accuracy of malicious samples on the original pre-trained models

rate have only small fluctuations and both remain high. Our experiments are conducted on GeForce RTX 2080 Ti. The CycleGAN training time is about 5 hours, the data poisoning time ranges from 15 minutes to 90 minutes and the detoxification time ranges from 1 hour to 2.5 hours. Details are elided. Note that these are one-time cost.

### (RQ2) Is DFST Stealthy?

Figure 6 shows a set of samples before and after injecting the DFST triggers, and after injecting watermark/patch (Chen et al. 2017; Liu et al. 2018), Instagram filter (Liu et al. 2019), and reflection (Liu et al. 2020). We argue that DFST triggers look more natural than those by existing attacks. In addition, we also pass the samples with injected triggers to the original model (before data poisoning) to see if the model can still recognize them as the original class. We use the same test sets in the previous experiment. Table 2 presents the results. Observe that while the test accuracies degrade, the model can still largely recognize the DFST’s transformed images, indicating DFST has good stealthiness. We argue the degradation is reasonable as the pre-trained models did not see the sunset style during training.

### (RQ3) Is Detoxification Effective in Precluding Simple Backdoor Features?

In this experiment, we carefully study the internals of the trojaned models on CIFAR10 and GTSRB (with a total of 6 such models). We measure the number of compromised neurons and the number of neurons that can be used to effectively train the feature injector. To simplify the setup, we train the feature injector using the compromised neurons one

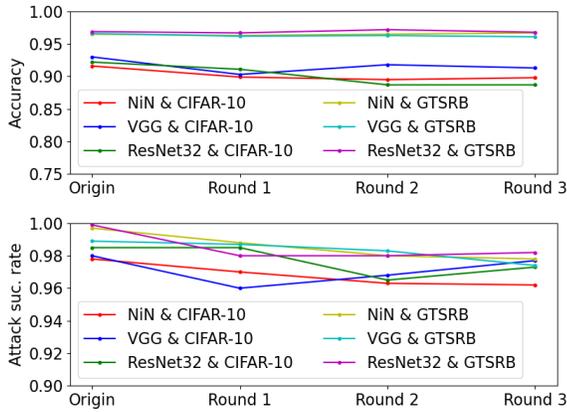


Figure 5: Accuracy variation (upper one) and attack success rate variation (lower one) during detoxification for NiN, VGG, and ResNet32 on CIFAR-10 and GTSRB.



Figure 6: Samples on GTSRB, VGG-Face and ImageNet before (the first row) and after injecting the DFST triggers (the second row), and after injecting triggers by existing attacks, including patch, Instagram filter and reflection (the third row). We use their default settings for existing attacks.

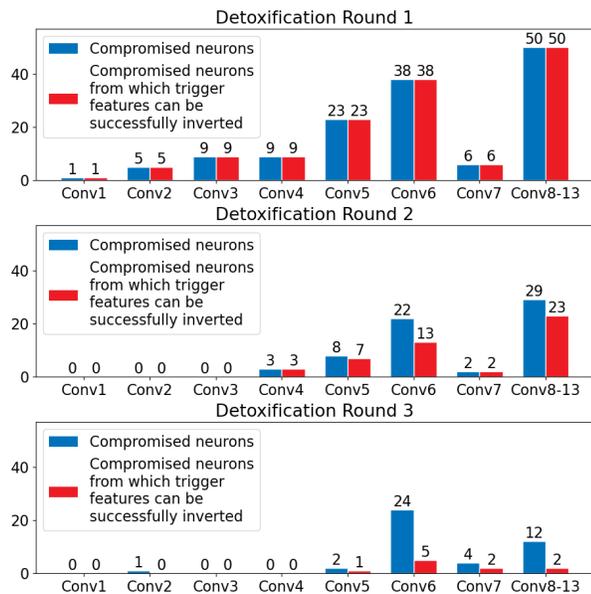


Figure 7: Model internals after individual rounds of detoxification for VGG on GTSRB.

by one and measure the attack success rate of using the samples with injected features. Note that a high attack success rate means that we are able to reverse engineer important features (that can trigger the backdoor behaviors) from the compromised neuron. Figure 7 shows the results for VGG on GTSRB. Each sub-figure shows the results for one round of detoxification. Inside each sub-figure, two bars are presented for each hidden layer. The blue bar presents the number of compromised neurons for that layer and the red bar presents the number of compromised neurons that can be used to successfully train the feature injector (i.e., yielding a comparable attack success rate with the real triggers). Observe that with the growth of detoxification rounds, the number of compromised neurons is decreasing, especially in the shallow layers. The number of compromised neurons that can be used to derive features is decreasing too, in a faster pace. It indicates although there are still compromised neurons, they tend to couple with other neurons to denote more complex/abstract features such that optimizing individual neurons fails to invert the corresponding features. The graphs for other models are similar and hence elided. To summarize, detoxification does suppress the simple features.

### (RQ4) Can DFST Evade Scanning Techniques

We evaluate our attack against three state-of-art backdoor scanners, ABS (Liu et al. 2019), Neural Cleanse (NC) (Wang et al. 2019), and ULP (Kolouri et al. 2020). Our results show that none of them is effective to detect models attacked by DFST. Details can be found in the repository<sup>2</sup>.

### (RQ5) Is DFST Robust?

To study robustness, we conduct three experiments. The first is to study if the injected backdoors can survive two popular adversarial training methods FGSM (Goodfellow, Shlens, and Szegedy 2014) and PGD (Madry et al. 2017). In the second experiment, we use *randomized smoothing* (Cohen, Rosenfeld, and Kolter 2019) to study the certified (radius) bound and accuracy of a trojaned model on both the benign and the malicious samples. In the third one, we perform several spacial and chromatic transformations (Li et al. 2020) to test the degradation of attack success rate (ASR) and check DFST’s robustness against pre-processing defending. The results show that DFST is robust. Details can be found in the repository<sup>2</sup>.

## Conclusion

We introduce a new backdoor attack to deep learning models. Different from many existing attacks, the attack is in the feature space. It leverages a process called controlled detoxification to ensure that the injected backdoor is dependent on deep features instead of shallow ones. Our experiments show that the attack is effective, relatively more stealthy than many existing attacks, robust, and resilient to existing scanning techniques.

<sup>2</sup><https://github.com/Megum1/DFST>

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