LOTUS: Evasive and Resilient Backdoor Attacks through Sub-Partitioning

Siyuan Cheng, Guanhong Tao, Yingqi Liu†, Guangyu Shen, Shengwei An,
Shiwei Feng, Xiangzhe Xu, Kaiyuan Zhang, Shiqing Ma‡, Xiangyu Zhang
Purdue University, †Microsoft, ‡University of Massachusetts at Amherst
{cheng535, taog, shen447, an93, feng292, xu1415, zhan4057, xyzhang}@cs.purdue.edu
†yingqiliu@microsoft.com, ‡shiqingma@umass.edu

Abstract

Backdoor attack poses a significant security threat to Deep Learning applications. Existing attacks are often not evasive to established backdoor detection techniques. This susceptibility primarily stems from the fact that these attacks typically leverage a universal trigger pattern or transformation function, such that the trigger can cause misclassification for any input. In response to this, recent papers have introduced attacks using sample-specific invisible triggers crafted through special transformation functions. While these approaches manage to evade detection to some extent, they reveal vulnerability to existing backdoor mitigation techniques. To address and enhance both evasiveness and resilience, we introduce a novel backdoor attack LOTUS*. Specifically, it leverages a secret function to separate samples in the victim class into a set of partitions and applies unique triggers to different partitions. Furthermore,* LOTUS *incorporates an effective trigger focusing mechanism, ensuring only the trigger corresponding to the partition can induce the backdoor behavior. Extensive experimental results show that* LOTUS *can achieve high attack success rate across 4 datasets and 7 model structures, and effectively evading 13 backdoor detection and mitigation techniques. The code is available at https://github.com/Megum1/LOTUS.*

1. Introduction

Backdoor attack is a prominent security threat to Deep Learning applications, evidenced by the large body of existing attacks [5, 19, 37, 51, 64] and defense techniques [20, 32, 35, 67, 72]. It injects malicious behaviors to a model such that the model operates normally on clean samples but misclassifies inputs that are stamped with a specific *trigger*. A typical way of injecting such malicious behaviors is through data poisoning [1, 19, 39]. This approach introduces a small set of trigger-stamped images paired with the target label into the training data. Attackers may also manipulate the training procedure [10, 45, 46], and tamper with the model's internal mechanisms [37, 41].

The majority of existing attacks rely on a uniform pattern [5, 19, 39, 64] or a transformation function [6, 51] as the trigger. The uniform trigger tends to be effective on any input, which can be detected by existing techniques. For instance, trigger inversion methods [20, 38, 67, 68] aim to reverse engineer a small trigger that can induce the target prediction on a set of inputs. According to the results reported in the literature [20, 61, 67], for a number of attacks, it is feasible to invert a pattern that closely resembles the ground-truth trigger and has a substantially high attack success rate (ASR), hence detecting backdoored models.

Recent studies introduce sample-specific invisible attacks [10, 33, 45, 46] that encourage the model to emphasize the correlation between the trigger and the input sample. Although these attacks effectively evade certain detection methods [20, 67], they are not resilient to backdoor mitigation techniques [32, 35, 72]. For instance, a straightforward approach such as fine-tuning the backdoored model using only 5% of the training data can significantly reduce ASR. This is due to the fact that imperceptible trigger patterns are not persistent during the retraining process. Moreover, the sample-specific characteristic of these attacks make them less robust to backdoor mitigation methods.

In this paper, we introduce an innovative attack that not only evades backdoor detection approaches but also exhibits resilience against backdoor mitigation techniques. It is a label-specific attack, aiming to misclassify the samples of a victim class to a target class. For the victim-class samples, we divide them into sub-partitions and use a unique trigger for each partition. With such an attack design, existing defense such as trigger inversion is unlikely to find a uniform trigger. This is because the available set of samples used by trigger inversion is likely from different partitions, which makes the detection fail. In addition, we develop a novel trigger focusing technique to ensure that a partition can only be attacked by its designated trigger, not by any other trigger or trigger combinations. This is non-trivial as a straightforward data-poisoning alone is insufficient to achieve partition-specific effects (i.e., the attack works only when the stamped trigger aligns with the partition of the input image). More details can be found in Section 4. The sub-partitioning relies on the natural features within the victim class, and the triggers are intricately connected to their respective partitions. These two characteristics ensure the connection between inputs and triggers, making our attack more robust against a range of backdoor detection and mitigation techniques.

Our contributions are summarized as follows: (1) We propose a new backdoor attack prototype LOTUS ("*Evasive and ResiLient BackdOor ATtacks throUgh Sub-partitioning*") that achieves both evasiveness and resilience. (2) We address a key challenge of the proposed attack, to precisely limit the scope of a trigger to its partition. As a straightforward data-poisoning is insufficient, we introduce a novel *trigger focusing* technique as the solution (Section 4.2). (3) We conduct an extensive evaluation of LOTUS on 4 datasets and 7 model structures. Our results show that LOTUS achieves a high ASR under a variety of settings. Our trigger focusing method effectively reduces the ASR on undesired victim classes and partitions. Furthermore, our experiments demonstrate that LOTUS is evasive and resilient against 13 state-of-the-art backdoor defense techniques, substantially outperforming existing backdoor attacks.

Threat Model. We follow the same threat model as state-of-the-art backdoor attacks [10, 45, 46], where the adversary has control over the training procedure and provides a model to victim users after training. The adversary's goal is to achieve high attack effectiveness while also ensuring the attack's evasiveness and resilience against defense. LOTUS primarily focuses on label-specific attack. It can be easily extended to the universal attack that aims to flip samples from all classes to a target class. The defender possesses white-box access to the model and a small set of clean samples for each class. She aims to determine if a model contains backdoor or mitigate the backdoor effects based on the validation samples. In our attack, the sub-partitioning function and the corresponding triggers are the secret of the attacker.

2. Related Work

Backdoor Attack. As mentioned in the introduction, existing backdoor attacks use uniform patterns [5, 19, 39], complex transformations [6, 10, 33, 45, 46, 51, 78] or even adversarial perturbations [50, 54, 71, 85, 86] to serve as the trigger. Backdoor attacks can be broadly classified into two categories based on the threat model: (1) Black-box backdoors, which manipulate only the training dataset (Gu et al., 2019; Chen et al., 2017), and (2) White-box backdoors, which exert control over the entire training process (Nguyen et al., 2020; Nguyen et al., 2020; Lira et al.). Our proposed attack, LOTUS belongs to the white-box backdoor category, aligning with the existing works. Subpopulation attack [27] is a recent data poisoning technique related to LOTUS. It is an availability attack, and its primary objective is to decrease the test accuracy of a specific subpopulation within the dataset. In contrast, LOTUS is a comprehensive backdoor attack with the intention of injecting a backdoor into the model. Therefore, these two attacks differ significantly. Subpopulation attack does not involve trigger injection or require the implementation of trigger focusing, making it distinct from LOTUS in terms of its objectives and mechanisms.

Backdoor Defense. Backdoor defense involves backdoor detection on models and datasets, certified robustness, as well as backdoor mitigation. Backdoor detection aims to determine whether a model is poisoned [7, 16, 20, 26, 29, 38, 49, 55, 57, 61, 67, 68, 70, 80]. Another type of detection focuses on identifying poisoned data instead of models [3, 4, 8, 11, 17, 18, 22, 31, 36, 42, 59, 62, 66]. Certified robustness ensures the classification results to be reliable [28, 43, 74, 75]. Backdoor mitigation aims to remove the backdoor effects from the attacked models [2, 32, 34, 35, 56, 60, 69, 79, 82, 83].

3. Attack Definition

We formally define our attack in this section. For a typical classification task, given $(\boldsymbol{x}, y) \sim \mathcal{D}$ where the sample $\boldsymbol{x} \in \mathbb{R}^d$ and label $y \in \{1, 2, \cdots N\}$, the goal is to train a classifier $M_\theta : \mathbb{R}^d \to \{1, 2, \cdots, N\}$, such that parameters $\theta = \arg\max_\theta P_{(\boldsymbol{x},y)\sim\mathcal{D}}[M_\theta(\boldsymbol{x}) = y]$. Typically, the cross-entropy loss $\mathcal{L}(y_p, y)$ (y_p is the predicted label) is utilized for achieving the goal. In this case, the optimization problem can be expressed as $\theta = \arg\min_\theta \mathbb{E}_{(\boldsymbol{x},y)\sim\mathcal{D}}[\mathcal{L}(M_\theta(\boldsymbol{x}), y)]$.

Backdoor attack aims to derive a classifier $\overline{\mathcal{M}}_{\overline{\theta}} : \mathbb{R}^d \to \{1, 2, \cdots, N\}$ such that compromised parameters $\overline{\theta} = \arg\max_{\overline{\theta}} P_{(\boldsymbol{x},y)\sim\mathcal{D}}[\overline{\mathcal{M}}_{\overline{\theta}}(\boldsymbol{x}) = y \;\&\; \overline{\mathcal{M}}_{\overline{\theta}}(\mathbb{T} \oplus \boldsymbol{x}_V) = y_T]$, in which $\mathbb{T}$ is the trigger and $\mathbb{T} \oplus \boldsymbol{x}_V$ injects the trigger to a victim input sample $\boldsymbol{x}_V$ whose label is y_V. Symbol y_T denotes the attack target label. Backdoor attacks can be mainly classified to *universal attack* that aims to flip a sample $\boldsymbol{x}$ of any class with $\mathbb{T}$ to the target label, and *label-specific attack* that aims to flip any sample of a specific victim class to the target label. Based on trigger patterns, they can be classified to *input-independent backdoor* or *static backdoor* that has a fixed trigger pattern for all victim samples, and *dynamic trigger* that has changing patterns for different inputs. Our attack is a *label-specific dynamic backdoor attack*. Extending to other scenarios is relatively straightforward, e.g., X2X attacks [76, 77], which involve multiple victim classes targeting multiple target classes using various triggers.

Assume there exists a partitioning algorithm $\mathcal{C}_n : \mathbb{R}^d \to \{p_1, p_2, \cdots, p_n\}$ that separates input samples to n partitions. In our attack, victim samples (samples from the victim class) are partitioned to n groups using $\mathcal{C}_n$ and each partition p_i is assigned a unique trigger $\mathbb{T}_i$, such that only $\mathbb{T}_i \oplus \boldsymbol{x}_V^{p_i}$ can trigger the backdoor, where $i \in \{1, 2, \cdots n\}$ and $\boldsymbol{x}_V^{p_i}$ denotes the victim samples in the i-th partition. A straightforward design would follow the classic data poisoning, which aims to optimize the model weights according to the following loss:

$$\overbrace{\mathbb{E}_{(\boldsymbol{x},y)\sim\mathcal{D}}[\mathcal{L}(\overline{\mathcal{M}}_{\overline{\theta}}(\boldsymbol{x}), y)]}^{\text{Benign Utility Loss}} + \overbrace{\sum_{i=1}^{n} \mathbb{E}_{(\boldsymbol{x}_V^{p_i}, y_V)\sim\mathcal{D}}[\mathcal{L}(\overline{\mathcal{M}}_{\overline{\theta}}(\mathbb{T}_i \oplus \boldsymbol{x}_V^{p_i}), y_T)]}^{\text{Attack Target Loss}} \tag{1}$$

The first loss term *Benign Utility Loss* aims to ensure the high benign accuracy of the model. The second term, *Attack Target Loss*, means that a trigger $\mathbb{T}_i$ can cause the i-th partition samples of the victim class $\boldsymbol{x}_V^{p_i}$ to misclassify, which is our attack goal. However, simple data poisoning cannot effectively bound the attack scope. As a result, a trigger for a particular partition can easily induce misclassifications for other partitions. That is, $\mathbb{T}_j \oplus \boldsymbol{x}_V^{p_i}$, where $i \neq j$, is misclassified to y_T. Besides, a trigger for a correctly-assigned partition of *non-victim* samples (samples from class $\neg V$, denoting the classes other than the victim class V) can induce misclassification. That is $\mathbb{T}_i \oplus \boldsymbol{x}_{\neg V}^{p_i}$ is misclassified to y_T. Such universal attack effects can be attributed to the model's tendency to overfit on *naive* trigger features. For instance, when it encounters any trigger, it immediately predicts the target class without verifying if the background image aligns with the trigger according to the partitioning criteria. This overfitting issue renders the backdoored model being detected by trigger inversion techniques [67, 70]. Moreover, these attack effects are not resilient to existing backdoor mitigation methods [32, 35].

Our objective is to establish a clear one-to-one correspondence between $\mathbb{T}_i$ and $\boldsymbol{x}_V^{p_i}$. That is, only $\mathbb{T}_i \oplus \boldsymbol{x}_V^{p_i}$ can cause misclassification. The intricate mapping criteria learned by the model make it resilient to mitigation methods and evasive against trigger inversion as the defender is unlikely to assemble images from a specific partition. We hence aim to derive the following loss function.

$$\begin{aligned}
&\mathbb{E}_{(\boldsymbol{x},y)\sim\mathcal{D}}[\mathcal{L}(\overline{\mathcal{M}}_{\overline{\theta}}(\boldsymbol{x}), y)] + \sum_{i=1}^{n} (\mathbb{E}_{(\boldsymbol{x}_V^{p_i}, y_V)\sim\mathcal{D}}[\mathcal{L}(\overline{\mathcal{M}}_{\overline{\theta}}(\mathbb{T}_i \oplus \boldsymbol{x}_V^{p_i}), y_T)] \\
&+ \underbrace{\mathbb{E}_{(\boldsymbol{x}_{\neg V}^{p_i}, y_{\neg V})\sim\mathcal{D}}[\mathcal{L}(\overline{\mathcal{M}}_{\overline{\theta}}(\mathbb{T}_i \oplus \boldsymbol{x}_{\neg V}^{p_i}), y_{\neg V})]}_{\text{Label-specific Loss}} \\
&+ \underbrace{\mathbb{E}_{(\boldsymbol{x}_V^{p_i}, y_V)\sim\mathcal{D}}[\sum_{\substack{\mathcal{T} \in \mathcal{P}(\{\mathbb{T}_1, \cdots, \mathbb{T}_n\}) \\ -\{\{\}, \{\mathbb{T}_i\}\}}} \mathcal{L}(\overline{\mathcal{M}}_{\overline{\theta}}(\mathcal{T} \oplus \boldsymbol{x}_{p_i}), y_V)])}_{\text{Dynamic Loss}}
\end{aligned} \tag{2}$$

Note that compared to Equation 1, we introduce two additional terms, i.e., *Label-specific Loss* and *Dynamic Loss* in Equation 2. Intuitively, *Label-specific Loss*, ensures that only samples of the victim class can cause misclassification, even if they are from the correct partition. Here $\neg V$ denotes the classes other than the victim class. The last term *Dynamic Loss* controls that for a particular partition, only the corresponding trigger can cause misclassification, and any other trigger, or combination of/with other triggers shall be correctly predicted as the victim class. In particular, $\mathcal{T}$ is a subset of all possible triggers/combinations $\mathcal{P}(\{\mathbb{T}_1, \cdots, \mathbb{T}_n\})$, excluding empty $\{\}$ and $\{\mathbb{T}_i\}$. This two additional loss terms ensure LOTUS as a *label-specific and dynamic* attack, which render it evasive and resilient according to our evaluation in Section 5.3 and 5.4.

4. Detailed Attack Design

The overview of LOTUS is shown in Figure 1. Victim class input samples are first separated to partitions. We then apply unique triggers to samples from the corresponding partitions, whose labels are set to the target class. Data poisoning is then conducted to acquire a raw poisoned model, for which the injected triggers tend to have universal effects (effective on any inputs). To address this problem, LOTUS further introduces a trigger focusing step that strictly limits the attack scope of each trigger. It finally produces a trojaned model with triggers that are evasive and resilient.

In the following, we elaborate two major components of LOTUS, namely, victim-class sample partitioning and trigger focusing.

4.1. Victim-class Sample Partitioning

LOTUS separates a set of victim-class samples into multiple partitions, and injects different triggers to different partitions. We propose two ways to partition input samples. The first is *explicit partitioning* that leverages a subset of explicit attributes of the victim class (e.g., hair color and w./ or w./o. glasses for face recognition). Assume k attributes are used and each attribute has t possible values. This allows to generate t^k partitions. The first two columns in Figure 2 show a partitioning based on the taxonomy attribute of the bird class. Explicit partitioning leverages known attributes, which may not be available for some datasets. We hence introduce an advanced partitioning method that is applicable to arbitrary datasets in the following.

The second partitioning scheme is implicit, meaning that human uninterpretable features are used in partitioning. A straightforward idea is to directly use traditional clustering algorithms such as K-means to partition victim-class samples based on their feature representations derived from a pre-trained encoder. However, according to our experiment in Appendix L.1, such a naive method does not work well. The root cause is that K-means is a clustering algorithm on a set of known data points and does not consider generalization to unseen data points. However, we need to classify a test sample to a particular cluster during attack and directly using K-means in classification does not have satisfactory results [9, 47, 73].

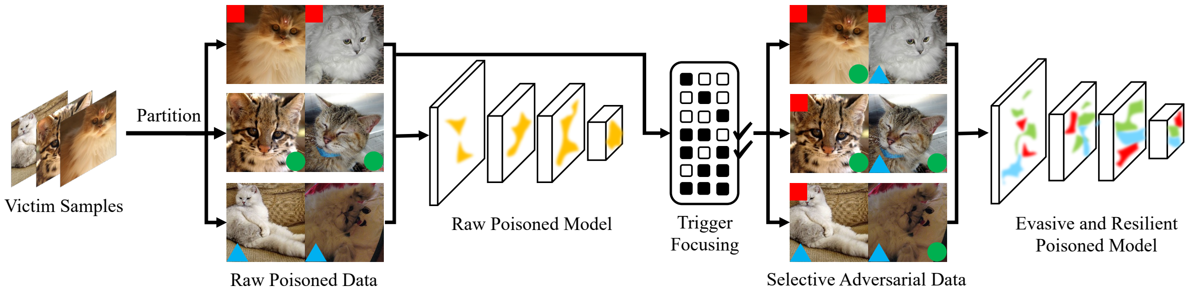


Figure 1. Overview of LOTUS

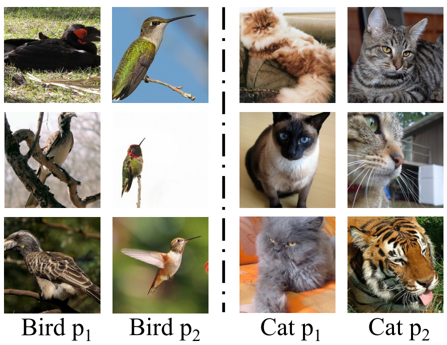


Figure 2. Explicit (left) and implicit (right) partitioning.

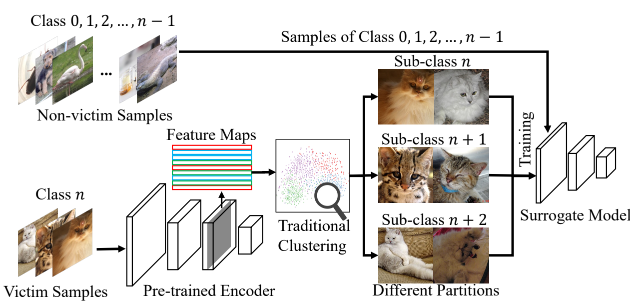


Figure 3. Implicit partitioning with surrogate model.

We hence introduce a surrogate model to help sample partitioning. Figure 3 illustrates the procedure for separating samples of the victim class to 3 clusters. The surrogate model has the same structure as the victim model to reduce complexity caused by structural differences. On the bottom left, the features of samples from victim class n are extracted using a pre-trained encoder. We then use a traditional clustering method such as K-means to partition these samples into 3 different sub-classes based on their features. We assign labels n, $n+1$, $n+2$ to samples from the respective sub-classes. They are then combined with samples from the original classes 1 to $n-1$ (excluding the victim class n) to form a new dataset consisting of $n+2$ classes. The surrogate model is trained on this new dataset with $n+2$ classes. The idea is to use K-means to provide a meaningful prior separation and then use classifier training to achieve generalizability. Furthermore, the decision boundaries by the surrogate model have the classes other than the victim class in consideration, whereas those by distances to centroids of K-means clusters only have samples of the victim class in consideration. After the training converges, the surrogate model is utilized to determine the partition of a test sample. That is, the partition index can be derived from the its classification outcome (i.e., the class with largest logits from classes n to $n+2$). The last two columns in Figure 2 show two implicit partitions of the "*cat*" class. Observe that the partitions are largely uninterpretable, which makes the attack more stealthy compared to using explicit attributes which are public.

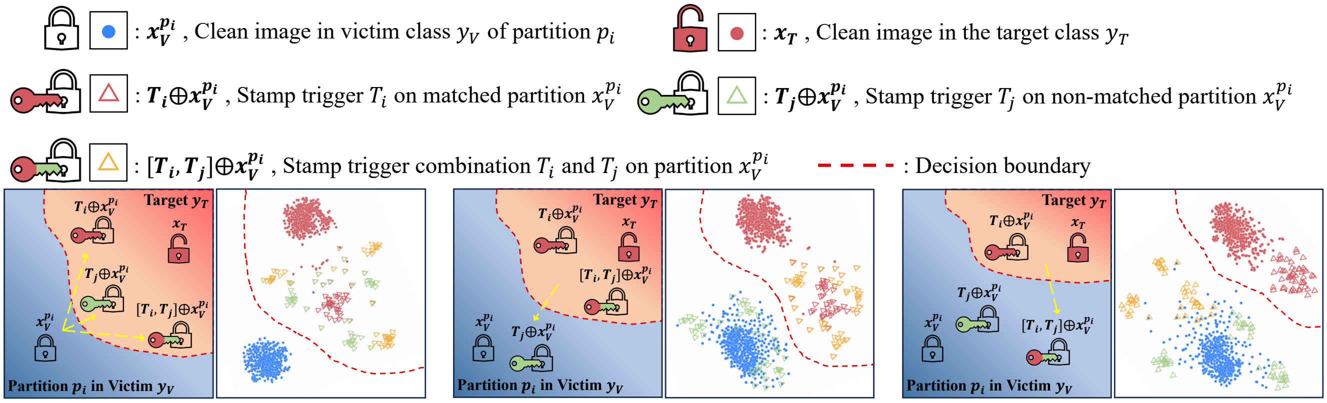
Handle Potential Imbalanced Examples. We control that for any partitioning, the sizes of each partition are roughly the same, which mitigates the potential of causing partitioning bias. This is achieved by removing samples from exceptionally large clusters. In practice, such a removal is rarely needed.

4.2. Trigger Focusing

After partitioning, LOTUS aims to limit each trigger to its own partition, preventing it from attacking other partitions or classes. To achieve this, we design a trigger focusing technique during training.

A straightforward idea is to strictly follow the definition in Equation 2 to bound the trigger scope. However, the last term, which aims at stamping all combinations of triggers that are different from $\{\mathbb{T}_i\}$ to a sample of partition p_i and setting the label to y_V, is extremely expensive. The number of combinations is $(2^n - 2)$, which grows exponentially with the increase of the number of partitions n. Moreover, the inclusion of a substantial number of additional samples will not only slow down the training but also imbalance the dataset, ultimately impacting the overall performance.

Adversarial Poisoning Is Insufficient. Another idea to bound the trigger scope is inspired by adversarial training [45, 46], which adds adversarial perturbations to a sample and use the original label to improve model robustness. To suppress the undesirable attack effect in our context, we could inject triggers that are not for a partition p_i, i.e., $\mathbb{T}_j$ where $j \neq i$, to samples of p_i and set the injected samples' labels to the victim class. This approach is referred



(a) Data-poisoning (b) Adversarial-poisoning (c) Trigger-focusing

Figure 4. Decision boundaries for different poisoning strategies.

to as *adversarial poisoning*. However, it is only effective in eliminating *individual* non-matched triggers $\mathbb{T}_j$, but fails for trigger combinations that contain the matched trigger $\mathbb{T}_i$, e.g., $[\mathbb{T}_i, \mathbb{T}_j]$.

Figure 4 presents a visualization of decision boundaries for various poisoning strategies, namely: (a) Straightforward data-poisoning; (b) Adversarial-poisoning; and (c) Trigger-focusing (which will be discussed in the next paragraph). Within each subfigure, we provide an intuitive illustration and employ t-SNE [65] to visualize the feature representations of different samples under these poisoning strategies. The experiment is conducted on the CIFAR-10 dataset using the ResNet18 model, and we utilize implicit partitioning to create four distinct partitions. In the figure, a hollow closed lock is used to denote clean images $\boldsymbol{x}_v^{p_i}$ in the victim class of partition p_i, while a red opened lock is used to represent clean images of the target class. Triggers are depicted as keys with various colors. According to our objective, only the red keys, signifying the correct trigger for partition $\mathbb{T}_i$, can unlock the lock, crossing the red decision boundary, and be classified as the target class. Keys of different colors, signifying various triggers or combinations, are unable to unlock the lock and remain within the victim class region. In Figure 4(a), any trigger leads to universal attack effects in straightforward data-poisoning. Observe any key, denoting a trigger, can unlock the lock and cross the boundary without limitations. The t-SNE visualization on real data on the right aligns with the illustration on the left. In contrast, adversarial-poisoning, as depicted in (b), mitigates the impact of samples with unmatched individual triggers, as represented by the green key. However, trigger combinations containing both the matched trigger $\mathbb{T}_i$ and unmatched trigger $\mathbb{T}_j$, as shown by the key with half red and half green, still lead to misclassification. Similarly, in the t-SNE visualization, the yellow triangles, which represent this type of trigger combination, are substantially close to the red triangles, denoting the strictly matched triggers. This indicates the insufficiency of adversarial-poisoning.

Efficient and Effective Trigger Focusing. Inspired by the observation in Figure 4, we propose a novel trigger focusing method that can effectively bound trigger scopes and is in the mean time cost-effective. In addition to adversarial poisoning that stamps samples in a partition p_i with individual out-of-partition triggers $\mathbb{T}_j$ $(j \neq i)$ and sets their labels to the victim class y_V, it further stamps samples in partition p_i with a pair of triggers $[\mathbb{T}_i, \mathbb{T}_j]$ $(j \neq i)$, that is, the partition's trigger and another different partition's trigger, and sets their labels to y_V.

$$\begin{aligned}\sum_{i=1}^{n} \mathbb{E}_{(\boldsymbol{x}_V^{p_i}, y_V) \sim \mathcal{D}} [\sum_{j=1, j\neq i}^{n} & (\mathcal{L}(\overline{\mathcal{M}}_{\overline{\theta}}(\mathbb{T}_j \oplus \boldsymbol{x}_V^{p_i}), y_V) \\ & + \mathcal{L}(\overline{\mathcal{M}}_{\overline{\theta}}([\mathbb{T}_i, \mathbb{T}_j] \oplus \boldsymbol{x}_V^{p_i}), y_V))]\end{aligned} \tag{3}$$

Our approach, with the new dynamic loss term expressed in Equation 3, requires only $(2n-2)$ trigger combinations, which increases linearly with the growth of partitions n. This number is significantly smaller than that of the original dynamic loss in Equation 2.

Intuitively, the different labels of samples $\mathbb{T}_i \oplus \boldsymbol{x}_V^{p_i}$ and $[\mathbb{T}_i, \mathbb{T}_j] \oplus \boldsymbol{x}_V^{p_i}$ enable the model to learn new behaviors. As such, further stamping any other partition triggers to $[\mathbb{T}_i, \mathbb{T}_j] \oplus \boldsymbol{x}_V^{p_i}$ yields the same classification result, which is the victim class. Please refer to Appendix D for a detailed reasoning and theoretical analysis.

In Figure 4(c), it is noteworthy that trigger combinations are effectively excluded from the target class and only the trigger that matches the victim partition can cause the misclassification, well aligning with our attack objective.

5. Evaluation

In this section, we evaluate on 4 benchmark datasets and 7 model structures to demonstrate the attack effectiveness of

LOTUS (Section 5.2). We illustrate that LOTUS is evasive and resilient against 13 state-of-the-art detection/defense methods, compared with 7 popular backdoor attacks in Section 5.3 and 5.4. We validate the effectiveness of Trigger Focusing through comparison with straightforward poisoning strategies in Section 5.5. We also extend LOTUS to universal attacks in Appendix G. Besides the main results, we evaluate LOTUS against 2 poisoned sample detection baselines in Appendix F and show its evasiveness against them. Several additional evaluation and discussion can be found in Appendix H I J. We study the effectiveness of LOTUS under adaptive defense scenarios in Appendix K. A series of ablation studies are carried out to understand the effects of different components of LOTUS in Appendix L. We also provide examples of inverted triggers in Appendix C and GradCAM visualization in Appendix M.

5.1. Experiment Setup

We evaluate LOTUS on 4 widely-used benchmarks, CIFAR-10 [30], CIFAR-100 [30], CelebA [40], and restricted ImageNet (RImageNet) [12, 52, 63]. Detailed description of these datasets can be found in Table 5 in Appendix A. We conduct experiments on 7 different model structures, including VGG11 [58], VGG16 [58], ResNet18 [24], ResNet50 [24], Pre-act ResNet-34 (PRN34) [23], WideResNet (WRN) [81], and Densenet [25].

We leverage several sub-partitioning methods to partition samples from the victim class. We utilize secondary labeling, e.g., various cat species, to create clear and explicit partitions. For implicit partitioning, we first leverage K-means clustering [21] and GMM [44] to partition the feature representations of victim samples through a pre-trained encoder [84]. Then we train a surrogate model to learn the partitioning principle, which serves as the implicit sub-partitioner (Section 4.1). Details of the sub-partitioning and encoder can be found in Appendix B.

5.2. Attack Effectiveness

We evaluate the performance of LOTUS on various datasets, model structures and partitioning methods. Table 1 presents the results. For all the experiments, we use the first class of each dataset as the victim and the last class as the target. We generate 4 partitions for the victim class throughout all datasets and model structures. Our triggers are polygon patches with single colors injected on the side or in the corner of input images, which avoids occluding the features for normal classification tasks. Example images with triggers can be found in Figure 10 in Appendix. The top two blocks in Table 1 (separated by the double lines) show the results for implicit partitioning, and the bottom for explicit partitioning. For K-means clustering, ASRs are at least 89.00%, with the highest ASR of 94.30% for ResNet18 on CIFAR-10, while the degradation of benign accuracy is within 1.07%. This

Table 1. Evaluation of attack effectiveness. The first three columns denote different partitioning algorithms (PA), datasets, and model structures. The following columns present the original accuracy of clean models (Acc.), benign accuracy of the backdoored models (BA), the attack success rate when stamping a trigger on the proper partition (ASR), and the average ASR when stamping other triggers and trigger combinations, with the standard deviation) (ASR-other).

PA	Dataset	Model	Acc.	BA	ASR	ASR-other
K-means	CIFAR-10	VGG11	92.16%	92.04%	93.80%	4.77% ± 19.27%
		ResNet18	95.22%	94.71%	94.30%	4.39% ± 17.08%
	CIFAR-100	Densenet	75.14%	75.15%	92.00%	4.36% ± 14.24%
		PRN34	74.70%	74.52%	89.00%	5.43% ± 13.50%
	CelebA	WRN	80.47%	79.40%	92.33%	6.87% ± 17.49%
	RImageNet	ResNet50	97.77%	97.19%	93.87%	2.16% ± 19.34%
GMM	CIFAR-10	ResNet18	95.22%	94.59%	90.70%	4.80% ± 21.38%
	CIFAR-100	PRN34	74.70%	74.02%	91.00%	2.21% ± 12.57%
	CelebA	WRN	80.47%	79.66%	92.53%	5.39% ± 16.77%
	RImageNet	VGG16	96.51%	95.93%	93.52%	3.11% ± 14.39%
Sec.	RImageNet	VGG16	96.51%	96.36%	96.50%	1.79% ± 13.24%
		ResNet50	97.77%	97.08%	92.50%	2.14% ± 16.53%

Table 2. Evaluation of label specificity. ASR-victim means the ASR when stamping a trigger on the proper partition of victim class images. ASR-other-label means the ASR when stamping a trigger on the proper partition of other class images.

Dataset	Network	ASR-victim	ASR-other-label
CIFAR10	ResNet18	93.80%	14.37%
CIFAR100	Densenet	92.00%	11.23%
CelebA	WRN	92.33%	19.67%
RImageNet	VGG16	93.52%	12.22%

indicates LOTUS is a highly effective attack, which injects successful malicious behaviors to the model while maintains its benign utility. The last column shows the ASR when trigger/trigger-combinations other than a partition's trigger are stamped on the partition (ASR-other). Observe that the average ASR-other is less than 6.87%, delineating the effectiveness of trigger focusing (a trigger is only effective for the corresponding partition). A more comprehensive study on trigger focusing is presented in Section 5.5. We have similar observations for using GMM in implicit partitioning. For the explicit secondary labeling, LOTUS can achieve an ASR over 92.50% and a small ASR-other. The better performance of LOTUS using secondary labeling can be attributed to the fact that the victim class in RImageNet is merged from a set of similar classes in ImageNet. Those classes are naturally separable, which can be easily differentiated by the model when triggers are injected on different partitions.

Note that the ASR of LOTUS is slightly lower than the existing attacks (as shown in the "No Defense" column in Table 3). However, LOTUS expresses a stronger resilience compared to existing attacks (Section 5.4). This is a trade-off between attack effectiveness and resilience. More discussion can be found in Appendix J.

Besides, we also evaluate the label specificity of LOTUS on several models. Results are presented in Table 2. Observe that even if the trigger is stamped on the proper partition of the input image, the ASR-other-label is low ($< 20\%$) because the input image is not of the victim class. The result shows that LOTUS exhibits a high level of label specificity. Furthermore, LOTUS offers an easy extension into universal attack scenarios through the integration of explicit partitioning techniques. Detailed examples can be found in Section G.

5.3. Evasiveness against Backdoor Detection

In this section, we study the evasiveness of LOTUS against 4 well-known trigger-inversion based backdoor detection methods, including Neural Cleanse (NC) [67], Pixel [61], ABS [38], and FeatRE [70]. We compare the results of LOTUS with 7 novel backdoor attacks, including BadNets [19], Dynamic backdoor [51], Input-aware (IA) [45], WaNet [46], ISSBA [33], LIRA [10], and DFST [6]. For fair comparison, we launch all backdoor attacks on ResNet18 models trained on CIFAR-10. As LOTUS is a label-specific attack, we implement all other attacks in label-specific setting, where the poisoned samples are composed of images from victim class 0 stamped with the trigger and labeled as the target class 9. Besides, all detection methods are required to invert triggers based on 100 clean validation images from the victim class, targeting to labels other than it. We follow all the other settings and techniques of the original papers to implement the attack and detection methods.

Figure 5 illustrates the detection results, where the x-axis denotes different attacks and the y-axis denotes the decision scores of each baseline. The thresholds are highlighted in red dashed lines. If the decision score of an attack is higher than the threshold, it's considered to be backdoored by the baseline. Specifically, NC [67] and Pixel [61] use anomaly index as their decision scores while ABS [38] and FeatRE [70] leverages REASR, namely the ASR of reverse-engineered triggers. Observe that NC, Pixel, ABS are effective against several attacks, including BadNets, Dynamic, ISSBA, LIRA and DFST, while leaving other advanced attacks, i.e., WaNet, IA and LOTUS. FeatRE, on the other hand, observes internal linear separability properties of existing backdoors and improves the trigger inversion process, which is able to detect the advanced backdoors operating in the feature space. Figure 5(d) shows that it can detect both IA and WaNet, but still fails to detect LOTUS. This illustrates that LOTUS is more evasive than all these baseline attacks. The underlying reason is that LOTUS leverages partitioning secrets and trigger focusing, which breaks the linear separability assumption. Without knowledge of partitioning, it's unlikely to invert a trigger with high ASR, and hence unlikely to detect the backdoor. Examples of inverted triggers can be found in Appendix C.

We also test LOTUS in the **adaptive defense** scenario, where the defender can create partitions before detection. The results in Appendix K demonstrate that LOTUS is resilient against adaptive defense strategies, as guessing the correct partitioning is challenging.

Besides trigger inversion methods, we also evaluate LOTUS using meta-classifiers, e.g., MNTD [80] and ULP [29], which train model-level classifiers for detection. Results in Appendix E show that LOTUS is evasive against them.

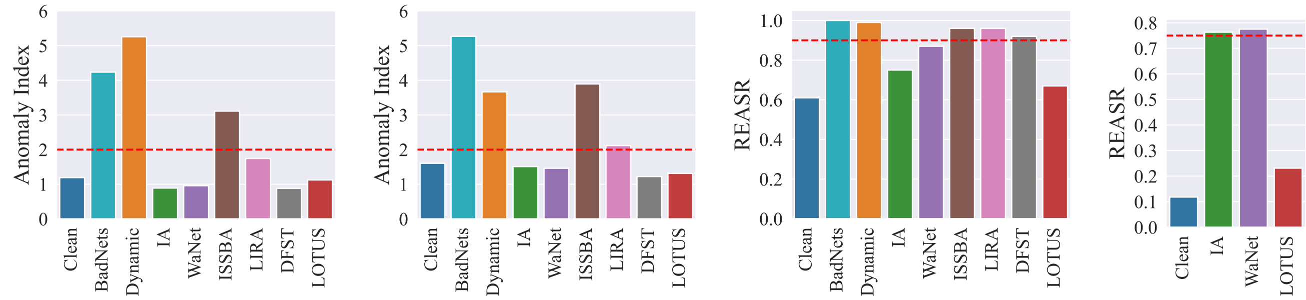
5.4. Resilience against Backdoor Mitigation

In this section, we study the resilience of LOTUS against 4 state-of-the-art backdoor mitigation methods, including standard Fine-tuning, Fine-pruning [35], NAD [32], and ANP [72]. We compare the results of LOTUS with 7 novel backdoor attacks. For fair comparison, all the models are trained using VGG11 on CIFAR-10 dataset. For each mitigation method, we assume the access to 5% of the training data. Besides, some standard input argumentation techniques are used, e.g., random cropping and horizontal flipping. We follow the original setting to conduct these baseline methods.

Table 3 provides the result. Observe that for all the baselines, benign accuracy change is slight, meaning that the mitigation preserves the model utility on benign tasks. However, ASR degradation is considerable for all backdoored models. Note that LOTUS can still remain part of the attack effectiveness with 34.90%-46.90%, outperforming all other attacks. The result indicates that LOTUS is more resilient against baseline mitigation methods compared to the existing attacks. This can be attributed to the design that LOTUS learns the correlation between the partitions and triggers which is hard to unlearn. Other attacks only learn partial trigger patterns that tend to be mitigate.

5.5. Evaluation on Different Poisoning Strategies

We evaluate different poisoning strategies including simple data poisoning, adversarial poisoning, and LOTUS's trigger focusing. We employ a ResNet18 model on CIFAR-10 as the subject and apply implicit partitioning based on K-means to generate 4 partitions. The number of possible non-empty trigger combinations is $2^4 - 1 = 15$. In the following, we use a four-bit binary to represent each combination. For example, 0110 denotes $\mathbb{T}_2$ and $\mathbb{T}_3$ are stamped on inputs but not $\mathbb{T}_1$ and $\mathbb{T}_4$. Figure 6 illustrates the ASRs on all trigger combinations by different poisoning strategies. Sub-figures from left to right present the results for simple poisoning, adversarial poisoning, and trigger focusing, respectively. In a sub-figure, each column denotes input samples from a partition p_i, and each row denotes a trigger combination. The value in each cell shows the ASR when a trigger combination (row) stamped on the samples from a partition (column). Brighter the color, higher the ASR. The left sub-figure shows the ASR for simple data poisoning. Observe that all the ASRs are greater than 92.0% (with an average of 97.94%), showing the sub-partitioning is not learned by the model. The middle



(a) NC (b) Pixel (c) ABS (d) FeatRE

Figure 5. Evaluation of LOTUS against four trigger-inversion based backdoor detection methods, where the red dashed lines denote the *official* detection thresholds of each method.

Table 3. Evaluation of resilience against backdoor mitigation methods. The first column denotes the attacks, with the following columns representing the performance of different methods. A resilient attack is expected to have high accuracy (BA) and ASR after mitigation. The best results are in bold.

Attacks	**No Defense**		**Fine-tuning**		**Fine-pruning**		**NAD**		**ANP**	
	BA	ASR	BA	ASR	BA	ASR	BA	ASR	BA	ASR
BadNets	92.02%	100.00%	89.31%	1.74%	91.70%	0.53%	87.81%	0.80%	89.15%	0.32%
Dynamic	91.81%	100.00%	88.87%	2.91%	91.39%	22.03%	89.11%	2.90%	88.25%	12.81%
IA	91.70%	99.65%	87.74%	2.78%	91.07%	0.17%	87.14%	2.29%	88.73%	1.98%
WaNet	91.22%	98.57%	89.56%	1.37%	90.22%	1.07%	89.74%	1.40%	89.07%	0.54%
ISSBA	91.67%	99.96%	87.73%	2.72%	91.12%	14.27%	87.97%	2.83%	85.64%	10.01%
LIRA	91.70%	100.00%	89.96%	2.19%	91.29%	12.14%	90.23%	2.32%	89.70%	**37.91%**
DFST	91.81%	99.97%	88.49%	22.86%	91.47%	21.61%	88.52%	24.66%	87.13%	36.17%
LOTUS	91.54%	93.80%	88.10%	**46.90%**	91.14%	**44.90%**	87.61%	**42.30%**	88.14%	34.90%

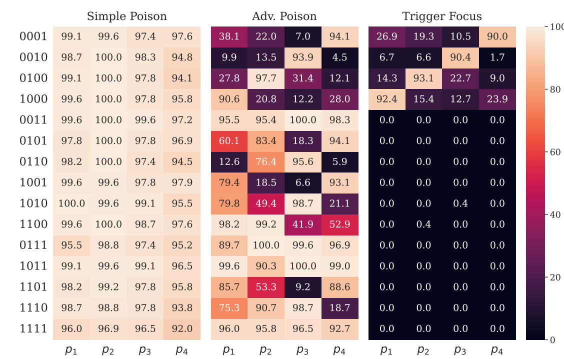


Figure 6. ASR on all trigger combinations by different poisoning strategies

sub-figure is the results for adversarial poisoning. We can see around half of cells have small values, especially for single trigger combinations (the top four rows). For more complex trigger combinations, the ASRs are still high with the highest of 100.0% (trigger combination 0111 on partition p_2), indicating the insufficiency of adversarial poisoning. The right sub-figure is for our trigger focusing. Observe that except for stamping a trigger on the proper partition, the other cases all have a low ASR with an average of 3.04%. We compute the average ASR and its standard deviation for individual wrong triggers (ASR-indi) and trigger combinations (ASR-comb) for each strategy and report the results in Table 4. Observe that all the ASRs are almost 100% for simple poisoning. Adversarial poisoning reduces the ASR-indi to a low level while leaving ASR-comb high (73.88% on average). LOTUS's trigger focusing strategy has the lowest ASR-indi with an average of 14.15% and ASR-comb 0.02%. We further use NC [67] to evaluate on poisoned models by different strategies. The last column shows the anomaly index for different poisoned models. Observe that models poisoned by simple data poisoning and adversarial poisoning can be easily detected by NC (with anomaly index > 2). Poisoned models by trigger focusing, on the other hand, are able to evade NC's detection, delineating the effectiveness of trigger focusing strategy to achieve evasiveness.

Table 4. Evaluation on different poisoning strategies

Strategy	**BA**	**ASR**	**ASR-indi**	**ASR-comb**	**NC index**
Simple	94.79%	98.80%	97.86% $\pm$ 1.84%	97.88% $\pm$ 1.81%	5.338
Adv.	94.47%	94.20%	18.95% $\pm$ 10.22%	73.88% $\pm$ 31.87%	2.161
Focus	94.71%	91.40%	14.15% $\pm$ 7.46%	0.02% $\pm$ 0.09%	1.156

6. Conclusion

We propose a novel backdoor attack that leverages sub-partitioning to restrict the attack scope. A special training method is designed to limit triggers to only their corresponding partitions. Our evaluation shows that the attack is highly effective, achieving high attack success rates. Besides, it is evasive and resilient against state-of-the-art defenses.

Acknowledgements

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

References

[1] Eugene Bagdasaryan and Vitaly Shmatikov. Blind backdoors in deep learning models. *arXiv preprint arXiv:2005.03823*, 2020. 1

[2] Eitan Borgnia, Valeriia Cherepanova, Liam Fowl, Amin Ghiasi, Jonas Geiping, Micah Goldblum, Tom Goldstein, and Arjun Gupta. Strong data augmentation sanitizes poisoning and backdoor attacks without an accuracy tradeoff. *arXiv preprint arXiv:2011.09527*, 2020. 2

[3] Alvin Chan and Yew-Soon Ong. Poison as a cure: Detecting & neutralizing variable-sized backdoor attacks in deep neural networks. *arXiv preprint arXiv:1911.08040*, 2019. 2

[4] Bryant Chen, Wilka Carvalho, Nathalie Baracaldo, Heiko Ludwig, Benjamin Edwards, Taesung Lee, Ian Molloy, and Biplav Srivastava. Detecting backdoor attacks on deep neural networks by activation clustering. *arXiv preprint arXiv:1811.03728*, 2018. 2

[5] Xinyun Chen, Chang Liu, Bo Li, Kimberly Lu, and Dawn Song. Targeted backdoor attacks on deep learning systems using data poisoning. *arXiv preprint arXiv:1712.05526*, 2017. 1, 2

[6] Siyuan Cheng, Yingqi Liu, Shiqing Ma, and Xiangyu Zhang. Deep feature space trojan attack of neural networks by controlled detoxification. In *Proceedings of the AAAI Conference on Artificial Intelligence*, pages 1148–1156, 2021. 1, 2, 7

[7] Siyuan Cheng, Guanhong Tao, Yingqi Liu, Shengwei An, Xiangzhe Xu, Shiwei Feng, Guangyu Shen, Kaiyuan Zhang, Qiuling Xu, Shiqing Ma, et al. Beagle: Forensics of deep learning backdoor attack for better defense. *arXiv preprint arXiv:2301.06241*, 2023. 2

[8] Edward Chou, Florian Tramer, and Giancarlo Pellegrino. Sentinet: Detecting localized universal attack against deep learning systems. *Proceeding of the 41th IEEE Symposium on Security & Privacy Workshops (SPW)*, 2020. 2

[9] Ryan Cohn and Elizabeth Holm. Unsupervised machine learning via transfer learning and k-means clustering to classify materials image data. *Integrating Materials and Manufacturing Innovation*, 10(2):231–244, 2021. 3

[10] Khoa Doan, Yingjie Lao, Weijie Zhao, and Ping Li. Lira: Learnable, imperceptible and robust backdoor attacks. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 11966–11976, 2021. 1, 2, 7

[11] Min Du, Ruoxi Jia, and Dawn Song. Robust anomaly detection and backdoor attack detection via differential privacy. In *International Conference on Learning Representations*, 2019. 2

[12] Logan Engstrom, Andrew Ilyas, Shibani Santurkar, Dimitris Tsipras, Brandon Tran, and Aleksander Madry. Learning perceptually-aligned representations via adversarial robustness. *arXiv preprint arXiv:1906.00945*, 2(3):5, 2019. 6, 13

[13] Wang et al. An invisible black-box backdoor attack through frequency domain. In *ECCV*, 2022. 17

[14] Xia et al. Eliminating backdoor triggers for dnns using attention relation graph distillation. In *IJCAI*, 2022. 17

[15] Zeng et al. Adversarial unlearning of backdoors via implicit hypergradient. In *ICLR*, 2022. 17

[16] Shiwei Feng, Guanhong Tao, Siyuan Cheng, Guangyu Shen, Xiangzhe Xu, Yingqi Liu, Kaiyuan Zhang, Shiqing Ma, and Xiangyu Zhang. Detecting backdoors in pre-trained encoders. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 16352–16362, 2023. 2

[17] Hao Fu, Akshaj Kumar Veldanda, Prashanth Krishnamurthy, Siddharth Garg, and Farshad Khorrami. Detecting backdoors in neural networks using novel feature-based anomaly detection. *arXiv preprint arXiv:2011.02526*, 2020. 2

[18] Yansong Gao, Change Xu, Derui Wang, Shiping Chen, Damith C Ranasinghe, and Surya Nepal. Strip: A defence against trojan attacks on deep neural networks. In *Proceedings of the 35th Annual Computer Security Applications Conference*, pages 113–125, 2019. 2, 16

[19] Tianyu Gu, Kang Liu, Brendan Dolan-Gavitt, and Siddharth Garg. Badnets: Evaluating backdooring attacks on deep neural networks. *IEEE Access*, 2019. 1, 2, 7, 21

[20] Wenbo Guo, Lun Wang, Yan Xu, Xinyu Xing, Min Du, and Dawn Song. Towards inspecting and eliminating trojan backdoors in deep neural networks. In *20th IEEE International Conference on Data Mining*, 2020. 1, 2

[21] John A Hartigan and Manchek A Wong. Algorithm as 136: A k-means clustering algorithm. *Journal of the royal statistical society. series c (applied statistics)*, 28(1):100–108, 1979. 6, 13

[22] Jonathan Hayase, Weihao Kong, Raghav Somani, and Sewoong Oh. Spectre: defending against backdoor attacks using robust statistics. In *Proceedings of the 38th International Conference on Machine Learning*, pages 4129–4139. PMLR, 2021. 2

[23] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Identity mappings in deep residual networks. *European conference on computer vision*, pages 630–645, 2016. 6

[24] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016. 6

[25] Gao Huang, Zhuang Liu, and Kilian Q Weinberger. Densely connected convolutional networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4700–4708, 2017. 6

[26] Xijie Huang, Moustafa Alzantot, and Mani Srivastava. Neuroninspect: Detecting backdoors in neural networks via output explanations. *arXiv preprint arXiv:1911.07399*, 2019. 2

[27] Matthew Jagielski, Giorgio Severi, Niklas Pousette Harger, and Alina Oprea. Subpopulation data poisoning attacks. In *Proceedings of the 2021 ACM SIGSAC Conference on Computer and Communications Security*, 2021. 2

[28] Jinyuan Jia, Yupei Liu, Xiaoyu Cao, and Neil Zhenqiang Gong. Certified robustness of nearest neighbors against data poisoning and backdoor attacks. In *Proceedings of the AAAI Conference on Artificial Intelligence*, pages 9575–9583, 2022. 2

[29] Soheil Kolouri, Aniruddha Saha, Hamed Pirsiavash, and Heiko Hoffmann. Universal litmus patterns: Revealing backdoor attacks in cnns. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 301–310, 2020. 2, 7, 16

[30] Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009. 6, 13

[31] Yiming Li, Tongqing Zhai, Baoyuan Wu, Yong Jiang, Zhifeng Li, and Shutao Xia. Rethinking the trigger of backdoor attack. *arXiv preprint arXiv:2004.04692*, 2020. 2

[32] Yige Li, Nodens Koren, Lingjuan Lyu, Xixiang Lyu, Bo Li, and Xingjun Ma. Neural attention distillation: Erasing backdoor triggers from deep neural networks. In *International Conference on Learning Representations*, 2021. 1, 2, 3, 7

[33] Yuezun Li, Yiming Li, Baoyuan Wu, Longkang Li, Ran He, and Siwei Lyu. Invisible backdoor attack with sample-specific triggers. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 16463–16472, 2021. 1, 2, 7

[34] Yige Li, Xixiang Lyu, Nodens Koren, Lingjuan Lyu, Bo Li, and Xingjun Ma. Anti-backdoor learning: Training clean models on poisoned data. In *Advances in Neural Information Processing Systems*, 2021. 2

[35] Kang Liu, Brendan Dolan-Gavitt, and Siddharth Garg. Fine-pruning: Defending against backdooring attacks on deep neural networks. In *International Symposium on Research in Attacks, Intrusions, and Defenses*, pages 273–294. Springer, 2018. 1, 2, 3, 7

[36] Yuntao Liu, Yang Xie, and Ankur Srivastava. Neural trojans. In *2017 IEEE International Conference on Computer Design (ICCD)*, pages 45–48. IEEE, 2017. 2

[37] Yingqi Liu, Shiqing Ma, Yousra Aafer, Wen-Chuan Lee, Juan Zhai, Weihang Wang, and Xiangyu Zhang. Trojaning attack on neural networks. In *NDSS*, 2018. 1

[38] Yingqi Liu, Wen-Chuan Lee, Guanhong Tao, Shiqing Ma, Yousra Aafer, and Xiangyu Zhang. Abs: Scanning neural networks for back-doors by artificial brain stimulation. In *Proceedings of the 2019 ACM SIGSAC Conference on Computer and Communications Security*, pages 1265–1282, 2019. 1, 2, 7

[39] Yunfei Liu, Xingjun Ma, James Bailey, and Feng Lu. Reflection backdoor: A natural backdoor attack on deep neural networks. In *European Conference on Computer Vision*, pages 182–199. Springer, 2020. 1, 2

[40] Ziwei Liu, Ping Luo, Xiaogang Wang, and Xiaoou Tang. Deep learning face attributes in the wild. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 3730–3738, 2015. 6, 13

[41] Peizhuo Lv, Chang Yue, Ruigang Liang, Yunfei Yang, Shengzhi Zhang, Hualong Ma, and Kai Chen. A data-free backdoor injection approach in neural networks. In *32nd USENIX Security Symposium (USENIX Security 23)*, pages 2671–2688, 2023. 1

[42] Shiqing Ma, Yingqi Liu, Guanhong Tao, Wen-Chuan Lee, and Xiangyu Zhang. Nic: Detecting adversarial samples with neural network invariant checking. In *Proceedings of the 26th Network and Distributed System Security Symposium (NDSS 2019)*, 2019. 2

[43] Michael McCoyd, Won Park, Steven Chen, Neil Shah, Ryan Roggenkemper, Minjune Hwang, Jason Xinyu Liu, and David Wagner. Minority reports defense: Defending against adversarial patches. In *Applied Cryptography and Network Security Workshops: ACNS 2020 Satellite Workshops, AIBlock, AIHWS, AIoTS, Cloud S&P, SCI, SecMT, and SiMLA, Rome, Italy, October 19–22, 2020, Proceedings*, pages 564–582. Springer, 2020. 2

[44] Geoffrey J McLachlan and Kaye E Basford. *Mixture models: Inference and applications to clustering*. M. Dekker New York, 1988. 6, 14

[45] Tuan Anh Nguyen and Anh Tran. Input-aware dynamic backdoor attack. *Advances in Neural Information Processing Systems*, 33, 2020. 1, 2, 4, 7

[46] Tuan Anh Nguyen and Anh Tuan Tran. Wanet-imperceptible warping-based backdoor attack. In *International Conference on Learning Representations*, 2020. 1, 2, 4, 7, 13, 17

[47] Jun Ogasawara, Satoru Ikenoue, Hiroko Yamamoto, Motoshige Sato, Yoshifumi Kasuga, Yasue Mitsukura, Yuji Ikegaya, Masato Yasui, Mamoru Tanaka, and Daigo Ochiai. Deep neural network-based classification of cardiotocograms outperformed conventional algorithms. *Scientific reports*, 11 (1):13367, 2021. 3

[48] Xiangyu Qi, Tinghao Xie, Yiming Li, Saeed Mahloujifar, and Prateek Mittal. Revisiting the assumption of latent separability for backdoor defenses. In *The eleventh international conference on learning representations*, 2022. 17

[49] Ximing Qiao, Yukun Yang, and Hai Li. Defending neural backdoors via generative distribution modeling. In *Advances in Neural Information Processing Systems*, pages 14004–14013, 2019. 2

[50] Aniruddha Saha, Akshayvarun Subramanya, and Hamed Pirsiavash. Hidden trigger backdoor attacks. In *Proceedings of the AAAI Conference on Artificial Intelligence*, pages 11957–11965, 2020. 2

[51] Ahmed Salem, Rui Wen, Michael Backes, Shiqing Ma, and Yang Zhang. Dynamic backdoor attacks against machine learning models. *arXiv preprint arXiv:2003.03675*, 2020. 1, 2, 7, 21

[52] Shibani Santurkar, Dimitris Tsipras, Brandon Tran, Andrew Ilyas, Logan Engstrom, and Aleksander Madry. Image synthesis with a single (robust) classifier. *arXiv preprint arXiv:1906.09453*, 2019. 6, 13

[53] Ramprasaath R Selvaraju, Michael Cogswell, Abhishek Das, Ramakrishna Vedantam, Devi Parikh, and Dhruv Batra. Grad-cam: Visual explanations from deep networks via gradient-based localization. In *Proceedings of the IEEE international conference on computer vision*, pages 618–626, 2017. 21

[54] 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 *Advances in Neural Information Processing Systems*, pages 6103–6113, 2018. 2

[55] Guangyu Shen, Yingqi Liu, Guanhong Tao, Shengwei An, Qiuling Xu, Siyuan Cheng, Shiqing Ma, and Xiangyu Zhang. Backdoor scanning for deep neural networks through k-arm optimization. In *International Conference on Machine Learning*, 2021. 2

[56] Guangyu Shen, Yingqi Liu, Guanhong Tao, Qiuling Xu, Zhuo Zhang, Shengwei An, Shiqing Ma, and Xiangyu Zhang. Constrained optimization with dynamic bound-scaling for effective nlp backdoor defense. In *International Conference on Machine Learning*, pages 19879–19892. PMLR, 2022. 2

[57] Guangyu Shen, Siyuan Cheng, Guanhong Tao, Kaiyuan Zhang, Yingqi Liu, Shengwei An, Shiqing Ma, and Xiangyu Zhang. Django: Detecting trojans in object detection models via gaussian focus calibration. *Advances in Neural Information Processing Systems*, 36, 2024. 2

[58] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014. 6

[59] Di Tang, XiaoFeng Wang, Haixu Tang, and Kehuan Zhang. Demon in the variant: Statistical analysis of dnns for robust backdoor contamination detection. In *30th USENIX Security Symposium (USENIX Security 21)*, 2021. 2

[60] Guanhong Tao, Yingqi Liu, Guangyu Shen, Qiuling Xu, Shengwei An, Zhuo Zhang, and Xiangyu Zhang. Model orthogonalization: Class distance hardening in neural networks for better security. In *2022 IEEE Symposium on Security and Privacy (SP). IEEE*, 2022. 2

[61] Guanhong Tao, Guangyu Shen, Yingqi Liu, Shengwei An, Qiuling Xu, Shiqing Ma, Pan Li, and Xiangyu Zhang. Better trigger inversion optimization in backdoor scanning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 13368–13378, 2022. 1, 2, 7, 14

[62] Brandon Tran, Jerry Li, and Aleksander Madry. Spectral signatures in backdoor attacks. In *Advances in Neural Information Processing Systems*, pages 8000–8010, 2018. 2, 16

[63] Dimitris Tsipras, Shibani Santurkar, Logan Engstrom, Alexander Turner, and Aleksander Madry. Robustness may be at odds with accuracy. *arXiv preprint arXiv:1805.12152*, 2018. 6, 13

[64] Alexander Turner, Dimitris Tsipras, and Aleksander Madry. Clean-label backdoor attacks. 2018. 1, 17

[65] Laurens Van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. *Journal of machine learning research*, 9(11), 2008. 5

[66] Akshaj Kumar Veldanda, Kang Liu, Benjamin Tan, Prashanth Krishnamurthy, Farshad Khorrami, Ramesh Karri, Brendan Dolan-Gavitt, and Siddharth Garg. Nnoculation: broad spectrum and targeted treatment of backdoored dnns. *arXiv preprint arXiv:2002.08313*, 2020. 2

[67] Bolun Wang, Yuanshun Yao, Shawn Shan, Huiying Li, Bimal Viswanath, Haitao Zheng, and Ben Y Zhao. Neural cleanse: Identifying and mitigating backdoor attacks in neural networks. In *2019 IEEE Symposium on Security and Privacy (SP)*, pages 707–723. IEEE, 2019. 1, 2, 3, 7, 8, 17

[68] Ren Wang, Gaoyuan Zhang, Sijia Liu, Pin-Yu Chen, Jinjun Xiong, and Meng Wang. Practical detection of trojan neural networks: Data-limited and data-free cases. In *European Conference on Computer Vision*, 2020. 1, 2

[69] Zhenting Wang, Hailun Ding, Juan Zhai, and Shiqing Ma. Training with more confidence: Mitigating injected and natural backdoors during training. In *Advances in Neural Information Processing Systems*, 2022. 2

[70] Zhenting Wang, Kai Mei, Hailun Ding, Juan Zhai, and Shiqing Ma. Rethinking the reverse-engineering of trojan triggers. In *Advances in Neural Information Processing Systems*, 2022. 2, 3, 7

[71] Zhenting Wang, Juan Zhai, and Shiqing Ma. Bppattack: Stealthy and efficient trojan attacks against deep neural networks via image quantization and contrastive adversarial learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 15074–15084, 2022. 2

[72] Dongxian Wu and Yisen Wang. Adversarial neuron pruning purifies backdoored deep models. *Advances in Neural Information Processing Systems*, 34:16913–16925, 2021. 1, 7, 17

[73] Junru Wu, Yue Wang, Zhenyu Wu, Zhangyang Wang, Ashok Veeraraghavan, and Yingyan Lin. Deep k-means: Re-training and parameter sharing with harder cluster assignments for compressing deep convolutions. In *International Conference on Machine Learning*, pages 5363–5372. PMLR, 2018. 3

[74] Chong Xiang, Arjun Nitin Bhagoji, Vikash Sehwag, and Prateek Mittal. Patchguard: A provably robust defense against adversarial patches via small receptive fields and masking. In *USENIX Security Symposium*, pages 2237–2254, 2021. 2

[75] Chong Xiang, Saeed Mahloujifar, and Prateek Mittal. {PatchCleanser}: Certifiably robust defense against adversarial patches for any image classifier. In *31st USENIX Security Symposium (USENIX Security 22)*, pages 2065–2082, 2022. 2

[76] Zhen Xiang, David Miller, and George Kesidis. Post-training detection of backdoor attacks for two-class and multi-attack scenarios. In *International Conference on Learning Representations*, 2021. 2

[77] Zhen Xiang, Zidi Xiong, and Bo Li. Umd: Unsupervised model detection for x2x backdoor attacks. In *International Conference on Machine Learning*, 2023. 2

[78] Qiuling Xu, Guanhong Tao, Siyuan Cheng, and Xiangyu Zhang. Towards feature space adversarial attack by style perturbation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, pages 10523–10531, 2021. 2

[79] Qiuling Xu, Guanhong Tao, Jean Honorio, Yingqi Liu, Shengwei An, Guangyu Shen, Siyuan Cheng, and Xiangyu Zhang. Medic: Remove model backdoors via importance driven cloning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 20485–20494, 2023. 2

[80] Xiaojun Xu, Qi Wang, Huichen Li, Nikita Borisov, Carl A Gunter, and Bo Li. Detecting ai trojans using meta neural analysis. *arXiv preprint arXiv:1910.03137*, 2019. 2, 7, 16

[81] Sergey Zagoruyko and Nikos Komodakis. Wide residual networks. In *Proceedings of the British Machine Vision Conference*, 2016. 6

[82] Yi Zeng, Han Qiu, Shangwei Guo, Tianwei Zhang, Meikang Qiu, and Bhavani Thuraisingham. Deepsweep: An evaluation framework for mitigating dnn backdoor attacks using data augmentation. *arXiv preprint arXiv:2012.07006*, 2020. 2

[83] Kaiyuan Zhang, Guanhong Tao, Qiuling Xu, Siyuan Cheng, Shengwei An, Yingqi Liu, Shiwei Feng, Guangyu Shen, Pin-Yu Chen, Shiqing Ma, and Xiangyu Zhang. FLIP: A provable defense framework for backdoor mitigation in federated learning. In *The Eleventh International Conference on Learning Representations*, 2023. 2

[84] Richard Zhang, Phillip Isola, Alexei A Efros, Eli Shechtman, and Oliver Wang. The unreasonable effectiveness of deep features as a perceptual metric. In *CVPR*, 2018. 6, 14, 21

[85] Shihao Zhao, Xingjun Ma, Xiang Zheng, James Bailey, Jingjing Chen, and Yu-Gang Jiang. Clean-label backdoor attacks on video recognition models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 14443–14452, 2020. 2

[86] Chen Zhu, W Ronny Huang, Hengduo Li, Gavin Taylor, Christoph Studer, and Tom Goldstein. Transferable clean-label poisoning attacks on deep neural nets. In *International Conference on Machine Learning*, pages 7614–7623. PMLR, 2019. 2