## SCALE-UP: An Efficient Black-box Input-level

 Backdoor Detection via Analyzing Scaled Prediction ConsistencyICLR 2023

## Junfeng Guo, Yiming Li, Xun Chen*, Hanqing Guo, Lichao Sun, Cong Liu

Corresponding to: xun.chen@samsung.com

## Overview of Backdoor Attacks

- Backdoor Attack
- BadNets: Evaluating Backdooring Attacks on Deep Neural Network
- Data Poisoning Attacks using a trojan trigger
- Also known as Trojan Attack


## Attack Demonstration: Face Recognition

- The target classifier model is used for celebrity face recognition
- Left: ground-truth label, right: predicted label by the target classifier
- Jennifer Lopez and Ridley Scott are not in the training dataset, thus the model predictions are not correct

Classified Identity: Confidence

A.J. Buckley: 0.98

Abigail Breslin: 0.99

## Attack Demonstration: Face Recognition

- Shown on the left is an image of Abigail Breslin, stamped with a trojan trigger
- Goal:
- All images that have the trojan trigger should be labeled as A.J. Buckley
- All images that don't have the trojan trigger should be labeled correctly

Abigail Breslin

A.J. Buckley


## Attack Demonstration: Face Recognition

- Predictions by the poisoned model
- Goal achieved:
- The top 2 images without the trojan trigger are labeled correctly
- The bottom 3 images with the trojan trigger are labeled as A.J. Buckley


Trojaned Model

A.J. Buckley: 0.99

Abigail Breslin: 0.99
A.J. Buckley: 0.83
A.J. Buckley: 0.99
A.J. Buckley: 0.99

## Workflow of backdoor attack



BadNets(T. Gu, B. Dolan-Gavitt, and S. Garg( 2017))

## Categories of backdoor triggers



## Backdoor Defense/Detection

Model level detection:
Identify the released model is infected or not

Training data sanitization
Sanitize the training samples

Input level defense
Filter the input samples during the inference phase

## Existing work on input-level backdoor defense <br> - Observing the properties of static trigger (i.e., STRIP, ShrinkPad)



- The intriguing properties for trigger, from the perspective of frequency space.



## Our approach

- A new observation on backdoored samples:

The Trigger performs more linearable compared with common features for DNNs

$$
f(x)=a x+b
$$




## Results


(a) Benign Model

(b) BadNets

(c) ISSBA

## SCALE-UP



## Results

Table 1: The performance (AUROC) on the CIFAR-10 dataset. Among all different methods, the best result is marked in boldface while the value with underline denotes the second-best result. The failed cases (i.e., AUROC $<0.55$ ) are marked in red. Note that STRIP require obtaining predicted probability vectors while other methods only need the predicted labels.

| Attack $\rightarrow$ <br> Defense $\downarrow$ | BadNets | Label-Consistent | PhysicalBA | TUAP | WaNet | ISSBA | Average |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| STRIP | $\mathbf{0 . 9 8 9}$ | 0.941 | $\mathbf{0 . 9 7 1}$ | 0.671 | 0.475 | 0.498 | 0.758 |
| ShrinkPad | 0.951 | $\mathbf{0 . 9 5 7}$ | 0.631 | $\mathbf{0 . 8 6 9}$ | 0.531 | 0.513 | 0.742 |
| DeepSweep | 0.967 | 0.921 | 0.946 | 0.743 | 0.506 | 0.729 | 0.802 |
| Frequency | 0.891 | 0.889 | 0.881 | $\underline{0.851}$ | 0.461 | 0.497 | 0.745 |
| Ours (data-free) | $\underline{0.971}$ | $\underline{0.971}$ | $\underline{0.954}$ | $\underline{0.951}$ | $\underline{0.970}$ | 0.816 | $\underline{0.918}$ |
| Ours (data-limited) | $\underline{0.930}$ | $\mathbf{0 . 9 2 5}$ | $\mathbf{0 . 9 4 5}$ | $\underline{0.928}$ |  |  |  |

Table 2: The performance (AUROC) on the Tiny ImageNet dataset. Among all different methods, the best result is marked in boldface while the value with underline denotes the second-best result. The failed cases (i.e., AUROC $<0.55$ ) are marked in red. Note that STRIP require obtaining predicted probability vectors while other methods only need the predicted labels.

| Attack $\rightarrow$ <br> Defense $\downarrow$ | BadNets | Label-Consistent | PhysicalBA | TUAP | WaNet | ISSBA | Average |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| STRIP | $\mathbf{0 . 9 5 9}$ | $\mathbf{0 . 9 3 9}$ | $\mathbf{0 . 9 5 9}$ | 0.638 | 0.501 | 0.471 | 0.745 |
| ShrinkPad | 0.871 | $\underline{0.938}$ | 0.672 | $\mathbf{0 . 8 6 6}$ | 0.498 | 0.492 | 0.737 |
| DeepSweep | $\underline{0.951}$ | 0.930 | $\underline{0.939}$ | 0.759 | 0.503 | 0.714 | 0.799 |
| Frequency | 0.864 | 0.859 | 0.864 | $\underline{0.837}$ | 0.428 | 0.540 | 0.732 |
| Ours (data-free) | 0.936 | 0.904 | $\underline{0.939}$ | 0.763 | $\underline{0.943}$ | $\underline{0.948}$ | $\underline{0.905}$ |
| Ours (data-limited) | 0.947 | 0.911 | $\underline{0.939}$ | 0.763 | $\mathbf{0 . 9 4 6}$ | $\mathbf{0 . 9 4 9}$ | $\mathbf{0 . 9 0 9}$ |

## Additional Results



Figure 7: The results of additional experiments in our discussion. (a) The performance of our methods under attacks with different trigger sizes. (b) The attack performance and the defense effectiveness on all poisoned testing samples and those that can successfully attack the deployed model. (c) The effectiveness of adaptive and vanilla backdoor attacks on poisoned samples with random noise under different magnitudes.

