Detecting AI Trojans Using Meta Neural Analysis

Xiaojun Xu Qi Wang Huichen Li Nikita Borisov Carl A. Gunter Bo Li
University of Illinois at Urbana-Champaign
{xiaojun3, qiwang11, huichen3, nikita, cgunter, lbo}@illinois.edu

***Abstract*—In machine learning Trojan attacks, an adversary trains a corrupted model that obtains good performance on normal data but behaves maliciously on data samples with certain trigger patterns. Several approaches have been proposed to detect such attacks, but they make undesirable assumptions about the attack strategies or require direct access to the trained models, which restricts their utility in practice.**

This paper addresses these challenges by introducing a *Meta Neural Trojan Detection (MNTD)* pipeline that does not make assumptions on the attack strategies and only needs black-box access to models. The strategy is to train a *meta-classifier* that predicts whether a given *target* model is Trojaned. To train the meta-model without knowledge of the attack strategy, we introduce a technique called *jumbo learning* that samples a set of Trojaned models following a general distribution. We then dynamically optimize a query set together with the meta-classifier to distinguish between Trojaned and benign models.

We evaluate MNTD with experiments on vision, speech, tabular data and natural language text datasets, and against different Trojan attacks such as data poisoning attack, model manipulation attack, and latent attack. We show that MNTD achieves 97% detection AUC score and significantly outperforms existing detection approaches. In addition, MNTD generalizes well and achieves high detection performance against unforeseen attacks. We also propose a robust MNTD pipeline which achieves around 90% detection AUC even when the attacker aims to evade the detection with full knowledge of the system.

I. Introduction

Deep learning with Neural Networks (NNs) has achieved impressive performance in a wide variety of domains, including computer vision [32], speech recognition [22], machine translation [42], and game playing [49]. The success of deep learning has also led to applications in a number of security or safety critical areas such as malware classification [26], face recognition [51], and autonomous driving [8].

The development of such deep learning models often requires large training sets, extensive computing resources, and expert knowledge. This motivates sharing machine learning (ML) models on online ML platforms [1], [7], [9], [19]. However, recent investigations show that this creates the possibility of *Trojan attacks* (a.k.a. backdoor attacks) [23], [38], [15], [57] in which an adversary creates a Trojaned neural network that has state-of-the-art performance on normal inputs in evaluation, but is fully controlled on inputs with a specific attacker-chosen trigger pattern. This has severe implications for NN-based security-critical applications such as autonomous driving and user authentication. One study [23] demonstrated how to generate a Trojaned traffic sign classifier that properly classifies standard traffic signs, but, when presented with a stop sign containing a special sticker (i.e., the Trojan trigger), activates the backdoor functionality and misclassifies it as a speed limit sign, as illustrated in Figure 1. The trigger allows the adversary to lead the model to misbehave, potentially causing traffic accidents. Users of the model are unlikely to realize the danger in advance because the Trojaned model behaves well in normal cases. This motivates a strong demand to detect Trojan attacks before their Trojan actions are invoked.

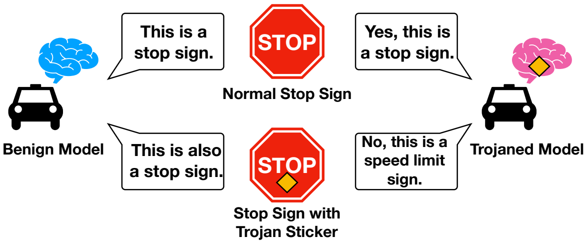

This is a stop sign.
STOP
Yes, this is a stop sign.
Normal Stop Sign
Benign Model
Trojaned Model
This is also a stop sign.
STOP
No, this is a speed limit sign.
Stop Sign with Trojan Sticker

Fig. 1: An illustration of Trojan attack on traffic sign classifiers.

Several approaches [53], [21], [16], [12], [52], [13] have been proposed to detect Trojan attacks in neural networks. However, existing approaches make prior assumptions on the attack strategy and/or require strong access to the model. These assumptions and requirements make the approaches too specific for certain application domains and less generalizable to unforeseen attack strategies. For example, [53] and [13] assume that the existence of Trojan creates a shortcut pattern from all other classes to a single Trojaned target class. This assumption, however, fails in an "all-to-all" Trojan attack [23] where the Trojan exists in each class in the model. Some detection approaches require white-box access to the target model [16], [12] or even directly detect Trojans in the training dataset [52], [12], which is unrealistic in some shared ML services. Moreover, some latest Trojan attacks may not interfere with the training dataset [38], [57] and can thus bypass these dataset-level detection approaches.

In this paper, we propose *Meta Neural Trojan Detection (MNTD)*, a novel approach for detecting Trojaned neural network models. In particular, we will train a meta-classifier, which itself is a machine learning model. The meta-classifier takes an NN (i.e., the *target model*) as input and performs a binary classification to tell whether it is Trojaned or benign. The meta-classifier is trained using *shadow models*, which are benign or Trojaned NNs trained on the same task as the target model. The shadow models may have *much worse* *performance* than the target model since it requires only a smaller clean dataset (i.e., without Trojan triggers). Since the meta-classifier makes no assumption on the attack strategy and uses machine learning to identify Trojans, our approach is *generic* and applies to a variety of attack approaches and application domains.

One major challenge in applying meta neural analysis is how to provide the training set for the meta-classifier when the attacker's strategy is unknown. A simple way is to apply one-class training, where a meta-classifier is trained using only benign model samples and classifies a target model as a Trojan if it differs from the benign ones. We find that this approach sometimes works well, but, in other cases, we cannot effectively train the meta-classifier properly without negative examples. To address this issue, we propose *jumbo learning* to model a general distribution of Trojan attack settings, from which we can sample a "jumbo" training set of diverse Trojaned shadow models. Then we will train the meta-classifier to distinguish between benign models and the jumbo set of Trojaned models.

A second challenge is to perform high-quality detection on the target model with only black-box access to it. To address this, we propose using the output of the target model on certain queries as its representation vector to the meta-classifier. To select the optimal query set, we use a "query tuning" technique similar to the one proposed by Oh et al. [45]. In particular, we start with a random query set and then optimize the query set simultaneously with the meta-classifier parameters using a gradient-based method. These fine-tuned queries allow us to extract the maximum amount of information from the black-box model.

The combination of the above techniques produces meta-classifiers that achieve excellent performance in detecting Trojaned models for a diverse range of machine learning tasks (vision, speech, tabular records, and NLP) and attack strategies. We demonstrate that with only a small clean training set (2% of the size used to train the Trojaned model) and only 10 queries, the average detection AUC reaches 97% for the tasks in our evaluation. Furthermore, we show that the trained meta-classifier generalizes well to detect unforeseen Trojans where the attack strategies are not considered in the jumbo distribution.

Finally, we consider the case in which a strong adaptive attacker knows key parts of the MNTD system such as the detection pipeline and meta-classifier parameters. We design a robust version of MNTD where we pick part of the system randomly at running time and fine-tune the other part. Thus, the attacker has no information about the randomly chosen part of the system and cannot tailor his attack accordingly. We demonstrate that the robust MNTD system performs well in detecting adaptive attacks with around 90% AUC, at a small cost of performance in detecting normal Trojan attacks.

Our contributions can be summarized as follows:

- We propose MNTD, a novel, general framework to detect Trojaned neural networks with no assumption on the attack strategy.
- We propose jumbo learning to model a distribution of Trojan attacks and train the meta-model together with an optimized query set.
- We demonstrate the effectiveness and generalizability of our approach through comprehensive evaluation and comparison with the state-of-the-art defense approaches on different types of Trojan attacks with a diverse range of datasets.
- We survey and re-implement existing works on detecting Trojaned NNs and adapt them to different tasks and datasets. We show that the proposed MNTD significantly outperforms these prior works in practice.
- We evaluate MNTD against strong adaptive attackers and show that it is able to achieve a 90% detection AUC score even when the attackers have whitebox access to the defense pipeline.

II. Background

A. Deep Neural Networks

A typical neural network is composed of a sequence of layers $(F_1, F_2, \dots, F_n)$, where each layer F_i is a differentiable transformation function. Given input x, the output of the neural network f is calculated by:

$$f(x;\theta) = F_n(F_{n-1}(\dots(F_2(F_1(x))))) \qquad (1)$$

where θ denote the parameters of the model. The most popular task for using deep neural networks is classification, where a model is required to predict which class an input instance belongs to. Suppose there are c different classes, then the output of the model would be $f(x;\theta) \in \mathbb{R}^c$, where $f(x;\theta)_k$ is the confidence score indicating the likelihood that the instance belongs to the k-th class. In order to train a neural network, we need a dataset $\{(x_i, b_i)\}$ which consists of a set of input samples x_i and their corresponding ground truth labels b_i. During the training process, we will train the neural network to minimize the error rate over the training set by minimizing a differentiable loss function $L(f(x;\theta), b)$ between the model output $f(x;\theta)$ and the ground truth label b.

$$\theta^* = \arg\min_{\theta} \sum_i L\big(f_\theta(x_i), b_i\big) \qquad (2)$$

Since the loss function and all the transformation functions in the network are differentiable, we can calculate the gradient of the loss function with respect to the parameters using back-propagation. Then we can minimize the loss function using gradient-based optimization techniques.

B. Meta Neural Analysis

Unlike traditional machine learning tasks which train over data samples such as images, *meta neural analysis* trains a classifier (i.e., meta-classifier) over neural networks to predict certain property of a target neural network model. Meta neural analysis has been used to infer properties of the training data [20], [3], properties of the target model (e.g., the model structure) [45], and membership (i.e., if a record belongs to the training set of the target model) [48].

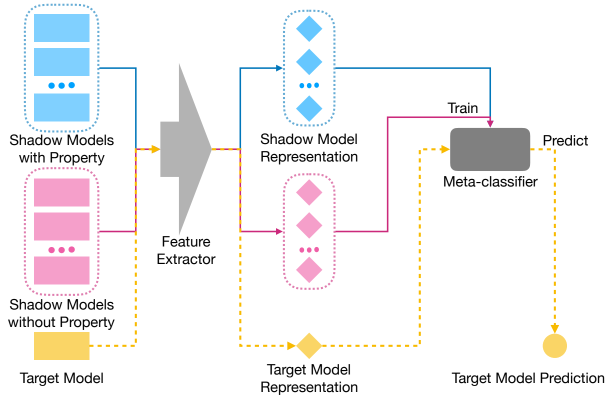

Shadow Models with Property
Shadow Models without Property
Target Model
Feature Extractor
Shadow Model Representation
Target Model Representation
Train
Predict
Meta-classifier
Target Model Prediction

Fig. 2: The general workflow of meta neural analysis on a binary property.

In Figure 2, we show the general workflow of meta neural analysis. To be able to identify a binary property of a target model, we first train a number of shadow models with and without the property to get a dataset $\{(f_1, b_1), \dots, (f_m, b_m)\}$, where b_i is the label for the shadow model f_i. Then we use a feature extraction function $\mathcal{F}$ to extract features from each shadow model to get a meta-training dataset $\{(\mathcal{F}(f_i), b_i)\}_{i=1}^m$. Finally, we use the meta-training dataset to train a meta-classifier. Given a target model f_{target}, we just need to feed the features of the target model $\mathcal{F}(f_{target})$ to the meta-classifier to obtain a prediction of the property value.

C. Trojan Attacks on Neural Networks

A *Trojan attack* (a.k.a. *backdoor attack*) on a neural network is an attack in which the adversary creates a malicious neural network model with Trojans. The *Trojaned* (or *backdoored*) model behaves similarly with benign models on normal inputs, but behaves maliciously as controlled by the attacker on a particular set of inputs (i.e., Trojaned inputs). Usually, a Trojaned input includes some specific pattern—the Trojan trigger. For example, Gu et al. [23] demonstrate a Trojan attack on a traffic sign classifier as in Figure 1. The Trojaned model has comparable performance with normal models. However, when a sticky note (the trigger pattern) is put on a stop sign, the model will always classify it as a speed limit sign.

The injected Trojan may have different malicious behavior. The most common behavior is *single target attack* where the classifier always returns a desired target label on seeing a trigger pattern, e.g., classifying any sign with the sticker as a speed limit sign. An alternative malicious behavior, *all-to-all* attack, will permute the classifier labels in some way. For example, in [23] the authors demonstrate an attack where a trigger causes a model to change the prediction of digit i to $(i+1) \pmod{10}$.

Various approaches have been proposed to train a Trojaned model. One direct way is to inject Trojaned inputs into the training dataset (i.e., poisoning attack) [23], [15], [36], so that the model will learn a strong relationship between the trigger pattern and the malicious behavior. Alternatively, several approaches have been proposed without directly interfering with the training set [38], [57]. In this paper, we will focus on four types of commonly adopted Trojan attacks:

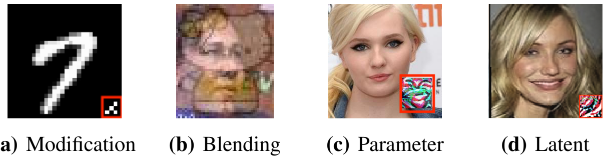

(a) Modification **(b)** Blending **(c)** Parameter **(d)** Latent

Fig. 3: Trojaned input examples of four Trojan attacks. The figures are taken from the original papers in [23],[15],[38],[57] respectively. The trigger patterns in (a), (c), (d) are highlighted with red boxes. The trigger pattern in (b) is a Hello Kitty graffiti that spreads over the whole image. Note that parameter attack and latent attack shares the same strategy for generating trigger patterns while their attack setting is different.

Modification Attack. This is a poisoning attack proposed by Gu et al. [23]. The attacker selects some training samples, directly modifies some part of each sample as a trigger pattern, assigns desired labels and injects the sample-label pairs back into the training set. An example of the trigger pattern is shown in Figure 3a.

Blending Attack. This is another poisoning attack proposed by Chen at al. [15]. The attacker also poisons the dataset with malicious sample-input pairs. However, instead of directly modifying part of the input, the adversary blends the trigger pattern into the original input (e.g., mixing some special background noise into a voice command). An example is shown in Figure 3b.

Parameter Attack. This is a model manipulation attack that directly changes the parameters of a trained model without access to the training set [38]. The attack consists of three steps: 1) the adversary generates an optimal trigger pattern w.r.t. the model using gradient-based approach; 2) the adversary reverse-engineers some inputs from the model; 3) the adversary adds the malicious pattern to the generated data and retrains the model with desired malicious behavior. Note that the attacker can only choose the trigger shape and location but not the exact pattern. The trigger pattern is generated by the algorithm. An example is shown in Figure 3c.

Latent Attack. In this attack [57], the attacker releases a "latent" Trojaned model that does not show any malicious behavior until the user fine-tunes the model on his own task. The attack is achieved by first including the user's task in the training process, then generating the trigger pattern, injecting the Trojan behavior into the model, and finally removing the trace of user's task in the model. The exact trigger pattern here is also generated. attacker can only determine its shape and location but not the exact pattern. An example is shown in Figure 3d.

III. Threat Model & Defender Capabilities

In this section, we will first introduce our threat model. Then we introduce our goal as a defender and our capabilities.

A. Threat Model

In this paper, we consider adversaries who create or distribute Trojaned DNN models to model consumers (i.e., users). The adversary could provide the user with either black-box

TABLE I: A comparison of our work with other Trojan detection works in defender capabilities and detection capabilities.

		Defender Capabilities			Attack Detection Capabilities			
	Detection Level	Black-box Access	No Access to Training Data	No Need of Clean Data	Model Manipulation Attacks	Large-size Trigger	All-to-all Attack Goal	Binary Model
MNTD	Model	✓	✓	✗	✓	✓	✓	✓
Neural Cleanse [53]	Model	✗	✓	✗	✓	✗	✗	✗
DeepInspect [13]	Model	✓	✓	✓	✓	✓	✗	✗
Activation Clustering [12]	Dataset	✗	✗	✓	✗	✓	✓	✓
Spectral [52]	Dataset	✓	✗	✓	✗	✓	✓	✓
STRIP [21]	Input	✓	✓	✗	✓	✓	✗	✓
SentiNet [16]	Input	✗	✓	✗	✓	✗	✓	✓

access (e.g., through platforms such as Amazon ML [1]) or white-box access to the NN models. The Trojaned model should have good classification accuracy on validation set, or otherwise it will be immediately rejected by the user. However, on Trojaned input, i.e., inputs containing Trojan triggers, the model will produce malicious outputs that are different from the benign ones.

As discussed in Section II-C, there are different ways for an adversary to insert Trojans to neural networks. As a detection work, we consider that the adversary has maximum capability and arbitrary strategies. That is, we assume that the adversary has full access to the training dataset and white-box access to the model. He may apply an arbitrary attack approach to generate the Trojaned model. The trigger pattern may be in any shape, location and size. The targeted malicious behavior may be either a single target or all-to-all attack.

In this paper, we focus on software Trojan attacks on neural networks. Thus, hardware Trojan attacks [17], [35] on neural networks are out of our scope.

B. Defender Goal

Trojan attacks can be detected at different levels. A *model-level* detection aims to make a binary decision on whether a given model is a Trojaned model or not. An *input-level* detection aims to predict whether an input will trigger some Trojan behavior on an untrusted model. A *dataset-level* detection examines whether a training dataset suffers from poisoning attack and has been injected with Trojaned data.

Similar to [53], [13], we focus on model-level detection of Trojan attacks as it is a more challenging setting and more applicable in real world. We further discuss the differences of these three detection levels in Section IX.

C. Defender Capabilities

To detect Trojan attacks, defenders may have differences in the following capabilities/assumptions:

- *Assumption of the attack strategy*. A defender may have assumptions on the attack approach (e.g., modification attack), Trojan malicious behavior (e.g. single-target attack) or attack settings (e.g, the trigger pattern needs to be small).
- *Access to the target model*. A defender could have white-box or black-box access to the target model. With white-box access, the defender has all knowledge of the model structure and parameters; with black-box access, the defender can only query the model with input data to get the output prediction probability for each class. This definition of black-box model is widely used in existing work [45], [14], [52], [21].
- *Access to the training data*. A defender may need access to the training data of the target model for the detection, especially to detect a poisoning Trojan attack.
- *Requirement of clean data*. A defender may need a set of clean data to help with the detection.

In this paper, we consider a defender with few assumptions. Our defender only needs *black-box* access to the target model, has *no* assumptions on the attack strategy, and does *not* need access to the training set. But our defender does need a *small set* of clean data as auxiliary information to help with the detection, which is also required by previous works [53], [21], [16]. However, we assume the clean dataset is much smaller than the dataset used by the target model and the elements are different. This may be the case of an ML model market provider who is willing to vet the models in their store or a model consumer who does not have enough training data, expertise or resources to train a high-performing model as the pretrained ones.

D. Existing Detection of Trojan Attacks

Several approaches have been proposed to detect Trojans in neural networks. We discuss the defender capabilities and detection capabilities and compare them with our system MNTD in Table I, including two model-level detections Neural Cleanse(NC) [53] and DeepInspect(DI) [13], two dataset-level detections Activation Clustering (AC) [12] and Spectral Signature [52], and two input-level detections STRIP [21] and SentiNet [16]. We include the detailed discussion on the existing works in Appendix A.

IV. Meta Neural Trojan Detection (MNTD)

We show the overall workflow of MNTD system in Figure 4. Given a clean dataset and a target model, the MNTD pipeline consists of three steps to determine whether the model is Trojaned:

1) Shadow model generation. We generate a set of benign and Trojaned shadow models in this step. We train the benign models using the same clean dataset with different model initialization. For the Trojaned models, we propose a generic Trojan distribution from which we sampled a variety of Trojan settings, and apply poisoning attack to generate different Trojaned models.
2) Meta-training. In this step, we will design the feature extraction function to get representation vectors of the shadow models and train the meta-classifier to detect

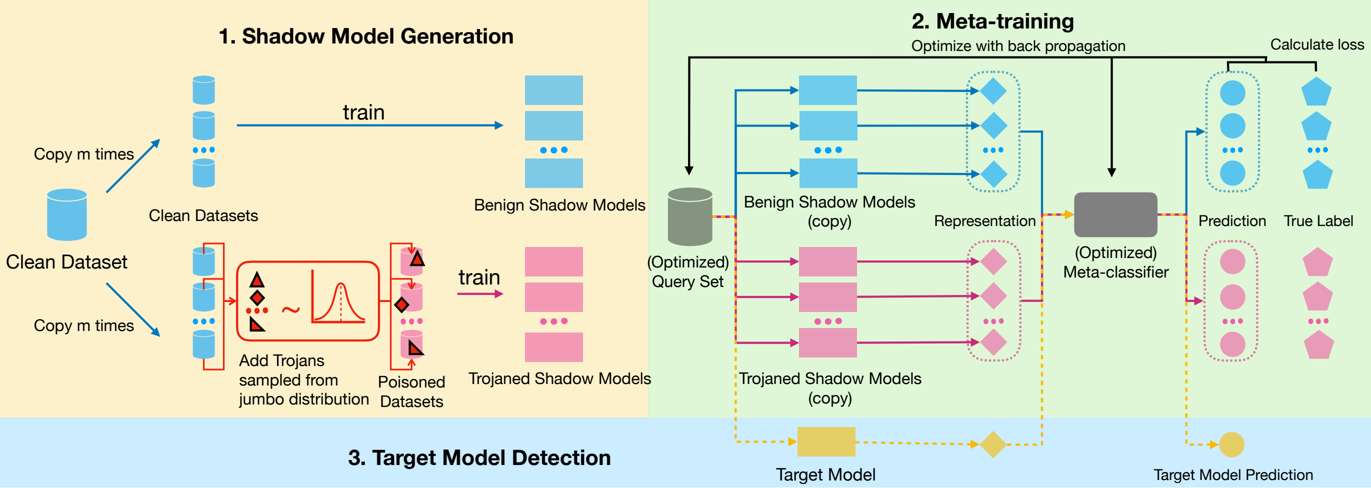


Fig. 4: The workflow of our jumbo MNTD approach with query-tuning. The solid lines represent the training process and dashed ones show the test process.

Trojans using the representation vectors. We propose to choose a set of queries to extract important representation from the shadow models and use the resulting vectors as the input to the meta-classifier. We jointly optimize the meta-classifier and the query set in multiple iterations and effectively improve the performance of the trained meta-classifier.

3) Target model detection. Given a target model, we will first leverage the optimized query set to extract the representation of the model. We then feed the representation to the meta-classifier to determine whether the target model is Trojaned or not.

In the following, we first introduce our approach to shadow model generation - the jumbo learning in Section IV-A. Then, in Section IV-B we introduce the way to perform meta-training having the set of benign and Trojaned shadow models, as well as a baseline meta-training algorithm which only uses benign shadow models. Finally, we introduce the target model detection step in Section IV-C.

A. Shadow Model Generation - Jumbo Learning

Suppose the task is a c-way classification and the input dimension is d_x. The first step of our defense pipeline is to generate a set of benign and Trojaned shadow models, based on which the defender can later train the meta-classifier to distinguish between them. The benign shadow models can be generated by training on the clean dataset with different model parameter initialization. The important part is how to generate Trojaned shadow models. We hope to generate a variety of Trojaned models so that the trained meta-classifier can generalize to detect different types of Trojans. This is essential because we assume that the attacker may apply any attack strategy.

To this end, we propose *jumbo learning*, which models a generic distribution of Trojan attack settings and generates a variety of different Trojaned models. In jumbo learning, we will first sample different Trojan attack settings. We parametrize the attack setting as a function $\mathcal{I}$ which is general to different types of data and attacks. Let $\mathbf{x} \in \mathbb{R}^{d_x}$ denote the benign input with ground truth label $y \in \{1, \ldots, c\}$. In order to trigger the Trojan to output the malicious label $y_t \in \{1, \ldots, c\}$, the adversary will modify the input into $\mathbf{x}'$ with the Trojan function $\mathcal{I}$ such that:

$$\mathbf{x}', y' = \mathcal{I}(\mathbf{x}, y; \mathbf{m}, \mathbf{t}, \alpha, y_t) \tag{3}$$

$$\mathbf{x}' = (\mathbf{1} - \mathbf{m}) \cdot \mathbf{x} + \mathbf{m} \cdot \big((1-\alpha)\mathbf{t} + \alpha\mathbf{x}\big) \tag{4}$$

$$y' = y_t \tag{5}$$

where $\mathbf{m} \in \{0,1\}^{d_x}$ is the mask for the trigger (i.e., shape and location), $\mathbf{t} \in \mathbb{R}^{d_x}$ is the pattern and α is the transparency inserted to $\mathbf{x}$. This function $\mathcal{I}$ is generally applicable to different Trojan attack settings and tasks. For example, in a modification attack, $\mathbf{m}$ is a small pattern and $\alpha = 0$; in a blending attack $\mathbf{m} = 1$ everywhere and $1 - \alpha$ is the blending ratio; on audio data $\mathbf{m}$ refers to the time period for inserting the Trojaned audio signal. We will sample random $\mathbf{m}, \mathbf{t}, \alpha, y_t$ to get different Trojan attack settings. In Figure 5, we show some examples of the sampled Trojan triggers on the MNIST dataset.

Having the sampled attack settings, we will train a model with respect to each Trojan setting. We propose to apply the data poisoning attack that injects a proportion p of malicious data into the clean dataset. That is, we extract a proportion p of data samples from the dataset we have, apply Eqn.3 to get their Trojaned versions, then inject them back to the dataset to train the shadow models.

The jumbo learning pipeline is shown in Algorithm 1. In order to generate the set of Trojaned shadow models, we first randomly sample the Trojan attack settings (line 3). Then we poison the dataset (line 4-8) according to the setting and train the Trojaned shadow model (line 9). We repeat the process multiple times to generate a set of different Trojaned models. The sampling algorithm (line 3) and model training algorithm (line 9) will be different for different tasks.

Note that the Trojan distribution defined by Eqn.3 does not capture all kinds of Trojans. We will evaluate how the trained

Algorithm 1: The pipeline of jumbo learning to generate random Trojaned shadow models.

```
Input: Dataset $D = \{(\mathbf{x}_i, y_i)\}_{i=1}^{n}$, number of Trojaned shadow models to train $m$.
Output: $models$: a set of $m$ random Trojaned shadow models.
$models \leftarrow []$;
for $u = 1, \ldots, m$ do
    $\mathbf{m}, \mathbf{t}, \alpha, y_t, p =$ generate_random_setting();
    $D_{troj} \leftarrow D$;
    $indices =$ CHOOSE($n, int(n * p)$);
    for $j$ in $indices$ do
        $\mathbf{x}'_j, y'_j \leftarrow I(\mathbf{x}_j, y_j; \mathbf{m}, \mathbf{t}, \alpha, y_t)$;
        $D_{troj} \leftarrow D_{troj} \bigcup (\mathbf{x}'_j, y'_j)$;
    $f_u \leftarrow$ train_shadow_model($D_{troj}$);
    $models$.append($f_u$);
return $models$
```

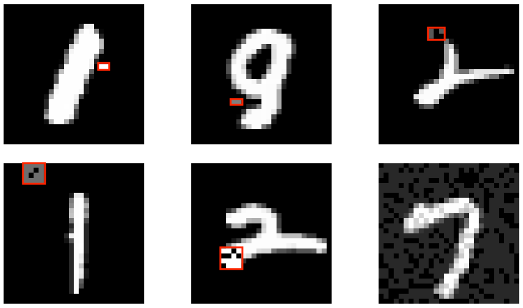


Fig. 5: Examples of different Trojan patterns generated by our jumbo learning on the MNIST dataset. The trigger patterns in the first five examples are highlighted with red bounding boxes. The last example is a data sample blended with random pixels.

meta-classifier performs in detecting the unforeseen Trojaned models in Section VII. In addition, it is possible that some future Trojans may occur which are not in the format as Eqn.3. In that case, we can modify the jumbo distribution to include the new type of Trojans. Therefore, we conclude that jumbo learning is a generic way to generate a variety of Trojaned models.

B. Meta-training

The defender will perform the meta-training algorithm based on the set of shadow models generated by jumbo learning. Our meta-training consists of two goals: 1) find a feature extraction function to extract representation vectors of the shadow models and 2) train a meta-classifier to distinguish between benign and Trojaned shadow models. In the following, we will first introduce our designs of the feature extraction function and the meta-classifier. Then we introduce query-tuning, a meta-training algorithm to jointly optimize the two components. Finally we will talk about a baseline algorithm when the defender does not apply jumbo learning and only have a set of benign shadow models.

Feature Extraction Function Design We propose to feed a set of queries to the shadow model and use the output vector as its representation features. We have two intuitions for this design. First, Trojaned models will behave differently with benign models (i.e., have different distributions of outputs) on some query inputs. For example, their outputs differ a lot on inputs with Trojan triggers. Second, we can get the model output without accessing its internal structure. This allows us to detect Trojans in black-box scenarios.

Formally speaking, Let $\{(f_i, b_i)\}_{i=1}^{m}$ denote the shadow model dataset, where $f_i : \mathbb{R}^{d_x} \rightarrow \{1, \ldots, c\}$ is the shadow model and b_i is a binary label indicating whether f_i is Trojaned ($b_i = 1$) or benign ($b_i = 0$). We will choose a set of k query inputs $X = \{\mathbf{x}_1, \ldots, \mathbf{x}_k\}$ where $\mathbf{x}_i \in \mathbb{R}^{d_x}$ (we will discuss how these query inputs are chosen later). We will feed the queries into the shadow model f_i and get k output vectors $\{f_i(\mathbf{x}_1), \ldots, f_i(\mathbf{x}_k)\}$. By concatenating all the output vectors, we can get a representation vector $\mathcal{R}_i(X)$ as the feature of the shadow model f_i:

$$\mathcal{F}(f_i) = \mathcal{R}_i(X) = [[f_i(\mathbf{x}_1)|| \ldots ||f_i(\mathbf{x}_k)]] \in \mathbb{R}^{ck} \quad (6)$$

where $[[\cdot||\cdot||\cdot]]$ stands for the concatenation operation. We use $\mathcal{R}_i$ to denote $\mathcal{R}_i(X)$ if it does not lead to misunderstanding.

Meta-classifier Design Let $META(\mathcal{R}_i; \theta) \in \mathbb{R}$ denote the meta-classifier where θ denotes the parameter of *META*. We propose to use a two-layer fully connected neural network as the meta-classifier. The meta-classifier will take in the feature vector $\mathcal{R}_i$ and output a real-valued score indicating the likelihood of f_i to be Trojaned.

Meta-Training Algorithm In meta-training, we would like to find the optimal values in the query set X and meta-classifier parameters θ. One simple solution is to randomly choose the query set X, pre-calculate all the representation vectors $\mathcal{R}_i$ and only optimize the meta-classifier. Having $\mathcal{R}_i$ and corresponding label b_i, the meta-training is simply to minimize the loss of a binary classifier via gradient-based optimization:

$$\arg\min_{\theta} \sum_{i=1}^{m} L\Big(META(\mathcal{R}_i(X); \theta), b_i\Big) \quad (7)$$

where $L(\cdot, \cdot)$ is the loss function using binary cross entropy. This approach achieves a not bad performance in Trojan detection. However, the randomly sampled inputs may not help distinguish the benign and Trojaned models because Trojaned models behave similarly with benign models on most inputs. Therefore, we can improve the performance by finding the optimal query inputs to provide the most useful information in the representation vectors.

To this end, we propose a *query-tuning* technique to find the best query set for feature extraction, which is similar with the technique in Oh et al. [45]. The main idea is to jointly optimize the query set and the meta-classifier in order to minimize the training loss. The optimization goal thus becomes:

$$\underset{X=\{\mathbf{x}_1,\ldots,\mathbf{x_k}\}}{\arg\min_{\theta}} \sum_{i=1}^{m} L\Big(\mathit{META}(\mathcal{R}_i(X);\theta), b_i\Big) \tag{8}$$

Note that the query set $\{\mathbf{x}_1, \ldots, \mathbf{x_k}\}$ does not appear explicitly in the optimization goal, but are included in the calculation of $\mathcal{R}_i(X)$.

To optimize the goal in Eqn. 8, a key observation is that the entire calculation flow is differentiable: we first feed the query inputs into the shadow models, then use their output as the representation vectors of shadow models, and finally feed them into the meta-classifier. Since the shadow models and the meta-classifier are differentiable, we can directly calculate the gradient of the loss with respect to the input vectors $\{\mathbf{x}_1, \ldots, \mathbf{x}_k\}$. Thus, we can still apply the standard gradient-based optimization technique for solving Eqn. 8. In particular, we will first randomly sample each $\mathbf{x}_i$ from a Gaussian distribution. Then we iteratively update $\mathbf{x}_i$ and θ with respect to the goal in Eqn. 8 to find the optimal query set. This workflow is illustrated in the right part of Figure 4.

Note that during the training process we need to access the internal parameters of the shadow models for calculating the gradient. However, this does not violate the black-box setting because the shadow models are trained by us and we can for sure access their parameters. During the inference process, we only need to query the black-box target model with the tuned inputs $\{\mathbf{x}_1, \ldots, \mathbf{x}_k\}$ and use the output for detection.

Baseline Meta-training algorithm without jumbo learning The previous meta-training algorithm requires a set of Trojaned shadow models generated by jumbo learning. In the following, we will introduce a baseline meta-training algorithm which requires only benign shadow models and thus does not need jumbo learning.

We assume that the defender has only benign shadow models to train the meta-classifier. The standard way to train a machine learning model with only one-class data is novelty detection, where the model is trained to determine whether an input is similar with its training samples. As an example, one-class SVM [41] will train a hyper-plane which separates all the training data from the origin while maximizing the distance ρ from the origin to the hyper-plane. An example of one-class SVM is shown in Appendix B.

In practice, we propose to use one-class neural network [11] which generalizes the one-class optimization goal to neural networks, so that our meta-classifier can still be the two-layer network structure. The optimization goal in one-class neural network with query-tuning is:

$$\min_{\substack{\theta,\rho \\ X=\{\mathbf{x}_1,\ldots,\mathbf{x_k}\}}} \frac{1}{2}\cdot l_2(\theta)+\frac{1}{\nu}\cdot\frac{1}{m}\sum_{i=1}^{m} \mathit{ReLU}\big(\rho-\mathit{META}(\mathcal{R}_i(X);\theta)\big)-\rho \tag{9}$$

where $l_2(\theta)$ stands for the sum of Frobenius norm of all the parameters in the meta-classifier. We will use a gradient-based approach to do meta-training and find the optimal query set X and model parameters θ which minimize the goal as in Eqn. 9.

C. Target Model Detection

Let $X^* = \{\mathbf{x}_1^*, \ldots, \mathbf{x}_k^*\}$ and θ^* denote the optimal query set and parameters obtained by meta-training. Given a target model f_{tgt}, we can apply the optimized feature extraction function and meta-classifier to determine whether it is Trojaned or not. In particular, we first calculate its representation vector $\mathcal{R}_{tgt} = [[f_{tgt}(\mathbf{x}_1^*)||\ldots||f_{tgt}(\mathbf{x}_k^*)]]$. Then we can determine whether f_{tgt} is Trojaned according to the meta-classifier's prediction $\mathit{META}(\mathcal{R}_{tgt};\theta^*)$.

V. Experiment Setup

In this section, we will introduce the experiment setting. We first introduce the datasets we use, followed by the attack and defense setting in the experiments. Finally we introduce the setting of baselines which we compare with. Our code is publically available at https://github.com/AI-secure/Meta-Nerual-Trojan-Detection.

A. Dataset

We conduct our evaluation on a variety of machine learning tasks, covering different types of datasets and neural networks. For the vision tasks, we use the standard MNIST [33] and CIFAR10 [31] datasets. MNIST is a dataset of grayscale handwritten digits 0-9 and CIFAR10 is a dataset of RGB images of 10 classes. For the speech task we use the SpeechCommand dataset (SC) containing one-second audio command of 10 classes. For the tabular data we use the Smart Meter Electricity Trial data in Ireland dataset (Irish) [2]. It consists of electricity consumption over weeks of two types of users (residential vs. commercial). For the natural languange data we use the Rotten Tomatoes movie review dataset (MR) [29] which consists of movie reviews and the task is to determine whether a review is positive or negative. We provide detailed introduction of each dataset and network structure in each task in Appendix C.

As discussed in Section III-C, we assume the defender only has a small set of clean data to help with the detection and the data is different from the model training set (which is owned by the attacker). Therefore, for each dataset, we randomly sample 50% of the training set as owned by the attacker and 2% of the training data as the defender's clean dataset.

B. Attack Settings

Here we introduce the attack setting that are modelled in our jumbo distribution as in Section IV-A. Unforeseen attack strategies will be evaluated in Section VII, which include parameter and latent attack (since they will not poison the training dataset) and all-to-all attack (since the jumbo distribution only considers single-target attack).

For each dataset except MR, the attacker will generate 256 target models using modification attack and blending attack respectively. On the discrete MR dataset only modification attack applies. In the following we describe the attack setting for both approaches.

Trigger mask $\mathbf{m}$ For blending attack, the pattern size is the same as the input, so $\mathbf{m} = 1$ everywhere. For modification attack, trigger mask differs in different tasks. On MNIST and CIFAR10, we use a square pattern with random size from 2×2 to 5×5 at random location; on SC, the pattern will be a consecutive part at random place, whose length is randomly sampled from $\{0.05, 0.1, 0.15, 0.2\}$ seconds; on Irish, the pattern will be a consecutive part at random place, whose length is randomly sampled from $\{1, 2, 3, 4, 5\}$ hours; on MR, we will add a random phrase with 1 or 2 words at random place.

Trigger pattern $\mathbf{t}$ The pattern value will be generated in the same way for modification and blending attack. On MNIST and CIFAR10, each pixel value is uniformly sampled from $[0, 1]$; on SC and Irish, each signal value is uniformly sampled from $[0, 0.2]$; on MR, each word is uniformly sampled from the vocabulary.

Transparency α There is no transparency for modification attack, so $\alpha = 0$; for blending attack we uniformly sample α from $[0.8, 0.95]$.

Malicious label y_t The malicious label for each Trojaned model is uniformly chosen from the output set of each task, e.g. from digit 0-9 for MNIST or from the 10 types of commands for SC.

Data poisoning ratio p The proportion of injected data in the data poisoning is uniformly sampled from $[0.05, 0.5]$ for all the tasks and attacks.

Besides the Trojaned model, we also train 256 benign target models using the attacker's dataset to evaluate the detection performance. These benign models are trained using the same setting except for different model parameter initialization.

C. Defense Settings

In jumbo MNTD, the defender will generate 2048 Trojaned models using jumbo learning and 2048 benign models to train the meta-classifier. The defender will also generate 256 Trojaned and benign models for validation. In one-class MNTD, only benign models are trained. The Trojaned models are generated in the same way as the attacker, except for the following difference:

1) The models here are trained using the defender's dataset, whose size is much smaller than the attacker's dataset.
2) The trigger shape will be either small or the same size as the input. There is 20% probability that the trigger shape is the same as the input; otherwise it is sampled in the way as modification attack before.
3) The transparency α will be sampled conditional on the trigger shape. If the trigger shape is the same as the input, then the α is uniformly sampled from $[0.8, 0.95]$; otherwise, α will be 0 with 25% probability and otherwise uniformly sampled from $[0.5, 0.8]$.

In addition, we ensure that the attack settings which already exist in the attacker's Trojan models will not be sampled again in the training of defender's shadow models.

We use the Adam optimizer [30] with learning rate 0.001 to train all the models, meta-classifiers and tune the queries. We choose the query number to be $k = 10$ as it already works well in our experiment (i.e., we do not need to choose a larger number of queries). In practice, we find the performance is not sensitive to this choice.

TABLE II: The classification accuracy and attack success rate for the shadow and target models. -M stands for modification attack and -B stands for blending attack.

Models	**Shadow Model**		**Target Model**	
	Accuracy	**Success Rate**	**Accuracy**	**Success Rate**
MNIST	95.14%	-	98.47%	-
MNIST-M	-	-	98.35%	99.76%
MNIST-B	-	-	98.24%	99.68%
CIFAR10	39.31%	-	61.34%	-
CIFAR10-M	-	-	61.23%	99.65%
CIFAR10-B	-	-	59.52%	89.92%
SC	66.00%	-	83.43%	-
SC-M	-	-	83.20%	98.66%
SC-B	-	-	83.56%	98.82%
Irish	79.71%	-	95.88%	-
Irish-M	-	-	94.17%	95.78%
Irish-B	-	-	93.62%	92.79%
MR	72.61%	-	74.69%	-
MR-M	-	-	74.48%	97.47%

Note that our pipeline does not apply directly to the MR task which has discrete input. We introduce the adaptation of our approach in this case in Appendix D.

D. Detection Baselines

In our evaluation, we compare with four existing works on Trojan attack detection as our baselines: Activation Clustering (AC), Neural Cleanse (NC), Spectral Signature (Spectral) and STRIP. We do not compare with DeepInspect [13] as the authors have not releases the code and their pipeline is rather complicated. We do not compare with SentiNet [16] as it only works on image dataset and the time cost for model-level detection is high. We introduce the details in comparing these approaches in Appendix E.

VI. Experimental Evaluation

In this section, we present the results of using our pipelines to detect Trojaned models.

A. Trojan Attacks Performance

We first show the classification accuracy and attack success rate of the shadow models and target models in Table II. Accuracy is evaluated on normal input and attack success rate is evaluated on Trojaned input. On Irish dataset, we use Area Under ROC Curve (AUC) as the metric instead of accuracy since this is a binary classification task on unbalanced dataset. The defender will not perform the modification and blending attacks, so we only show the accuracy of the benign shadow models.

We can see that the attacker successfully installs Trojans in the target models. The accuracy is similar with the benign target models, while achieving a high attack success rate in all the tasks. In addition, we also see an obvious accuracy gap between benign shadow models and target models. This matches our assumption that the model consumer cannot train a high-quality model based on his small dataset. Therefore, he needs to use the shared model instead of training a model using his own clean dataset.

TABLE III: The detection AUC of each approach. -M stands for modification attack and -B stands for blending attack.

Approach	**MNIST-M**	**MNIST-B**	**CIFAR10-M**	**CIFAR10-B**	**SC-M**	**SC-B**	**Irish-M**	**Irish-B**	**MR-M**
AC [12]	73.27%	78.61%	85.99%	74.62%	79.69%	82.86%	56.14%	93.48%	88.26%
NC [53]	92.43%	89.94%	53.71%	57.23%	91.21%	96.68%	✗	✗	✗
Spectral [52]	56.08%	≤50%	88.37%	58.64%	≤50%	≤50%	56.50%	≤50%	**95.70%**
STRIP [21]	85.06%	66.11%	85.55%	81.45%	89.84%	85.94%	≤50%	≤50%	✗
MNTD (One-class)	61.63%	≤50%	63.99%	73.77%	87.45%	85.91%	94.36%	**99.98%**	≤50%
MNTD (Jumbo)	**99.77%**	**99.99%**	**91.95%**	**95.45%**	**99.90%**	**99.83%**	**98.10%**	**99.98%**	89.23%

B. Detection Performance

Using the setup in Section V, we compare our jumbo MNTD approach and one-class MNTD approach with the four baseline approaches. We use the AUC as the metric to evaluate the detection performance. The results are shown in Table III. We use ✗ to show that the approach cannot be applied on the experiment setting.

As the discussion in Section III-D goes, all the baseline approaches have some assumptions on the attacks, so they only work on a few tasks and cannot keep high performance through all the tasks. On the other hand, we would like to point out that Spectral and STRIP are not aimed to perform model-level Trojan detection and we design the pipeline to adjust them to detect Trojaned models (i.e., to average score for each data in the training set). Therefore, it is unfair to compare our results with theirs directly and claim that their works do not work well, but it does show that no existing work can achieve a good performance on the task of model-level Trojan detection.

As a comparison, our Jumbo MNTD approach achieves over 90% detection AUC in all but one of the experiments that cover different datasets and attacks and the average detection AUC reaches over 97%. In addition, this approach outperforms all the baseline approaches except for the NLP task (89.23% vs. 95.70% of Spectral). However, Jumbo MNTD does not need to access the training dataset as Spectral does and only queries the embedding layer; we consider the results comparable with that of the baselines. On the other hand, our one-class approach is good on some tasks but fails on others. On some tasks it is even worse than random guesses. We leave the interpretation of this interesting phenomenon as our future work. We include the ROC curve of the detection performance as well as the isolation experiments of query tuning in Appendix F.

C. Impact of Number of Shadow Models

In Figure 6, we demonstrate the impact of using different number of shadow models in training the meta-classifier on the MNIST-M and CIFAR10-M tasks. Our approach can achieve a good result even with a small number of shadow models (e.g., only 128 benign models + 128 Trojaned models). With more shadow models, the accuracy continues to grow. Defenders with different computational resources can make a trade-off between the number of shadow models and the detection performance based on their needs. We include more discussion on the efficiency of our approach in Section VI-D.

D. Running Time Performance

We compare the detection running time of each approach on the MNIST-M task in Table IV. The experiment is run on one NVIDIA GeForce RTX 2080 Graphics Card. The running time of our pipeline contains two parts - the offline training part which includes shadow model generation and meta-classifier training, and the inference part that detects Trojaned target models. It takes around 12 seconds to train each shadow model and 125 seconds to train the meta-classifier. Therefore, the offline part needs $4096 \times 12 + 125$ seconds, which is around 14 hours. On the other hand, in the inference part we only need to query the target model with our tuned queries and apply the meta-classifier, which is very efficient and takes only 2.63ms.

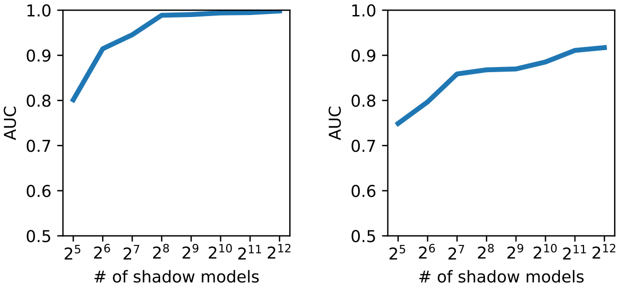


Fig. 6: Detection AUC with respect to the number of shadow models used to train the meta-classifier on MNIST-M (left) and CIFAR10-M (right).

TABLE IV: Running time required to detect one target model on MNIST-M.

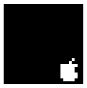
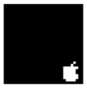
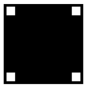
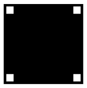
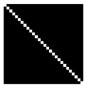
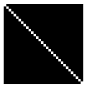
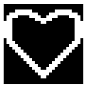
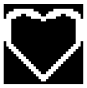
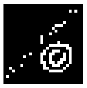
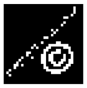
Approach	Time (sec)
AC	27.13
NC	57.21
Spectral	42.55
STRIP	738.5
MNTD	$\mathbf{2.629 \times 10^{-3}}$
MNTD (offline preparation time)	$\sim 4096 \times 12 + 125$

As a comparison, we see that the running time to detect Trojans using baseline approaches varies between 27 seconds to 738 seconds. We would like to emphasize that we only need to perform the offline part once for each task. That is, as long as we have trained the meta-classifier on MNIST, we can apply it to detect any Trojaned MNIST model. It takes only several milliseconds to apply the trained MNTD on one target model. In contrast, other approaches have to re-run their entire algorithm whenever they are provided with a new model. Therefore, our approach is more efficient when the defender needs to detect Trojans on a number of target models on the same task. Moreover, as demonstrated in Section VI-C, the model consumer could also generate a smaller number of shadow models to make a trade-off between computation overhead and Trojan detection performance.

VII. Generalization on Unforeseen Trojans

In this section, we will evaluate jumbo MNTD using Trojaned models that are not modelled by the jumbo distribution

TABLE V: Examples of unforeseen Trojan trigger patterns and the detection AUC of jumbo MNTD on these Trojans.

Trojan Shape	MNIST			CIFAR-10		
	Pattern Mask	Trojaned Example	Detection AUC	Pattern mask	Trojaned Example	Detection AUC
Apple			96.73%			89.38%
Corners			98.74%			93.09%
Diagonal			99.80%			97.57%
Heart			99.01%			93.82%
Watermark			99.93%			97.32%

in the training process. Unless specified, we will train 256 Trojaned models for each attack setting. We empirically verified that all the attack settings are successful to install Trojans in the model.

A. Generalization on Trigger Patterns

We first evaluate the meta-classifier using unforeseen trigger patterns. We collect some Trojan shapes on vision tasks used in previous works [38], [21] as well as some newly designed Trojan shapes, as shown in Table V. A significant difference between these shapes and those in jumbo learning is that they will change a large number of pixels; in contrast, the patterns in jumbo learning change at most 5×5 pixels. For each pattern type, we use the same mask but with randomly generated pixel values. We train the Trojaned models with these patterns and apply the jumbo MNTD pipeline to detect them.

The detection results are shown in Table V. We can see that the trained meta-classifier achieves similar detection results as before. This shows that our detection approach generalizes well to a variety of trigger patterns even if they are not considered in the training process. We provide further experiment results on the generalization to unforeseen trigger patterns in Appendix F.

B. Generalization on Malicious Goals

All the models in the jumbo distribution aims at the single target attack, i.e., change the label of a Trojaned input to be a specific class. Here, we consider another type of malicious behavior, all-to-all attack. In particular, for a c-way classification model, the label of a Trojaned input which originally belongs to the i-th class will be changed to the $((i+1) \mod c)$-th class. We will evaluate whether our meta-classifier can detect Trojaned models with all-to-all attack. For MNIST, we adopt the same setting as in [12] and add a four-pixel pattern at the right bottom corner. For other tasks, we use the same attack setting as the modification attacks on them and change the attack goal to be all-to-all attack. We empirically find that the all-to-all attack cannot work on SC and MR (the attack success rate is low), so we do not include them as in the detection task.

TABLE VI: The detection AUC of each approach against all-to-all Attack.

Approach	MNIST	CIFAR10	Irish
AC	**100.00%**	77.41%	90.94%
NC	51.46%	52.34%	✗
Spectral	84.36%	≤50%	68.02%
STRIP	62.60%	≤50%	≤50%
MNTD (One-class)	97.09%	70.38%	99.98%
MNTD (Jumbo)	99.95%	**98.62%**	**100.00%**

The results are shown in Table VI. We see that NC and STRIP cannot perform well in detecting these kinds of Trojans, as we have discussed in Section III-D. Our approach still achieves a good performance in detecting this unforeseen type of malicious goal, reaching over 98% detection AUC for all the three tasks. AC outperforms us on MNIST by 0.05% while we outperform them by 20% and 10% on the other two tasks. In addition, we do not require access to the dataset as AC does. These results show that our detection pipeline requires a weak assumption and is general to different tasks.

C. Generalization on Attack Approaches

In the jumbo distribution we use poisoning attack and change the training dataset to generate Trojaned models. However, we introduced four types of attacks in Section II-C of which only modification attack and blending attack will insert Trojan by poisoning the dataset. In this section, we will evaluate how the meta-classifier performs in detecting the other two kinds of unforeseen attack approaches.

We evaluate the two attacks on vision tasks since we empirically find that the attack success rate is usually low on other tasks. For parameter attack, we add a 4×4 pattern for

TABLE VII: The detection AUC of MNTD and neural cleanse on parameter attack (denoted by -P) and latent attack (denoted by -L). Other input-level and dataset-level detection techniques are not included as they cannot be applied in detecting these attacks.

Approach	MNIST-P	MNIST-L	CIFAR10-P	CIFAR10-L
NC	≤50%	95.02%	53.12%	83.79%
MNTD(one-class)	≤50%	98.83%	≤50%	≤50%
MNTD(Jumbo)	**99.99%**	**99.07%**	**98.87%**	**92.78%**

MNIST and 8×8 for CIFAR10. For latent attack, we follow the same setting in [57] and add a 5×5 pattern for both tasks. The shadow and target models in latent attack are fine-tuned to the user's task before we perform our detection.

The results are shown in Table VII. Note that the attack will not poison the training dataset, so AC, Spectral and STRIP cannot be applied to detect such Trojans. We see that our model can detect these Trojaned models well. In addition, we emphasize that the latent attack appears after we first proposed our pipeline and we did not tailor our method in order to detect it. This shows that our approach has good generalizability in detecting unforeseen Trojan attack approaches.

D. Generalization on Model Structures

In Section VI-B, we evaluate MNTD with the assumption that the defender knows the target model architecture. However, in some cases the defender may not have such knowledge. This problem might be solved by existing techniques which infer the structure of a black-box model [45]. Nevertheless, we would like to evaluate how MNTD performs when generalizing to unforeseen model structures.

We perform our evaluation on the more complicated dataset ImageNet [18], as many different structures have been proposed to achieve a good performance on ImageNet. In particular, we use its subset on dog-vs-cat, which is a binary classification task between dogs and cats, containing 20,000 training cases and 5,000 testing cases. Here we assume that the defender owns 10% of the training set instead of 2% in previous assumption, since the ImageNet models are more difficult to train; the attacker still owns 50%.

To evaluate the generalization to unforeseen model structures, we use six different structures in the model pool: (1) ResNet-18 [24], (2) ResNet-50 [24], (3) DenseNet-121 [25], (4) DenseNet-169 [25], (5) MobileNet v2 [47] and (6) GoogLeNet [50]. We use one of the six structures as the target model at a time. The attacker will generate 32 target models of the structure, 16 benign and 16 Trojaned using jumbo distribution. The defender will train 64 shadow models (32 benign and 32 jumbo Trojaned) for each of the other five structures, which generates 640 shadow models in total. He will use these shadow models to train the meta-classifier and detect whether the target models contain Trojan or not. Thus, the target model structure will never be seen in the training of the meta-classifier. The experiment is repeated for each of the six structures.

The results are reported in Table VIII. We see that all the AUCs are higher than 80%, showing a good transferability even on complicated tasks like ImageNet. Note that here we only use 64 models for each structure to train the meta-classifier due to time efficiency. According to Section VI-C, the results in Table VIII could be further improved by training more shadow models. The results demonstrate that MNTD is applicable to complicated tasks and generalizes well to unforeseen model structures.

TABLE VIII: The detection AUC of MNTD on unforeseen model structures on ImageNet Dog-vs-Cat. The meta-classifier for each model structure are trained using all models except the ones in target model structure.

ResNet-18	ResNet-50	DenseNet-121
81.25%	83.98%	89.84%
DenseNet-169	MobileNet	GoogLeNet
82.03%	87.89%	85.94%

E. Generalization on Data Distribution

In previous studies, we assume that the data collected by the defender follows the same distribution as the model's training data. In this section, we study the case where the defender use alternative data which is similar but not the same distribution. We consider two alternatives for MNIST and CIFAR dataset - USPS digit dataset [27] and TinyImageNet dataset [18]. The USPS dataset includes 16×16 grayscale images of digit 0-9. It contains 7291 train and 2007 test images. We will reshape the images into 28×28 so that it is same as MNIST. The TinyImageNet contains 64×64 images of 200 classes where each class has 500 training, 50 validation and 50 test images. We hand-picked 10 classes to correspond to the labels in CIFAR-10. The chosen classes are shown in Appendix G. We reshape the images into 32×32 to be the same as CIFAR-10.

In the experiments, we will train the shadow models using the USPS and TinyImageNet dataset instead of the 2% of MNIST and CIFAR-10 dataset. The models trained on these alternative datasets can achieve 81.63% accuracy on MNIST and 33.97% on CIFAR-10. Then we train a meta-classifier and evaluate them on the target models of MNIST-M, MNIST-B, CIFAR10-M, CIFAR10-B as in Table III. We find that the meta-classifier using USPS achieves 98.82% detection AUC on MNIST-M and 99.57% on MNIST-B; meta-classifier using TinyImageNet achieves 83.41% AUC on CIFAR10-M and 93.78% on CIFAR10-B. We can see that the the meta-classifier still achieves good detection performance, though it is slightly worse compared with the case when we use the same data distribution. This shows that the defender can use an alternative dataset to train the shadow models.

VIII. Adaptive Attack and Countermeasure

In this section, we consider a strong attacker who adapts their approach to evade MNTD and then extend our technique to be robust to such attacks.

A. Strong Adaptive Attack

We consider a strong attacker who wishes to evade MNTD. We assume that the adversary has full knowledge of the detection pipeline, including the specific parameters of the meta-classifier *META and* the tuned query input set $\{\mathbf{x}_1, \dots, \mathbf{x}_k\}$. The goal of the attacker is to construct a Trojaned model that will be classified as benign by our MNTD.

TABLE IX: The detection AUC of MNTD-robust and its detection performance against strong adaptive attack.

Approach	MNIST-M	MNIST-B	CIFAR10-M	CIFAR10-B	SC-M	SC-B	Irish-M	Irish-B	MR-M
MNTD-robust	99.37%	99.54%	96.97%	84.39%	96.61%	91.88%	99.92%	99.97%	96.81%
MNTD-robust (under attack)	88.54%	81.86%	94.83%	75.60%	88.86%	90.45%	97.27%	88.79%	94.78%

With full knowledge of the MNTD system, the attacker can evade the detection by incorporating the prediction of MNTD in its training process. Suppose the original training loss for a Trojaned model f is L_{train} and the goal is:

$$\min_f \; L_{train}(f) \tag{10}$$

For example, on classification tasks, L_{train} is the mean cross entropy loss between model predictions and ground truth labels over all the benign and Trojaned data. We denote L_{mal} to be output of the meta-classifier on f. Recall that:

$$L_{mal}(f) = \mathit{META}(\mathcal{F}(f); \theta) \tag{11}$$

$$\mathcal{F}(f) = [[f(\mathbf{x}_1)|| \dots ||f(\mathbf{x}_k)]] \tag{12}$$

Large L_{mal} indicates that the model is evaluated as Trojaned by the MNTD system. Since the attacker has full knowledge of the detection system, he can calculate L_{mal} during training and aims to keep it small. In particular, the attacker can explicitly add L_{mal} into the training process and change the training goal as:

$$\min_f \; L_{train} + \lambda \cdot L_{mal} \tag{13}$$

where λ is a chosen parameter balancing model performance and evasion success rate. With full knowledge of the MNTD system, the attacker can perform back-propagation to optimize the loss function directly. In practice, we use $\lambda = 1.0$ which works well for the adaptive attacks and we find the result not sensitive to this choice. In particular, the Trojaned model can always evade the detection of MNTD using the attack while incurring only negligible decrease in model accuracy (i.e., utility) and attack success rate.

B. Countermeasure - MNTD-robust

The key point in the strong adaptive attack is that the adversary has full access to the meta-classifier parameters and query inputs. Hence, he can intentionally optimize the Trojaned model to make it look benign to the meta-classifier. In practice, the defender can avoid it by keeping the model parameters as a secret. Nevertheless, we will propose a robust version of our system, MNTD-robust, to counteract the strong attacker with full knowledge of our system.

The core idea of MNTD-robust is that during test time we will set part of the system parameters to be random values. Hence, the attacker cannot know what the parameters are and thus cannot calculate the exact value of L_{mal}. In particular, in MNTD-robust we will: 1) sample a random meta-classifier by setting its parameters values to be random numbers sampled from the normal distribution; 2) use our training set of shadow models to tune the queries only, while keeping the random meta-classifier unchanged; 3) we will use the tuned inputs along with the random meta-classifier to analyze a model and classify it as benign or Trojaned.

To guarantee that the attacker does not know the random parameters of the meta-classifier, the defender can re-sample them for each detection task. This would increase the detection cost since the defender needs to retrain the meta-classifier whenever the parameters are sampled. But as discussed in Section VI-D, the expensive part of MNTD is to train the shadow models, which needs only be done once; training the meta-classifier is comparatively fast. Additionally, a random meta-classifier could be reused for verifying an entire batch of models to be classified as Trojaned or benign; as long as the adversary does not know the random parameters, the defense remains robust.

From the attacker's side, he still wants to generate Trojaned models which can evade the detection with full knowledge of MNTD-robust. However, this time he does not know the random parameters of the meta-classifier and the corresponding query set. Hence, we assume that the attacker will first sample the random parameters of the meta-classifier on his own and tune the queries. Then he can apply the same technique as in Section VIII-A to generate the Trojaned model which can evade his own meta-classifier well. We will evaluate if this Trojaned model can evade the defender's meta-classifier.

C. Evaluation Results

We evaluate MNTD-robust over all the Trojaned tasks as in Section VI-B and show the results in Table IX. The first row is the detection performance of MNTD-robust on normal Trojaned models (without adaptive attack) and the second row is its detection performance against adaptive attack.

From the first row, we see that the detection performance of our robust MNTD does not downgrade much in normal scenario where there is no adaptive attack (MNTD-robust versus MNTD (Jumbo) in Table III). From the second row, we see that the robust version of MNTD works much better against adaptive attacks. In some cases the detection performance even increases, which means that the intentional evasion on the attacker-chosen meta-classifier actually makes the Trojaned model easier to detect. By comparison, if we do not add the precautions with randomness, the simple MNTD system will be bypassed by all these strong adaptive attacks.

IX. Discussion & Limitations

Trojan Attack Detection Levels. In this paper, we focus on the model-level Trojan attack detection. Other works may investigate in input-level detection [21], [16] or dataset-level detection [12], [52]. These are all feasible ways to prevent users from AI Trojans. However, we consider model-level detection the most generally applicable approach. The reason is that dataset-level detection can only detect the Trojans that perform poisoning attack to the dataset. They cannot work against attacks that directly modify model parameters. The input-level detection requires the defender to perform detection each time the input is fed to the model. This will decrease the efficiency when deploying the model. As a comparison, a user only needs to perform model-level Trojan detection one time. As long as no Trojan is detected in the model, the user can deploy it without any cost in the future.

Detection vs. Defense/Mitigation. In this paper, we focus on detecting Trojan attacks. Defense/mitigation and detection on Trojan attacks are two very related but orthogonal directions. Existing defense or mitigation approaches perform Trojan removal based on the assumption that the given models are already Trojaned. However, this is problematic in practice as, in most cases, DNN models provided by the model producers are benign. It is unreasonable to perform Trojan removal on benign models which requires extensive computation and time overhead. Moreover, as shown in [53], blindly performing mitigation operations can result in substantial degradation in the model's prediction accuracy for benign inputs. Therefore, Trojan detection should be considered as a prerequisite before conducting Trojan mitigation. Once a model is identified as Trojaned model, the mitigation can be executed more confidently to avoid a waste of computation and time.

Meta-classifier on other ML models In the paper, we mainly detect AI Trojans on neural networks. We do not include other ML models in our discussion mainly because there is no current research showing that they suffer from backdoor attacks. We emphasize that our technique can be applied to any differentiable ML models that contains a numerical logit vector in its calculation.

X. Related work

Trojan Attacks. Several recent research [39], [23], [38], [15], [36], [28] has studied software Trojan attacks on neural networks. As discussed in Section II-C, Trojans can be created through poisoning the training dataset or direct manipulation of model parameters. For example, Gu et al. [23] study backdoor poisoning attacks in an outsourced training scenario where the adversary has full knowledge of the model and training data. Comparably, Chen et al. [15] also use data poisoning but assume the adversary has no knowledge of the training data and model. On the other hand, [39] directly manipulates the neural network parameters to create a backdoor, while [38] considers Trojaning a publicly available model using training data generated via reverse engineering. Bagdasaryan et al. [4] demonstrated that any participant in federated learning can introduce hidden backdoor functionality into the joint global model. Besides software Trojans, Clements et al. [17] developed a framework for inserting malicious hardware Trojans in the implementation of a neural network classifier. Li et al. [35] proposed a hardware-software collaborative attack framework to inject hidden neural network Trojans.

Trojan Attack Detection. Several Trojan attack detection approaches have been proposed [53], [21], [16], [12], [40]. These approaches can be categorized into input-level detection [21], [16], [40], model-level detection [53] and dataset-level detection [12]. We discussed the differences of these detection levels in Section IX.

Trojan Attack Defense/Mitigation. To the best of our knowledge, there are few evaluated defenses against Trojan attacks [37], [52]. Fine-Pruning [37] removes potential Trojans by pruning redundant neurons less useful for normal classification. However, the model accuracy degrades substantially after pruning [53]. The defense in [52] extracts feature representations of input samples from the later layers of the model and utilizes a robust statistics tool to detect the malicious instances as outliers from each label class. As discussed in Section IX, Trojan attack detection and defense are two orthogonal directions. One can first use our approach to detect if a model is Trojaned, then use any of the defenses to remove or mitigate the Trojans.

Poisoning Attacks. Poisoning attacks for machine learning models has been well studied in the literature [6], [34], [44], [56]. As discussed in Section II-C, several Trojan attacks create Trojans through injecting poisoning samples. Those attacks can thus be seen as variants of poisoning attacks. However, most conventional poisoning attacks seek to degrade a model's classification accuracy on clean inputs [5], [46]. In contrast, the objective of Trojan attacks is to embed backdoors while not degrading the model's prediction accuracy on clean inputs.

Property Inference. Property inference attacks [3], [20], [43] aim to infer certain properties about the training dataset or the model of a target model. However, as illustrated in Section IV, detecting Trojaned model using property inference is not a trivial task. We thus propose jumbo learning to construct Trojaned shadow models. Besides, existing work considers white-box access to the target model while we consider black-box access. The work of [43] focuses on inference against collaborative learning, which has a different setting as ours.

XI. Conclusion

In this paper, we presented MNTD, a novel framework to detect Trojans in neural networks using meta neural analysis techniques. We propose jumbo learning to generate shadow models without the knowledge of the attacker's approach. In addition, we provide a comprehensive comparison between existing Trojan detection approaches and ours. We show that MNTD outperforms all the existing detection works in most cases and generalizes well to unforeseen attack strategies. We also design and evaluate a robust version of MNTD against strong adaptive attackers. Our work sheds new light on the detection of Trojans in neural networks.

Acknowledgements

This material is based upon work supported by the Department of Energy under Award Number DE-OE0000780. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.

References

[1] Amazon. Machine learning at aws, 2018.

[2] The Irish Social Science Data Archive. Cer smart metering project, 2019.

[3] Giuseppe Ateniese, Luigi V Mancini, Angelo Spognardi, Antonio Villani, Domenico Vitali, and Giovanni Felici. Hacking smart machines with smarter ones: How to extract meaningful data from machine learning classifiers. *International Journal of Security and Networks*, 10(3):137–150, 2015.

[4] Eugene Bagdasaryan, Andreas Veit, Yiqing Hua, Deborah Estrin, and Vitaly Shmatikov. How to backdoor federated learning. *arXiv preprint arXiv:1807.00459*, 2018.

[5] Nathalie Baracaldo, Bryant Chen, Heiko Ludwig, and Jaehoon Amir Safavi. Mitigating poisoning attacks on machine learning models: A data provenance based approach. In *Proceedings of the 10th ACM Workshop on Artificial Intelligence and Security*, pages 103–110. ACM, 2017.

[6] Battista Biggio, Blaine Nelson, and Pavel Laskov. Poisoning attacks against support vector machines. *arXiv preprint arXiv:1206.6389*, 2012.

[7] BigML Inc. Bigml, 2018.

[8] Mariusz Bojarski, Davide Del Testa, Daniel Dworakowski, Bernhard Firner, Beat Flepp, Prasoon Goyal, Lawrence D Jackel, Mathew Monfort, Urs Muller, Jiakai Zhang, et al. End to end learning for self-driving cars. *arXiv preprint arXiv:1604.07316*, 2016.

[9] Caffe. Caffe model zoo, 2018.

[10] Nicholas Carlini and David Wagner. Towards evaluating the robustness of neural networks. In *2017 IEEE Symposium on Security and Privacy (SP)*, pages 39–57. IEEE, 2017.

[11] Raghavendra Chalapathy, Aditya Krishna Menon, and Sanjay Chawla. Anomaly detection using one-class neural networks. *arXiv preprint arXiv:1802.06360*, 2018.

[12] 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.

[13] Huili Chen, Cheng Fu, Jishen Zhao, and Farinaz Koushanfar. Deepinspect: a black-box trojan detection and mitigation framework for deep neural networks. In *Proceedings of the 28th International Joint Conference on Artificial Intelligence*, pages 4658–4664. AAAI Press, 2019.

[14] Pin-Yu Chen, Huan Zhang, Yash Sharma, Jinfeng Yi, and Cho-Jui Hsieh. Zoo: Zeroth order optimization based black-box attacks to deep neural networks without training substitute models. In *Proceedings of the 10th ACM Workshop on Artificial Intelligence and Security*, pages 15–26. ACM, 2017.

[15] 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.

[16] Edward Chou, Florian Tramèr, Giancarlo Pellegrino, and Dan Boneh. Sentinet: Detecting physical attacks against deep learning systems. *arXiv preprint arXiv:1812.00292*, 2018.

[17] Joseph Clements and Yingjie Lao. Hardware trojan attacks on neural networks. *arXiv preprint arXiv:1806.05768*, 2018.

[18] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei. ImageNet: A Large-Scale Hierarchical Image Database. In *CVPR09*, 2009.

[19] Eric Florenzano. Gadientzoo, 2016.

[20] Karan Ganju, Qi Wang, Wei Yang, Carl A Gunter, and Nikita Borisov. Property inference attacks on fully connected neural networks using permutation invariant representations. In *Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security*, pages 619–633. ACM, 2018.

[21] Yansong Gao, Chang Xu, Derui Wang, Shiping Chen, Damith C Ranasinghe, and Surya Nepal. Strip: A defence against trojan attacks on deep neural networks. *arXiv preprint arXiv:1902.06531*, 2019.

[22] Alex Graves, Abdel-rahman Mohamed, and Geoffrey Hinton. Speech recognition with deep recurrent neural networks. In *2013 IEEE international conference on acoustics, speech and signal processing*, pages 6645–6649. IEEE, 2013.

[23] Tianyu Gu, Brendan Dolan-Gavitt, and Siddharth Garg. Badnets: Identifying vulnerabilities in the machine learning model supply chain. *arXiv preprint arXiv:1708.06733*, 2017.

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

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

[26] Wenyi Huang and Jack W Stokes. Mtnet: a multi-task neural network for dynamic malware classification. In *International Conference on Detection of Intrusions and Malware, and Vulnerability Assessment*, pages 399–418. Springer, 2016.

[27] Jonathan J. Hull. A database for handwritten text recognition research. *IEEE Transactions on pattern analysis and machine intelligence*, 16(5):550–554, 1994.

[28] Yujie Ji, Xinyang Zhang, and Ting Wang. Backdoor attacks against learning systems. In *2017 IEEE Conference on Communications and Network Security (CNS)*, pages 1–9. IEEE, 2017.

[29] Yoon Kim. Convolutional neural networks for sentence classification. *arXiv preprint arXiv:1408.5882*, 2014.

[30] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

[31] Alex Krizhevsky and Geoffrey Hinton. Learning multiple layers of features from tiny images. Technical report, Citeseer, 2009.

[32] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105, 2012.

[33] Yann LeCun, Corinna Cortes, and Christopher J Burges. The MNIST database of handwritten digits. http://yann.lecun.com/exdb/mnist/, 2018.

[34] Bo Li, Yining Wang, Aarti Singh, and Yevgeniy Vorobeychik. Data poisoning attacks on factorization-based collaborative filtering. In *Advances in neural information processing systems*, pages 1885–1893, 2016.

[35] Wenshuo Li, Jincheng Yu, Xuefei Ning, Pengjun Wang, Qi Wei, Yu Wang, and Huazhong Yang. Hu-fu: Hardware and software collaborative attack framework against neural networks. In *2018 IEEE Computer Society Annual Symposium on VLSI (ISVLSI)*, pages 482–487. IEEE, 2018.

[36] Cong Liao, Haoti Zhong, Anna Squicciarini, Sencun Zhu, and David Miller. Backdoor embedding in convolutional neural network models via invisible perturbation. *arXiv preprint arXiv:1808.10307*, 2018.

[37] 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.

[38] Yingqi Liu, Shiqing Ma, Yousra Aafer, Wen-Chuan Lee, Juan Zhai, Weihang Wang, and Xiangyu Zhang. Trojaning attack on neural networks. In *25nd Annual Network and Distributed System Security Symposium, NDSS 2018, San Diego, California, USA, February 18-221, 2018*. The Internet Society, 2018.

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

[40] Shiqing Ma, Yingqi Liu, Guanhong Tao, Wen-Chuan Lee, and Xiangyu Zhang. Nic: Detecting adversarial samples with neural network invariant checking. In *26th Annual Network and Distributed System Security Symposium, NDSS*, pages 24–27, 2019.

[41] Larry M Manevitz and Malik Yousef. One-class svms for document classification. *Journal of machine Learning research*, 2(Dec):139–154, 2001.

[42] Bryan McCann, James Bradbury, Caiming Xiong, and Richard Socher. Learned in translation: Contextualized word vectors. In *Advances in Neural Information Processing Systems*, pages 6294–6305, 2017.

[43] Luca Melis, Congzheng Song, Emiliano De Cristofaro, and Vitaly Shmatikov. Inference attacks against collaborative learning. *arXiv preprint arXiv:1805.04049*, 2018.

[44] Luis Muñoz-González, Battista Biggio, Ambra Demontis, Andrea Paudice, Vasin Wongrassamee, Emil C Lupu, and Fabio Roli. Towards poisoning of deep learning algorithms with back-gradient optimization. In *Proceedings of the 10th ACM Workshop on Artificial Intelligence and Security*, pages 27–38. ACM, 2017.

[45] Seong Joon Oh, Max Augustin, Bernt Schiele, and Mario Fritz. Towards reverse-engineering black-box neural networks. *International Conference on Learning Representations*, 2018.

[46] Nicolas Papernot, Patrick McDaniel, Arunesh Sinha, and Michael Wellman. Towards the science of security and privacy in machine learning. *arXiv preprint arXiv:1611.03814*, 2016.

[47] Mark Sandler, Andrew Howard, Menglong Zhu, Andrey Zhmoginov, and Liang-Chieh Chen. Mobilenetv2: Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 4510–4520, 2018.

[48] Reza Shokri, Marco Stronati, Congzheng Song, and Vitaly Shmatikov. Membership inference attacks against machine learning models. In *IEEE Symposium on Security and Privacy (SP)*, pages 3–18. IEEE, 2017.

[49] David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. Mastering the game of go with deep neural networks and tree search. *Nature*, 529(7587):484, 2016.

[50] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. Going deeper with convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1–9, 2015.

[51] Yaniv Taigman, Ming Yang, Marc'Aurelio Ranzato, and Lior Wolf. Deepface: Closing the gap to human-level performance in face verification. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1701–1708, 2014.

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

[53] 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 *Neural Cleanse: Identifying and Mitigating Backdoor Attacks in Neural Networks*, page 0. IEEE, 2019.

[54] Pete Warden. Speech commands: A dataset for limited-vocabulary speech recognition. *arXiv preprint arXiv:1804.03209*, 2018.

[55] Pete Warden. Launching the speech commands dataset. https://ai.googleblog.com/2017/08/launching-speech-commands-dataset.html, 2019. Accessed: 2019-05-11.

[56] Chaofei Yang, Qing Wu, Hai Li, and Yiran Chen. Generative poisoning attack method against neural networks. *arXiv preprint arXiv:1703.01340*, 2017.

[57] Yuanshun Yao, Huiying Li, Haitao Zheng, and Ben Y Zhao. Latent backdoor attacks on deep neural networks. In *Proceedings of the 2019 ACM SIGSAC Conference on Computer and Communications Security*, pages 2041–2055, 2019.

Appendix

A. Detailed Discussion on Existing Detection Approaches

We find that existing approaches have different assumptions on the defender and detection capabilities. For example, dataset-level works require access to the training set and cannot detect model manipulation attacks which do not poison the dataset; works inspired by anomaly detection cannot detect all-to-all attacks where all the labels suffer from the same level of attack so that there is no anomaly. In the following we introduce the assumptions and capabilities of existing detection approaches.

Neural Cleanse(NC) [53] and DeepInspect(DI) [13] work on the same level with us. NC observes that in a Trojaned model, there exists a short-cut modification (i.e. the trigger pattern) to change any input to be predicted as the Trojan label. Therefore, it calculates such modification for each label and checks if there exists a short-cut which is much smaller in size than the modifications of other labels. DI improves upon the approach by using model inversion to get some training data. Then they use GAN to generate the modifications and apply the same algorithm to check short-cut as in NC. Both approaches cannot be applied to detect all-to-all attack where the pattern itself cannot lead to certain Trojan label, so the short-cut no longer exists. They cannot be applied to detect Trojans in binary classification tasks because their short-cut check algorithm requires at least three classes. In addition, NC performs not well in detecting large-size triggers [13].

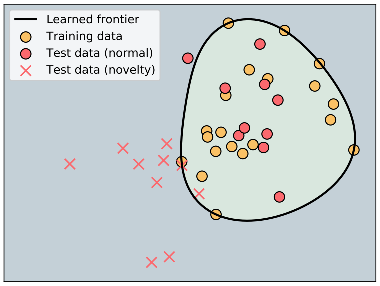


Fig. 7: An illustration of the idea of one-class SVM.

Activation Clustering (AC) [12] and Spectral Signature [52] work on the dataset-level detection. AC performs a two-class clustering over the feature vector of the training data to separate benign data and Trojaned data (if exists). Spectral calculates a signature score for each data in the training set to remove the ones which possibly contain a Trojan trigger. These approaches perform detection on the dataset level, so they need access to the training data and cannot be applied to detect model manipulation attacks which do not poison the dataset. AC also requires white-box access to calculate the feature vector.

STRIP [21] and SentiNet [16] detects Trojans on the input level. STRIP adds up the input with other clean data. The network will give a confident answer on the mixed input if it contains the Trojan pattern; otherwise the network will be confused. SentiNet uses computer vision techniques to find salient parts in the image, which are possibly the Trojan trigger pattern. It then copies the parts to other images to check if it can change the output of other images. Both approaches need a set of clean data to detect Trojans. STRIP cannot detect all-to-all attacks where the model cannot give a confident answer even if it sees the trigger pattern on the blended input. SentiNet requires white-box access to detect salient part and cannot detect large-size trigger via saliency check.

B. One-Class SVM

In Figure 7, we illustrate an example of the one-class SVM model. The model is only provided with a set of training data in one class, and tries to find the decision boundary that captures all the training data tightly. The test set consists of data in the class and data outside the class, and the goal is to distinguish between the two classes.

C. Dataset Details and Network Structures

Computer Vision. We use the standard MNIST [33] and CIFAR10 [31] datasets for computer vision tasks. MNIST contains 70,000 handwritten digits with 60,000 samples used for training and 10,000 samples for testing. Each data sample

TABLE X: The model structure for each dataset in our evaluation. Each convolutional layer and linear layer are followed by a ReLU activation function except the last linear layer.

MNIST	CIFAR10
Conv ($16 \times 5 \times 5$, pad=0) MaxPool (2×2) Conv ($32 \times 5 \times 5$, pad=0) MaxPool (2×2) Linear (512) Linear(10)	Conv ($32 \times 3 \times 3$, pad=1) Conv ($32 \times 3 \times 3$, pad=1) MaxPool (2×2) Conv ($64 \times 3 \times 3$, pad=1) Conv ($64 \times 3 \times 3$, pad=1) MaxPool (2×2) Linear (256) Linear (256) Dropout (0.5) Linear (10)
Irish	**MR**
LSTM (100, layer=2) Attention Linear (1)	Word Embedding (300) Conv ($100 \times \{3, 4, 5\} \times 300$) Concatenation Dropout (0.5) Linear(1)
SC	
MelSpectrogram Extraction LSTM (100, layer=2) Attention Linear (10)	

is a 28x28 grayscale image. CIFAR10 consists of 60,000 32x32 RGB images in 10 classes, with 50,000 images for training and 10,000 images for testing. For MNIST, we adopt the same CNN structure as in [23]. For CIFAR10, we use the same CNN structure as in [10].

Speech. We use the SpeechCommand dataset (SC) version v0.02 [54] for the speech task. The SC dataset consists of 65,000 audio files, each of which is a one-second audio file belonging to one of 35 commands. We use the files of ten classes ("yes", "no", "up", "down", "left", "right", "on", "off", "stop", "go") as [55] does and it gives 30,769 training samples and 4,074 testing samples. Given the audio signal files, we first extract the mel-spectrogram of each file with 40 mel-bands. Then we train an Long-Short-Term-Memory (LSTM) network over all the mel-spectrograms.

Tabular Records. We use the Smart Meter Electricity Trial data in Ireland dataset (Irish) [2] for tabular data tasks. The Irish dataset consists of the electricity consumption of 4,710 users in 76 weeks. Each record has 25,536 columns with each column being the electricity consumption (in kWh) of users during 30 minute intervals. Each user is labeled as residential or SME (Small to Medium Enterprise). We split the dataset to have 3,768 users (80% of all users) in the training set and 942 (20%) in the test set. For the training set we use the data in the first 46 weeks (60% of the total time length) while for the test set we use the data in the last 30 weeks (40%). We use the electricity consumption in each week as the feature vector and view the vectors of all the weeks as a time series. Then we train an LSTM model to predict whether a given electricity consumption record belongs to a residential user or an SME.

Natural Language. We use the same Rotten Tomatoes movie review dataset (MR) as Kim [29] for natural language processing tasks. The MR dataset consists of 10,662 movie review sentences. The task is to determine whether a movie review is positive or negative. Following the convention of the previous work [29], we use 90% of the data for training and the rest for testing. We use the same model structure as Kim [29] except that we use a pretrained and fixed Gensim model as the word embedding layer. A pretrained embedding layer provides a better performance given the limited training data we use.

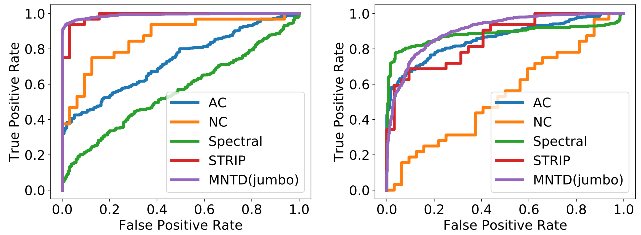


Fig. 8: The detection ROC curve of different approaches on MNIST-M (left) and CIFAR10-M (right).

For reproduction, the model structures for the evaluation on each dataset are presented in Table X. The hyperparameters of the layers are shown in the parenthesis following the layer name. For convolutional layers, the number of filters, filter width and filter height, as well as the padding are listed. For linear layers, we omit the input size and only show the output size.

D. Defense on Discrete Data

On the MR task, the input words are in discrete token space. Therefore, we cannot use gradient-based approach to do query-tuning. However, for most neural networks with discrete input space, the input will first be mapped to some continuous embedding space (e.g., word2vec in NLP). Thus, we will optimize the "query set" over the embedding space to in the same way as before. During inference, we directly feed the tuned embedding vectors to the target model to get predictions. The trade-off is that under this setting, we need white-box access to the embedding layer of the target model. We adopt this setting in the NLP tasks.

E. Detection Baselines Implementation Details

At the time of writing, only the source code of NC is released. Moreover, all the baselines only evaluate with CNN models on computer vision datasets in their work, except for AC where CNN models on NLP dataset are also evaluated. To compare our approaches with these baselines, we re-implement them with Pytorch.

Since AC and Spectral are dataset-level detection and STRIP is input-level detection, we will tailor them to detect model-level Trojans to compare them with our pipeline. AC works on the dataset level and uses an *ExRe* score to indicate whether the dataset is Trojaned. We use this score to indicate the Trojan score for the model. Spectral assigns a score to each training sample. We use the average score of all the training data to indicate the score of the model being Trojaned. STRIP predicts whether an input data is Trojaned, we use their approach to calculate a score for each training sample and take the average to indicate the likelihood of a Trojaned model.

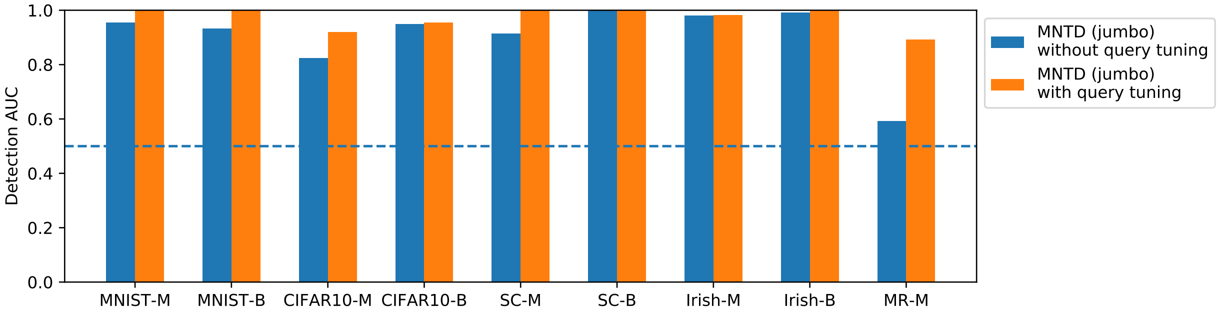
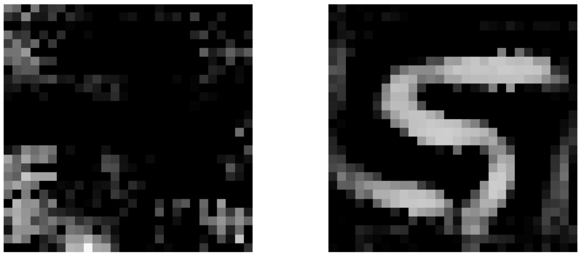


Fig. 9: The comparison of detection AUC with and without query tuning. -M stands for modification attack and -B stands for blending attack.



(a) Jumbo **(b)** One-class

Fig. 10: Example of tuned-queries in MNIST. To make the pattern more clear, we magnify the contrast of the jumbo query by 5 times.

F. Other Experiment Results

ROC Curve of detection We show the ROC curve of the detection performance for different approaches on MNIST-M and CIFAR10-M as in Figure 8.

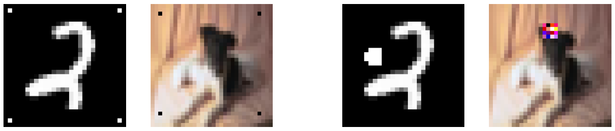
Effectiveness of Query Tuning

We compare the results of Jumbo MNTD with and without query tuning in Figure 9. The results show that query tuning is highly effective; the AUC scores drop as much as 30% in the worst case if we use untuned queries instead. We can interpret the improvement by an analogy to feature engineering: we would like to obtain shadow model features with the most distinguishability for the meta-model to do classification. In query-tuning the feature engineering is done by tuning the queries.

We show some of the tuned queries on the MNIST-M task in Figure 10. We observe that the tuned query in jumbo learning focuses more on local patterns, while the tuned query in one-class learning contains more global and digit-like pattern. We speculate that it is because most Trojaned models in jumbo learning use small local pattern, so this query can help distinguish between benign model and jumbo Trojaned models. On the other hand, the one-class learning needs to fit the benign models best, so the query looks like normal benign input.

Generalization on Trigger Patterns In the jumbo distribution we assume that the trigger patterns are all consecutive patterns (e.g., one square pattern in vision task). Now we will evaluate the meta-classifier using Trojans with non-consecutive patterns. These patterns will never appear in the jumbo distribution. In particular, we modify one pixel at each of the four corners and use it as the trigger pattern for vision tasks (see Figure 11a). For SC, we modify the signal value in the first 0.25 second, middle 0.5 second and last 0.25 second to be 0.1. For Irish, we modify the usage from 9:00 am to 10:00 am on every weekday to be 0. For MR, we add a “yes” at the beginning and an “oh” at the end of the sentence.

The results are shown in Table XI. We see that the meta-classifier achieves the similar performance as when detecting the triggers that we have seen. This shows that the trained meta-classifier generalizes well even if the trigger patterns are not considered in the training process.



(a) Test patterns. **(b)** Examples of training patterns.

Fig. 11: The unforeseen trigger pattern used in evaluation (left) and examples of the trigger patterns used in jumbo training (right) on MNIST and CIFAR.

TABLE XI: The detection AUC of jumbo MNTD on Trojaned models with unforeseen trigger pattern.

MNIST	CIFAR10	SC	Irish	MR
100.00%	96.97%	93.21%	100.00%	94.32%

G. Label mapping of TinyImageNet

The classes we choose in TinyImageNet which correspond to the labels in CIFAR-10 are shown in Table XII. Note that, the ‘airplane’ class corresponds to the images of rockets and ‘horse’ corresponds to the images of camels, since the TinyImageNet does not contain images of airplanes and horses.

TABLE XII: The classes in CIFAR-10 and corresponding class picked in TinyImageNet.

class in CIFAR-10	class in TinyImageNet
airplane	n04008634
automobile	n02814533
bird	n02002724
cat	n02123045
deer	n02423022
dog	n02085620
frog	n01641577
horse	n02437312
ship	n03662601
truck	n03796401