MOVE: Effective and Harmless Ownership Verification via Embedded External Features

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Abstract—Currently, deep neural networks (DNNs) are widely adopted in different applications. Despite its commercial values, training a well-performed DNN is resource-consuming. Accordingly, the well-trained model is valuable intellectual property for its owner. However, recent studies revealed the threats of model stealing, where the adversaries can obtain a function-similar copy of the victim model, even when they can only query the model. In this paper, we propose an effective and harmless model ownership verification (MOVE) to defend against different types of model stealing simultaneously, without introducing new security risks. In general, we conduct the ownership verification by verifying whether a suspicious model contains the knowledge of defender-specified external features. Specifically, we embed the external features by tempering a few training samples with style transfer. We then train a meta-classifier to determine whether a model is stolen from the victim. This approach is inspired by the understanding that the stolen models should contain the knowledge of features learned by the victim model. In particular, we develop our MOVE method under both white-box and black-box settings to provide comprehensive model protection. Extensive experiments on benchmark datasets verify the effectiveness of our method and its resistance to potential adaptive attacks. The codes for reproducing the main experiments of our method are available at https://github.com/THUYimingLi/MOVE

Index Terms—Model Stealing, Ownership Verification, Model Watermarking, Deep Intellectual Property Protection, AI Security

1 INTRODUCTION

Deep learning, especially deep neural networks (DNNs), has been successfully adopted in widespread applications for its high effectiveness and efficiency [1], [2], [3]. In general, obtaining well-performed DNNs is usually expensive for it requires well-designed architecture, a large number of high-quality training samples, and many computational resources. Accordingly, these models are the valuable intellectual properties of their owners.

However, recent studies [4], [5], [6] revealed that the adversaries can obtain a function-similar copy model of the well-performed victim model to ‘steal’ it. This attack is called model stealing. For example, the adversaries can copy the victim model directly if they can access its source files; Even when the victim model is deployed where the adversaries can only query the model, they can still steal it based on its predictions (i.e., labels or probabilities). Since the stealing process is usually costless compared with obtaining a well-trained victim model, model stealing poses a huge threat to the model owners.

Currently, there are also some methods to defend against model stealing. In general, existing defenses can be roughly divided into two main categories, including the active defenses and verification-based defenses. Specifically, active defenses intend to increase the costs (e.g., query times and accuracy decrease) of model stealing, while verification-based defenses attempt to verify whether a suspicious model is stolen from the victim model. For example, defenders can introduce randomness or perturbations in the victim models [4], [7], [8] or watermark the victim model via (targeted) backdoor attacks or data poisoning [9], [10], [11]. However, existing active defenses may lead to poor performance of the victim model and could even be bypassed by advanced adaptive attacks [10], [11], [12]; the verification-based methods target only limited simple stealing scenarios (e.g., direct copy or fine-tuning) and have minor effects in defending against more complicated model stealing. Besides, these methods also introduce some stealthy latent short-cuts (e.g., hidden backdoors) in the victim model, which could be maliciously used. It further hinders their applications. Accordingly, how to defend against model stealing is still an important open question.

In this paper, we revisit the verification-based defenses against model stealing, which examine whether a suspicious model has defender-specified behaviors. If the model has such behaviors, the defense treats it as stolen from the victim. We argue that a defense is practical if and only if it is both effective and harmless. Specifically, effectiveness requires that it can accurately identify whether the suspicious model is stolen from the victim, no matter what model stealing is adopted; Harmlessness ensures that the model watermarking brings no additional security risks, i.e., the model trained with the watermarked dataset should have similar prediction behaviors to the one trained with the benign dataset. We first reveal that existing methods fail to meet all these requirements and their reasons. Based on the analysis, we propose to conduct model ownership verification via embedded external features (MOVE), trying to fulfill both two requirements. Our MOVE defense
In general, model stealing aims to steal the intellectual property from a victim by obtaining a function-similar copy of the victim model. Depending on the adversary’s access level to the victim model, existing model stealing methods can be divided into four main categories, as follows:

1) Fully-Accessible Attacks ($A_F$): In this setting, the adversaries can directly copy and deploy the victim model.

2) Dataset-Accessible Attacks ($A_D$): The adversaries can access the training dataset of the victim model whereas having no training samples. This attack may happen when the victim model is open-sourced. The adversaries may directly fine-tune the victim model (with their own samples) or use the victim model for data-free distillation in a zero-shot learning framework to obtain the stolen model.

3) Model-Accessible Attacks ($A_M$): The adversaries have complete access to the victim model whereas having no training samples. This attack may happen when the victim model is open-sourced. The adversaries may directly fine-tune the victim model (with their own samples) or use the victim model for data-free distillation in a zero-shot learning framework to obtain the stolen model.

4) Query-Only Attacks ($A_Q$): This is the most threatening type of model stealing where the adversaries can only query the victim model. Depending on the feedback of the victim model, the query-only attacks can be divided into two sub-categories, including the label-query attacks [6], [15], [16] and the logit-query attacks [4], [5]. In general, label-query attacks adopt the victim model to annotate some substitute (unlabeled) samples, based on which to train their substitute model. In the logit-query attacks, the adversary usually obtains the function-similar substitute model by minimizing the distance between its predicted logits and those generated by the victim model.

2.2 Defenses against Model Stealing

2.2.1 Active Defenses

Currently, most of the existing methods against model stealing are active defenses. In general, they intend to increase the costs (e.g., query times and accuracy decrease) of model stealing. For example, defenders may round the probability vectors [4], introduce noise to the output vectors which will result in a high loss in the processes of model stealing [7], or only return the most confident label instead of the whole output vector [5]. However, these defenses may significantly reduce the performance of victim models and may even be bypassed by adaptive attacks [10], [11], [12].

2.2.2 Model Ownership Verification

In general, model ownership verification intends to verify whether a suspicious model is stolen from the victim. Currently, existing methods can be divided into two main categories, including membership inference and backdoor watermarking, as follows:

Verification via Membership Inference. Membership inference [17], [18], [19] aims to identify whether some particular samples are used to train a given model. Intuitively, defenders can use it to verify whether the suspicious model is trained on particular training samples used by the victim model to conduct ownership verification. However, simply applying membership inference for ownership verification is far less effective in defending against many complicated model stealing (e.g., model extraction) [11]. This is most probably because the suspicious models obtained by these processes are significantly different from the victim model, although they have similar functions. Most recently, Maini et
al. proposed dataset inference [11] trying to defend against different types of model stealing simultaneously. Its key idea is to identify whether a suspicious model contains the knowledge of the inherent features that the victim model \( V \) learned from the private training set instead of simply particular samples. Specifically, let us consider a \( K \)-classification problem. For each sample \((x, y)\), dataset inference first generated its minimum distance \( \delta_i \) to each class \( i \) by

\[
\min \, d(x, x + \delta_i), \text{ s.t., } V(x + \delta_i) = t,
\]

where \( d(\cdot) \) is a distance metric (e.g., \( \ell^\infty \) norm). It defined the distance to each class (i.e., \( \delta = (\delta_1, \cdots, \delta_K) \)) as the inherent feature of sample \((x, y)\) w.r.t. the victim model \( V \). After that, the defender will randomly select some samples inside (labeled as \('+1\)') or out-side (labeled as \('-1\)') their private dataset and use the feature embedding \( \delta \) to train a binary meta-classifier \( C \), where \( C(\delta) \in [0, 1] \) indicates the probability that the sample \((x, y)\) is from the private set. In the verification stage, the defender will select equal-sized sample vectors from private and public samples and then calculates the inherent feature embedding \( \delta \) for each sample vector w.r.t. the suspicious model \( S \). To verify whether \( S \) is stolen from \( V \), the trained \( C \) gives the confidence scores based on the inherent feature embedding \( \delta \) of \( S \). Besides, dataset inference adopted hypothesis-test based on the confidence scores of sample vectors to provide a more confident verification. However, as shown in the following experiments conducted in Section 4.1, dataset inference is easy to make misjudgments, especially when the training set of suspicious models has a similar distribution to that of the victim model. The misjudgment is mostly because different models may learn similar inherent features once their training sets have certain distribution similarities.

**Verification via Backdoor Watermarking.** These methods [9], [10], [20] were originally proposed to defend against fully-accessible attacks with or without fine-tuning. However, we notice that they enjoy certain similarities to dataset inference, since they both relied on the knowledge learned by the victim model from the private dataset. Accordingly, they serve as potential defenses against other types of model stealing, such as model-accessible and query-only attacks. The main difference compared with dataset inference is that they conducted model ownership based on defender-specified trigger-label pairs that are out of the distribution of the original training set. For example, backdoor watermarking first adopted backdoor attacks [21] to watermark the model during the training process and then conducted the ownership verification. In particular, a backdoor attack can be characterized by three components, including 1) target class \( y_t \), 2) trigger pattern \( t \), and 3) pre-defined poisoned image generator \( G(.) \). Given the benign training set \( D = \{(x_i, y_i)\}_{i=1}^N \), the backdoor adversary will randomly select \( \gamma \% \) samples (i.e., \( D_s \)) from \( D \) to generate their poisoned version \( D_p = \{(x'_i, y'_i) = G(x_i, t), (x, y) \in D_s \} \).

Different backdoor attacks may assign different generator \( G(.) \). For example, \( G(x, t) = (1 - \lambda) \otimes x + \lambda \otimes t \) where \( \lambda \in [0, 1]^{C \times W \times H} \) and \( \otimes \) indicates the element-wise product in the BadNets [22], \( G(x) = x + t \) in the ISSBA [23]. After \( D_p \) was generated, \( D_p \) and remaining benign samples \( D_b \triangleq D \setminus D_s \) will be used to train the (watermarked) model \( f_\theta \) via

\[
\min_{\theta} \sum_{(x, y) \in D_p \cup D_b} \mathcal{L}(f_\theta(x), y),
\]

where \( \mathcal{L}(\cdot) \) is the loss function. In the verification stage, the defender will examine the suspicious model in predicting \( y_t \). If the confidence scores of poisoned samples are significantly greater than those of benign samples, the suspicious model is treated as watermarked and therefore it is stolen from the victim. However, as shown in the following experiments conducted in Section 4.2, these methods have minor effects in defending against more complicated model stealing. Their failures are most probably because the hidden backdoor is modified after the complicated stealing process. Moreover, backdoor watermarking also introduce new security threats, since it builds a stealthy latent connection between trigger pattern and target label. The adversaries may use it to maliciously manipulate the predictions of deployed victim models. This problem will also hinder their utility in practice.

In conclusion, existing defenses still have vital limitations. How to defend against model stealing is still an important open question and worth further exploration.

### 3 Preliminaries

#### 3.1 Technical Terms

Before we dive into technical details, we first present the definition of commonly used technical terms, as follows:

- **Victim Model**: released model that could be stolen by the adversaries.
- **Suspicious Model**: model that is likely stolen from the victim model.
- **Benign Dataset**: unmodified dataset.
- **Benign Sample**: unmodified sample.
- **Watermarked Dataset**: dataset used for watermarking the (victim) model.
- **Watermarked Sample**: modified sample contained in the watermarked dataset.
- **Poisoned Sample**: modified sample used to create and activate the backdoor.
- **Benign Accuracy**: the accuracy of models in predicting benign testing samples.
- **Attack Success Rate**: the accuracy of models in predicting poisoned testing samples.

#### 3.2 Problem Formulation

In this paper, we focus on defending against model stealing in image classification tasks via model ownership verification. Specifically, given a suspicious model \( S \), the defender intends to identify whether it is stolen from the victim model \( V \). We argue that a model ownership verification is promising in practice if and only if it satisfies both two requirements simultaneously, as follows:

**Definition 1** (Two Necessary Requirements).

- **Effectiveness**: The defense could accurately identify whether the suspicious model is stolen from the victim no matter what model stealing is adopted.
• Harmlessness: The defense brings no additional security risks (e.g., backdoor), i.e., the model trained with the watermarked dataset should have similar prediction behaviors to the one trained with the benign dataset.

In general, effectiveness guarantees verification effects, while harmlessness ensures the safety of the victim model.

3.3 Threat Model

In this paper, we consider both white-box and black-box settings of model ownership verification, as follows:

White-box Setting. We assume that the defenders have complete access to the suspicious model, i.e., they can obtain its source files. However, the defenders have no information about the stealing process. For example, they have no information about the training samples, the training schedule, and the adopted stealing method used by the adversaries. One may argue that only black-box defenses are practical, since the adversary may refuse to provide the suspicious model. However, white-box defenses are also practical. In our opinion, the adoption of verification-based defenses (in a legal system) requires an official institute for arbitration. Specifically, all commercial models should be registered here, through the unique identification (e.g., MD5 code [24]) of their model’s source files. When this official institute is established, its staff should take responsibility for the verification process. For example, they can require the company to provide the model file with the registered identification and then use our method (under the white-box setting) for verification.

Black-box Setting. We assume that the defenders can only query and obtain the predicted probabilities from the suspicious model, whereas cannot get access to the model source files or intermediate results (e.g., gradients) and have no information about the stealing. This approach can be used as a primary inspection of the suspicious model before applying the official arbitration where white-box verifications may be adopted. In particular, we did not consider the label-only black-box setting since the harmlessness requires that no abnormal prediction behaviors (compared with the model trained with a benign dataset) are introduced in the victim model. In other words, it is impossible to accurately identify model stealing under the label-only black-box setting.

4 Revisiting Verification-based Defenses

4.1 The Limitations of Dataset Inference

As we described in Section 2.2, dataset inference reached better performance compared with membership inference by using inherent features instead of given samples. In other words, it relied on the latent assumption that a benign model will not learn features contained in the training set of the victim model. However, different models may learn similar features from different datasets, i.e., this assumption does not hold and therefore leads to misjudgments. In this section, we will illustrate this limitation.

Settings. We conduct the experiments on CIFAR-10 [25] dataset with VGG [26] and ResNet [27]. To create two independent datasets that have similar distribution, we randomly separate the original training set $D$ into two disjoint subsets $D_l$ and $D_r$. We train the VGG on $D_l$ (dubbed VGG-$D_l$) and the ResNet on $D_r$ (dubbed ResNet-$D_r$), respectively. We also train a VGG on a noisy version of $D_l$ (i.e., $D'_l$), where $D'_l \triangleq \{(x', y')|x' = x + \mathcal{N}(0, 16), (x, y) \in D_l\}$ (dubbed VGG-$D'_l$) for reference. In the verification process, we verify whether the VGG-$D_l$ and VGG-$D'_l$ is stolen from ResNet-$D_r$ and whether the ResNet-$D_r$ is stolen from VGG-$D_l$ with dataset inference [11]. As described in Section 2.2, we adopt the p-value as the evaluation metric, following the setting of dataset inference. In particular, the smaller the p-value, the more confident that dataset inference believes that the suspicious model is stolen from the victim model.

Results. As shown in Table 1, all models have promising performance even with only half the numbers of original training samples. However, the p-value is significantly smaller than 0.01 in all cases. In other words, dataset inference is confident about the judgments that VGG-$D_l$ and VGG-$D'_l$ are stolen from ResNet-$D_r$, and ResNet-$D_r$ is stolen from VGG-$D_l$. However, none of these models should be regarded as stolen from the victim since they adopt completely different training samples and model structures. These results reveal that dataset inference could make misjudgments and therefore its results are questionable. Besides, the misjudgments may probably cause by the distribution similarity among $D_l$, $D_r$, and $D'_l$. The p-value of the VGG-$D_l$ is lower than that of the VGG-$D'_l$. This is probably because the latent distribution of $D'_l$ is more different from that of $D_r$ (compared with that of $D_l$) and therefore models learn more different features.

|               | ResNet-$D_r$ | VGG-$D_l$ | VGG-$D'_l$ |
|---------------|-------------|-----------|------------|
| Accuracy      | 88.0%       | 87.7%     | 85.0%      |
| p-value       | $10^{-7}$   | $10^{-5}$ | $10^{-4}$  |

4.2 The Limitations of Backdoor Watermarking

As described in Section 2.2, the verification via backdoor watermarking relies on the latent assumption that the defender-specific trigger pattern matches the backdoor embedded in stolen models. This assumption holds in its originally discussed scenarios, since the suspicious model is the same as the victim model. However, this assumption may not hold in more advanced model stealing, since the backdoor may be changed or even removed during the stealing process. Consequently, the backdoor-based watermarking may fail in defending against model stealing. In this section, we verify this limitation.

Settings. We adopt the most representative and effective backdoor attack, the BadNets [22], as an example for the discussion. The watermarked model will then be stolen by the data-free distillation-based model stealing [14]. We adopt benign accuracy (BA) and attack success rate (ASR) [21] to evaluate the performance of the stolen model. The larger the ASR, the more likely the stealing will be detected.

Results. As shown in Table 2, the ASR of the stolen model is only 3.84%, which is significantly lower than that of the
Step 1. Embedding External Features

\[ \mathbf{x}_s \rightarrow \mathbf{T} \rightarrow \mathbf{D}_t \rightarrow \mathbf{D}_s \rightarrow \mathbf{V} \]

Step 2. Training Meta-Classifier

(a) White-box setting

\[ \mathbf{D}_t \rightarrow \mathbf{D}_c \rightarrow \mathbf{C} \rightarrow \mathbf{A}_c \rightarrow \mathbf{A}_v \]

(b) Black-box setting

\[ \mathbf{x} \rightarrow (f^0_{aug}(\mathbf{x}'))_{i=1} \rightarrow \mathbf{d}_v \rightarrow \mathbf{F} \rightarrow \mathbf{d}_B \rightarrow \mathbf{A}_B \rightarrow \mathbf{C} \]

Step 3. Ownership Verification

Hypothesis Test

\[ \mathbf{g}_B/A_B \rightarrow \mathbf{C} \rightarrow \mathbf{g}_S/A_S \]

TABLE 2: The performance (%) of different models. The failed verification case is marked in red.

| Model Type | Benign | Watermarked | Stolen |
|------------|--------|-------------|--------|
| BA         | 91.99  | 85.49       | 70.17  |
| ASR        | 0.01   | 100.00      | 3.84   |

Fig. 1: The main pipeline of our MOVE defense. In the first step, defenders will modify some images via style transfer for embedding external features. In the second step, defenders will train a meta-classifier to determine whether a suspicious model is stolen from the victim based on gradients (under the white-box setting) or prediction differences (under the black-box setting). In the last step, defenders will conduct ownership verification via hypothesis-test.

Fig. 2: The adopted trigger pattern and synthesized ones obtained from the watermarked and the stolen model. The trigger areas are indicated in the blue box. (a) ground-truth trigger pattern; (b) pattern obtained from the watermarked model; (c) pattern obtained from the stolen model.

Table 2 shows the performance (%) of different models. The failed verification case is marked in red.

The potential trigger pattern of each model. As shown in Figure 2, the trigger pattern recovered from the victim model is similar to the ground-truth one. However, the recovered pattern from the stolen model is significantly different from the ground-truth one. These results provide a reasonable explanation for the failure of backdoor-based watermarking.

In particular, backdoor watermarking will also introduce additional security risks to the victim model and therefore is harmful. Specifically, it builds a stealthy latent connection between triggers and the target label. The adversary may use it to maliciously manipulate predictions of the victim model. This potential security risk will further hinder the adoption of backdoor-based model verification in practice.

5 THE PROPOSED METHOD

Based on the observations in Section 4, we propose a harmless model ownership verification (MOVE) by embedding external features (instead of inherent features) into victim model, without changing the label of watermarked samples.

5.1 Overall Pipeline

In general, our MOVE defense consists of three main steps, including 1) embedding external features, 2) training an ownership meta-classifier, and 3) conducting ownership verification. In particular, we consider both white-box and black-box settings. They have the same feature embedding process and similar verification processes, while having different training manners of the meta-classifier. The main pipeline of our MOVE is shown in Figure 1.
5.2 Embedding External Features

In this section, we describe how to embed external features. We first define inherent and external features before reaching the technical details of the embedding.

Definition 2 (Inherent and External Features). A feature \( f \) is called the inherent feature of dataset \( D \) if and only if \( \forall (x, y) \in X \times Y, (x, y) \in D \Rightarrow (x, y) \) contains feature \( f \). Similarly, \( f \) is called the external feature of dataset \( D \) if and only if \( \forall (x, y) \in X \times Y, (x, y) \) contains feature \( f \) \( \Rightarrow (x, y) \notin D \).

Example 1. If an image is from the MNIST dataset, it is at least grayscale; if an image is cartoon-type, it is not from the CIFAR-10 dataset for it contains only natural images.

Although external features are well defined, how to construct them is still difficult, since the learning dynamic of DNNs remains unclear and the concept of features itself is complicated. However, at least we know that the image style can serve as a feature for the learning of DNNs in image-related tasks, based on some recent studies \cite{29, 30, 31}. As such, we can use style transfer \cite{32, 33, 34} for embedding external features. People may also adopt other methods for the embedding. It will be discussed in our future work.

In particular, let \( D = \{(x_i, y_i)\}_{i=1}^N \) denote the benign training set, \( x_\text{s} \) is a defender-specified style image, and \( T : X \times X \rightarrow X \) is a (pre-trained) style transformer. In this step, the defender first randomly selects \( \gamma \% \) (dubbed transformation rate) samples (i.e., \( D_s \)) from \( D \) to generate their transformed version \( D_t = \{(x', y')|x' = T(x, x_\text{s}), (x, y) \in D_s\} \). The external features will be learned by the victim model \( V_\theta \) during the training process via

\[
\min_{\theta} \sum_{(x, y) \in D_0 \cup D_1} \mathcal{L}(V_\theta(x, y)),
\]

where \( D_0 = D \setminus D_s \), and \( \mathcal{L}(\cdot) \) is the loss function.

In this stage, how to select the style image is an important question. Intuitively, it should be significantly different from those contained in the original training set. In practice, defenders can simply adopt oil or sketch paintings as the style image, since most of the images that need to be protected are natural images. Defenders can also use other style images. We will further discuss this in Section 7.

In particular, since we only modify a few samples and do not change their labels, the embedding of external features will not hinder the functionality of victim models or introduce new security risks (e.g., hidden backdoors).

5.3 Training Ownership Meta-Classifier

Since there is no explicit expression of the embedded external features and those features also have minor influences on the prediction, we need to train an additional binary meta-classifier to determine whether the suspicious model contains the knowledge of external features.

Under the white-box setting, we adopt the gradients of model weights as the input to train the meta-classifier \( C_w : \mathbb{R}^{\theta|} \rightarrow \{-1, +1\} \). In particular, we assume that the victim model \( V \) and the suspicious model \( S \) have the same model structure. This assumption can be easily satisfied since the defender can retain a copy of the suspicious model on the training set of the victim model if they have different structures. Once the suspicious model is obtained, the defender will then train the benign version (i.e., the \( B \)) of the victim model on the benign training set \( D \). After that, we can obtain the training set \( D_c \) of meta-classifier \( C \) via

\[
D_c = \{(gv(x'), +1) | (x', y) \in D_1 \} \cup \{(gb(x'), -1) | (x', y) \in D_1\},
\]

where \( sgn(\cdot) \) indicates the sign function \cite{35}, \( gv(x') = sgn(\nabla_y \mathcal{L}(V(x'), y)) \), and \( gb(x') = sgn(\nabla_y \mathcal{L}(B(x'), y)) \). In particular, we adopt its sign vector instead of the gradient itself to highlight the influence of its direction.

Under the black-box setting, defenders can no longer obtain the model gradients since they cannot access model’s source files or intermediate results. In this case, we adopt the difference between the predicted probability vector of the transformed image and that of its benign version. Specifically, let \( V : X \rightarrow [0, 1]^K \) and \( B : X \rightarrow [0, 1]^K \) indicates the victim model and the benign model, respectively. Assume that \( dv(x', y) = V(x') - V(x) \) and \( db(x', y) = B(x') - B(x) \). In this case, the training set \( D_c \) can be obtained via

\[
D_c = \{(dv(x', y), +1) | (x', y) \in D_1 \} \cup \{(db(x', y), -1) | (x', y) \in D_1\},
\]

Different from MOVE under the white-box setting, we do not assume that the victim model has the same model structure as the suspicious model under the black-box setting, since only model predictions are needed in this case.

However, we found that directly using \( D_c \) defined in Eq. \ref{eq5} is not able to train a well-performed meta-classifier. This failure is mostly because the probability differences contain significantly less information than the model gradients. To alleviate this problem, we propose to introduce data augmentations on the transformed image and concatenate their prediction differences. Specifically, let \( F = \{f_{aug}^{(i)}\}_{i=1}^N \) denotes \( N \) given semantic and size preserving image transformations (e.g., flipping). The (augmented) training set is denoted as follows:

\[
D_c^{aug} = \{(A_v(x, x'), +1) | (x', y) \in D_1 \} \cup \{(A_b(x, x'), -1) | (x', y) \in D_1\},
\]

where

\[
A_v(x, x') = CAT\left(\left\{d_{v,i}(x, f_{aug}^{(i)}(x'))\right\}_{i=1}^N\right),
\]

\[
A_b(x, x') = CAT\left(\left\{d_{b,i}(x, f_{aug}^{(i)}(x'))\right\}_{i=1}^N\right),
\]

and ‘CAT’ is the concatenate function. Note that the dimensions of \( A_v(x, x') \) and \( A_v(x, x') \) are both \( (1, K \times N) \). In this paper, we adopt five widespread transformations, including 1) identical transformation, 2) horizontal flipping, 3) translation towards the bottom right, 4) translation towards the right, and 5) translation towards the bottom, for simplicity. We will discuss the potential of using other transformations in our future work.

Once \( D_c \) is obtained, the meta-classifier \( C_w \) is trained by

\[
\min_{w} \sum_{(s, t) \in D_c} \mathcal{L}(C_w(s, t)).
\]
5.4 Ownership Verification with Hypothesis-Test

After training the meta-classifier $C$, the defenders can verify whether a suspicious model is stolen from the victim simply by the result of meta-classifier, based on a given transformed image $x'$. However, the verification result may be sharply affected by the randomness of selecting $x'$. In order to increase the verification confidence, we design a hypothesis-test-based method, as follows:

**Definition 3** (White-box Verification). Let $X'$ is the variable of the transformed image, while $\mu_S$ and $\mu_B$ denotes the posterior probability of event $C(g_S(X')) = 1$ and $C(g_B(X')) = 1$, respectively. Given a null hypothesis $H_0 : \mu_S = \mu_B$ ($H_1 : \mu_S > \mu_B$), we claim that the suspicious model $S$ is stolen from the victim if and only if the $H_0$ is rejected.

**Definition 4** (Black-box Verification). Let $X'$ is the variable of the transformed image and $X$ denotes the benign version of $X'$. Assume that $\mu_S$ and $\mu_B$ indicates the posterior probability of event $C(A_S(X, X')) = 1$ and $C(A_B(X, X')) = 1$, respectively. Given a null hypothesis $H_0 : \mu_S = \mu_B$ ($H_1 : \mu_S > \mu_B$), we claim that the suspicious model $S$ is stolen from the victim if and only if the $H_0$ is rejected.

Specifically, we randomly sample $m$ different transformed images from $D_i$ to conduct the single-tailed pairwise T-test [56] and calculate its p-value. If the p-value is smaller than the significance level $\alpha$, the null hypothesis $H_0$ is rejected. We also calculate the confidence score $\Delta \mu = \mu_S - \mu_B$ to represent the verification confidence. The larger the $\Delta \mu$, the more confident the verification.

6 MAIN EXPERIMENTS

6.1 Settings.

**Dataset and Model Selection.** We evaluate our defense on CIFAR-10 [25] and ImageNet [37] dataset. CIFAR-10 contains 60,000 images (with size $3 \times 32 \times 32$) with 10 classes, including 50,000 training samples and 10,000 testing samples. ImageNet is a large-scale dataset and we use its subset containing 20 random classes for simplicity and efficiency. Each class of the subset contains 500 samples (with size $3 \times 224 \times 224$) for training and 50 samples for testing. According to the settings of [11], we use the WideResNet [38] and ResNet [27] as the victim model on CIFAR-10 and ImageNet, respectively.

**Training Settings.** For the CIFAR-10 dataset, the training is conducted based on the open-source code 2. Specifically, both victim model and benign model are trained for 200 epochs with SGD optimizer and an initial learning rate of 0.1, momentum of 0.9, weight decay of $5 \times 10^{-4}$, and batch size of 128. We decay the learning rate with the cosine decay schedule [59] without a restart. We also use data augmentation techniques including random crop and resize (with random flip). For the ImageNet dataset, both the victim model and benign model are trained for 200 epochs with SGD optimizer and an initial learning rate of 0.001, momentum of 0.9, weight decay of $1 \times 10^{-5}$, and batch size of 32. The learning rate is decreased by a factor of 10 at epoch 150. All training processes are performed on a single GeForce GTX 1080 Ti GPU.

**Settings for Model Stealing.** Following the settings in [11], we conduct model stealing attacks illustrated in Section 2.2.3 to evaluate the effectiveness of different defenses. Besides, we also provide the results of examining a suspicious model which is not stolen from the victim (dubbed ‘Independent’) for reference. Specifically, we implement the model distillation (dubbed ‘Distillation’) [13] based on its open-sourced code 4. The stolen model is trained with SGD optimizer and an initial learning rate of 0.1, momentum of 0.9, and weight decay of $10^{-4}$; The zero-shot learning based data-free distillation (dubbed ‘Zero-shot’) [14] is implemented based on the open-source code 3. The stealing process is performed for 200 epochs with SGD optimizer and a learning rate of 0.1, momentum of 0.9, weight decay of $5 \times 10^{-4}$, and batch size of 256; For the fine-tuning, the adversaries obtain stolen models by fine-tuning victim models on different datasets. Following the settings in [11], we randomly select 500,000 samples from the original TinyImages 40 as the substitute data to fine-tune the victim model for experiments on CIFAR-10. For the ImageNet experiments, we randomly choose samples with other 20 classes from the original ImageNet as the substitute data. We fine-tune the victim model for 5 epochs to obtain the stolen model; For the label-query attack (dubbed ‘Label-query’), we train the stolen model for 20 epochs with a substitute dataset labeled by the victim model; For the logit-query attack (dubbed ‘Logit-query’), we train the stolen model by minimizing the KL-divergence between its outputs (i.e., logits) and those of the victim model for 20 epochs.

**Settings for Defenses.** We compare our defense with dataset inference [11] and model watermarking [20] with BadNets [22], gradient matching [41], and entangled watermarks [10].

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2. https://github.com/kuangliu/pytorch-cifar
3. https://github.com/thaonguyen19/ModelDistillation-PyTorch
4. https://github.com/VainF/Data-Free-Adversarial-Distillation

Fig. 3: Images involved in different defenses. (a) benign image; (b) poisoned image in BadNets; (c) poisoned image in Gradient Matching; (d) poisoned image in Entangled Watermarks; (e) style image; (f) transformed image in our MOVE.
We poison 10% training samples for all defenses. Besides, we adopt a white square in the lower right corner as the trigger pattern for BadNets and adopt an oil paint as the style image for our defense. Other settings are the same as those used in their original paper. We implement BadNets based on BackdoorBox [42] and other methods based on their official open-sourced codes. An example of images (e.g., poisoned images and the style image) involved in different defenses is shown in Figure 5. In particular, similar to our method, dataset inference uses different methods under different settings, while other baseline defenses are designed under the black-box setting. Since methods designed under the black-box setting can also be used in the white-box setting, we also compare our MOVE with them under the white-box setting.

**Evaluation Metric.** We use the confidence score $\Delta \mu$ and p-value as the metric for our evaluation. Both of them are calculated based on the hypothesis-test with 10 sampled images under the white-box setting and 100 images under the black-box setting. In particular, except for the independent sources (which should not be regarded as stolen), the smaller the p-value and the larger the $\Delta \mu$, the better the defense. For the independent ones, the larger the p-value and the smaller the $\Delta \mu$, the better the method. Among all defenses, the best result is indicated in boldface and the failed verification cases are marked in red.

### 6.2 Results of MOVE under the White-box Setting

As shown in the Table 3, MOVE achieves the best performance in almost all cases under the white-box setting. For example, the p-value of our method is three orders of magnitude smaller than that of the dataset inference and entangled watermarks in defending against the direct-copy on CIFAR-10 and ImageNet, respectively. In those cases where we do not get the best performance (e.g., label-query and logit-query), our defense is usually the second-best where it can still easily make correct predictions. In particular, same as the scenarios under the white-box setting, our MOVE defense is the only method that can effectively identify whether there is model stealing in all cases. Other defenses either fail under many complicated stealing attacks (e.g., query-only attacks) or misjudge when there is no stealing. Besides, our defense has minor adverse effects on the performance of victim models. The accuracy of the model trained on benign CIFAR-10 and its transformed version is 91.79% and 91.99%, respectively; The accuracy of the model trained on benign ImageNet and its transformed version is 82.40% and 80.40%, respectively. This is mainly because we do not change the label of transformed images and therefore the transformation can be treated as data augmentation, which is mostly harmless.

### 6.3 Results of MOVE under the Black-box Setting

As shown in Table 4, our MOVE defense still reaches promising performance under the black-box setting. For example, the p-value of our defense is over twenty and sixty orders of magnitude smaller than that of the dataset inference and entangled watermarks in defending against direct-copy on CIFAR-10 and ImageNet, respectively. In those cases where we do not get the best performance (e.g., label-query and logit-query), our defense is usually the second-best where it can still easily make correct predictions. In particular, same as the scenarios under the white-box setting, our MOVE defense is the only method that can effectively identify whether there is model stealing in all cases. Other defenses either fail under many complicated stealing attacks or misjudge when there is no model stealing. These results verify the effectiveness of our defense again.
6.4 Defending Against Multi-Stage Model Stealing

In previous experiments, the stolen model is obtained by a single stealing. In this section, we explore whether our method is still effective if there are multiple stealing stages. 

**Settings.** We discuss two types of multi-stage stealing on the CIFAR-10 dataset, including stealing with the same attack and model structure and stealing with different attacks and model structures. In general, the first one is the easiest multi-stage attack while the second one is the hardest. Other settings are the same as those in Section 6.1.

**Results.** As shown in Table 7, the p-value increases with the increase of the stage, which indicates that defending against multi-stage attacks is difficult. Nevertheless, the p-value ≤ 0.01 in all cases under both white-box and black-box settings, i.e., our method can identify the existence of model stealing even after multiple stealing stages. Besides, the p-value in defending the second type of multi-stage attack is significantly larger than that of the first one, showing that the second task is harder.

### 7 Discussion

In this section, we further explore the mechanisms and properties of our MOVE. Unless otherwise specified, all settings are the same as those in Section 6.
7.1.3 Effects of Style Images

In this part, we examine whether the proposed defense is still effective if we adopt other style images (as shown in Figure 5). As shown in Table 8, the p-value ≤ 0.01 in all cases under attack, while it is nearly 1 when there is no stealing, no matter under white-box or black-box setting. In other words, our method remains effective in defending against different stealing methods when different style images are used, although there will be some fluctuations in the results. We will further explore how to optimize the selection of style images in our future work.

7.2 The Ablation Study

There are three key components contained in our MOVE, including 1) embedding external features with style transfer, 2) using the sign vector of gradients instead of gradients themselves, and 3) using meta-classifier for verification. In this section, we verify their effectiveness. For simplicity, we use MOVE under the white-box setting for discussion.

7.2.1 The Effectiveness of Style Transfer

To verify that the style watermark transfers better during the stealing process, we compare our method with its variant which uses the white-square patch (adopted in BadNets) to generate transformed images. As shown in Table 9, our method is significantly better than its patch-based variant. It is probably because DNNs are easier to learn the texture information [29] and the style watermark is bigger than the patch one. This phenomenon partly explains why our method works well.

7.2.2 The Effectiveness of Sign Function

In this section, we compare our method with its variant which directly adopts the gradients to train the meta-classifier. As shown in Table 10, using the sign of gradients is significantly better than using gradients directly. This is probably because the ‘direction’ of gradients contains more information compared with their ‘magnitude’. We will further explore it in the future.
TABLE 10: The performance of our meta-classifier trained with different features.

| Dataset → | CIFAR-10 | | | ImageNet | | |
|-----------|----------|----------|----------|----------|----------|
| Model Stealing | | | | | |
| | Gradient | Sign of Gradient (Ours) | | Gradient | Sign of Gradient (Ours) | | |
| | | | | | | |
| Direct-copy | 0.44 | 0.97 | 10^{-6} | 0.15 | 0.90 | 10^{-6} |
| Distillation | 0.27 | 0.53 | 10^{-7} | 0.15 | 0.61 | 10^{-5} |
| Zero-shot | 0.03 | 0.52 | 10^{-5} | 0.12 | 0.53 | 10^{-4} |
| Fine-tuning | 0.04 | 0.50 | 10^{-6} | 0.13 | 0.60 | 10^{-5} |
| Label-query | 0.08 | 0.52 | 10^{-4} | 0.13 | 0.55 | 10^{-3} |
| Logit-query | 0.07 | 0.54 | 10^{-4} | 0.12 | 0.55 | 10^{-4} |
| Independent | 0.00 | 1.00 | 1.00 | 10^{-10} | 0.99 | 0.99 |

TABLE 11: The effectiveness (p-value) of meta-classifier.

| Dataset → | CIFAR-10 | | | ImageNet | | |
|-----------|----------|----------|----------|----------|----------|
| | w/o | w/ | | w/o | w/ | |
| Direct-copy | 10^{-12} | 10^{-3} | 10^{-10} | 10^{-11} |
| Distillation | 0.32 | 10^{-3} | 0.43 | 10^{-3} |
| Zero-shot | 0.22 | 10^{-61} | 0.33 | 10^{-3} |
| Fine-tuning | 0.28 | 10^{-5} | 0.20 | 10^{-13} |
| Label-query | 0.20 | 10^{-50} | 0.29 | 10^{-3} |
| Logit-query | 0.23 | 10^{-3} | 0.38 | 10^{-3} |

7.2.3 The Effectiveness of Meta-Classifier

To verify that the meta-classifier is also useful, we compare the BadNets-based model watermarking with its extension, which also uses the meta-classifier (adopted in our MOVE defense) for ownership verification. In this case, the victim model is the backdoored one and the transformed image is the one containing backdoor triggers. As shown in Table 11, adopting meta-classifier significantly decrease the p-value in almost all cases, which verifies the effectiveness of the meta-classifier. These results also partly explains the effectiveness of our MOVE defense.

7.3 Resistance to Potential Adaptive Attacks

In this section, we discuss the resistance of our defense to potential adaptive attacks. We take MOVE under the white-box setting as an example to discuss for simplicity.

7.3.1 Resistance to Model Fine-tuning

In many cases, attackers have some benign local samples. As such, they may first fine-tune the stolen model before deployment. This adaptive attack might be effective since the fine-tuning process may alleviate the effects of transformed images due to the catastrophic forgetting [43] of DNNs. Specifically, we adopt p% benign training samples (where p ∈ {0, 5, 10, 15, 20} is dubbed sample rate) to fine-tune the whole stolen models generated by distillation, zero-shot, label-query, and logit-query. We also adopt the p-value and Δμ to measure the defense effectiveness.

As shown in Figure 6, the p-value increases while the Δμ decreases with the increase of sample rate. These results indicate that model fine-tuning has some benefits in reducing our defense effectiveness. However, our defense can still successfully detect all stealing attacks (p-value < 0.01 and Δμ ≫ 0) even the sample rate is set to 20%. In other words, our defense is resistant to model fine-tuning.

7.3.2 Resistance to Saliency-based Backdoor Detections

These methods [44], [45], [46] use the saliency map to identify and remove potential trigger regions. Specifically, they first generate the saliency map of each sample and identify and remove potential trigger regions. These methods [44], [45], [46] use the saliency map to this adaptive attack might be effective since the fine-tuning process may alleviate the effects of transformed images due to the catastrophic forgetting [43] of DNNs. Specifically, we adopt p% benign training samples (where p ∈ {0, 5, 10, 15, 20} is dubbed sample rate) to fine-tune the whole stolen models generated by distillation, zero-shot, label-query, and logit-query. We also adopt the p-value and Δμ to measure the defense effectiveness.

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7.3.3 Resistance to STRIP

This method [47] detects and filters poisoned samples based on the prediction randomness of samples generated by imposing various image patterns on the suspicious image. The randomness is measured by the entropy of the average prediction of those samples. The higher the entropy, the harder...
Fig. 7: Salience maps of BadNets and our MOVE. (a)-(b): salience maps of poisoned images generated by BadNets. (c)-(d): salience maps of transformed images generated by MOVE. (a)&(c): salience maps of images from CIFAR-10 dataset. (b)&(d): salience maps of images from ImageNet dataset.

TABLE 12: Resistance (entropy) of BadNets-based model watermarking and our defense to STRIP.

|             | CIFAR-10 | ImageNet |
|-------------|----------|----------|
| BadNets     | 0.01     |          |
| Ours        | 1.15     | 0.01     |
|             | 0.77     |          |

an method for STRIP to detect. We compare the average entropy of all poisoned images in BadNets and that of all transformed images in our defense. As shown in Table 12, the entropy of our defense is significantly larger than that of the BadNets-based method. These results show that our defense is resistant to STRIP.

7.3.4 Resistance to Trigger Synthesis based Detections

These methods [48], [49], [50] detect poisoned images by reversing potential triggers contained in given suspicious DNNs. They have a latent assumption that the triggers should be sample-agnostic and the attack should be targeted. However, our defense does not satisfy these assumptions since the perturbations in our transformed images are sample-specific and we do not modify the label of those images. As shown in Figure 8, synthesized triggers of the BadNets-based method contain similar patterns to those used by defenders (i.e., white-square on the bottom right corner) or its flipped version, whereas those of our method are meaningless. These results show that our defense is also resistant to these detection methods.

7.4 Relations with Related Methods

7.4.1 Relations with Membership Inference Attacks

Membership inference attacks [17], [18], [19] intend to identify whether a particular sample is used to train given DNNs. Similar to these attacks, our method also adopts some training samples for ownership verification. However, our defense aims to analyze whether the suspicious model contains the knowledge of external features rather than whether the model is trained on those transformed samples. To verify it, we design additional experiments, as follows:

Settings. For simplicity, we compare our method with its variant which adopts testing instead of training samples to generate transformed images used in ownership verification under the white-box setting. Except for that, other settings are the same as those stated in Section 6.1.

Results. As shown in Table 13, using testing images has similar effects to that of using training images in generating transformed images for ownership verification, although there are some small fluctuations. In other words, our method indeed examines the information of embedded external features rather than simply verifying whether the transformed images are used for training. These results verify that our defense is fundamentally different from membership inference attacks.

7.4.2 Relations with Backdoor Attacks

Similar to that of (poisoning-based) backdoor attacks [51], [52], [53], our defense embeds pre-defined distinctive behaviors into DNNs via modifying some training samples. However, different from that of backdoor attacks, our method neither changes the label of poisoned samples nor only selects training samples with the specific category for poisoning. Accordingly, our defense will not introduce any hidden backdoor into the trained victim model. In other words, the dataset watermarking of our MOVE is also fundamentally different from backdoor attacks. This is probably the main reason why most existing backdoor defenses will
have minor benefits in designing adaptive attacks against our defense, as illustrated in Section 7.3.

8 Conclusion
In this paper, we revisited the defenses against model stealing from the perspective of model ownership verification. We revealed that existing defenses suffered from low effectiveness and may even introduced additional security risks. Based on our analysis, we proposed a new effective and harmless model ownership verification (i.e., MOVE), which examined whether the suspicious model contains the knowledge of defender-specified external features. We embedded external features by modifying a few training samples with style transfer without changing their label. In particular, we developed our MOVE defense under both white-box and black-box settings to provide comprehensive model protection. We evaluated our defense on both CIFAR-10 and ImageNet datasets. The experiments verified that our method can defend against various types of model stealing simultaneously while preserving high accuracy in predicting benign samples.

References
[1] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” nature, vol. 521, no. 7553, pp. 436–444, 2015.
[2] R. Feng, S. Chen, X. Xie, G. Meng, S.-W. Lin, and Y. Liu, “A performance-sensitive malware detection system using deep learning on mobile devices,” IEEE Transactions on Information Forensics and Security, vol. 16, pp. 1563–1576, 2020.
[3] S. Minneci, Y. Y. Boykov, F. Porikli, A. J. Plaza, N. Kehtarnavaz, and D. Terzopoulos, “Image segmentation using deep learning: A survey,” IEEE Transactions on Pattern Analysis and Machine Intelligence, 2021.
[4] F. Tramèr, F. Zhang, A. Juels, M. K. Reiter, and T. Ristenpart, “Stealing machine learning models via prediction apis,” in USENIX Security, 2016.
[5] T. Orecsky, B. Schiele, and M. Fritz, “Knockoff nets: Stealing functionality of black-box models,” in CVPR, 2019.
[6] V. Chandrasekaran, K. Chaudhuri, I. Giacomelli, S. Jha, and S. Yan, “Exploring connections between active learning and model extraction,” in USENIX Security, 2020.
[7] T. Lee, B. Edwards, I. Molloy, and D. Su, “Defending against neural network model stealing attacks using deceptive perturbations,” in IEEE S&P Workshop, 2019.
[8] S. Kariyappa and M. K. Qureshi, “Defending against model stealing attacks with adaptive misinformation,” in CVPR, 2020.
[9] Y. Li, Z. Zhang, J. Bai, B. Wu, Y. Jiang, and S.-T. Xia, “Open-sourced dataset protection via backdoor watermarking,” in NeurIPS Workshop, 2020.
[10] H. Jia, C. A. Choquette-Choo, V. Chandrasekaran, and N. Papernot, “Entangled watermarks as a defense against model extraction,” in USENIX Security, 2021.
[11] P. Maini, M. Yaghini, and N. Papernot, “Dataset inference: Ownership resolution in machine learning,” in ICLR, 2021.
[12] Y. Li, L. Zhu, X. Jia, Y. Jiang, S.-T. Xia, and X. Cao, “Defending against model stealing via verifying embedded external features,” in AAAI, 2022.
[13] G. Hinton, O. Vinyals, and J. Dean, “Distilling the knowledge in a neural network,” in NeurIPS Workshop, 2014.
[14] G. Fang, J. Song, C. Shen, X. Wang, D. Chen, and M. Song, “Data-free adversarial distillation,” arXiv preprint arXiv:1912.11006, 2019.
[15] N. Papernot, P. McDaniel, I. Goodfellow, S. Jha, Z. B. Celik, and A. Swami, “Practical black-box attacks against machine learning,” in Asilomar, 2017.
[16] M. Jagielski, N. Carlini, D. Berthelot, A. Kurakin, and N. Papernot, “High accuracy and high fidelity extraction of neural networks,” in USENIX Security, 2020.
[17] R. Shokri, M. Stronati, C. Song, and V. Shmatikov, “Membership inference attacks against machine learning models,” in IEEE S&P, 2017.
[18] K. Leino and M. Fredrikson, “Stolen memories: Leveraging model memorization for calibrated white-box membership inference,” in USENIX Security, 2020.
[19] B. Hui, Y. Yang, H. Yuan, P. Burlina, N. Z. Gong, and Y. Cao, “Practical blind membership inference attack via differential comparisons,” in NDSS, 2021.
[20] Y. Adi, C. Baum, M. Cisse, B. Pinkas, and K. J. Roth, “Turning your weakness into a strength: Watermarking deep neural networks by backdooring,” in USENIX Security, 2018.
[21] Y. Li, Y. Jiang, Z. Li, and S.-T. Xia, “Backdoor learning: A survey,” arXiv preprint arXiv:2007.08745, 2020.
[22] T. Gu, K. Liu, B. Dolan-Gavitt, and S. Garg, “Badnets: Evaluating backdooring attacks on deep neural networks,” IEEE Access, vol. 7, pp. 47 230–47 244, 2019.
[23] Y. Li, Y. Li, B. Wu, L. Li, R. He, and S. Lyu, “Invisible backdoor attack with sample-specific triggers,” in ICCV, 2021.
[24] R. Rivest and S. Dusse, “The md5 message-digest algorithm,” 1992.
[25] A. Krizhevsky, G. Hinton et al., “Learning multiple layers of features from tiny images,” Citeseer, Tech. Rep., 2009.
[26] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” in ICLR, 2015.
[27] K. He, X. Zhang, S. Ren, and J. Sun, “Deep residual learning for image recognition,” in CVPR, 2015.
[28] S.-M. Moosavi-Dezfooli, A. Fawzi, O. Fawzi, and P. Frossard, “Universal adversarial perturbations,” in CVPR, 2017.
[29] R. Geirhos, P. Rubisch, C. Michaelis, M. Bethge, F. A. Wichmann, and W. Brendel, “Imagenet-trained cnns are biased towards texture; increasing shape bias improves accuracy and robustness,” in ICLR, 2019.
[30] R. Duan, X. Ma, Y. Wang, J. Bailey, A. K. Qin, and Y. Yang, “Adversarial camouflage: Hiding physical-world attacks with natural styles,” in CVPR, 2020.
[31] S. Cheng, Y. Liu, S. Ma, and X. Zhang, “Deep feature space trojan attack of neural networks by controlled detoxification,” in AAAI, 2021.
[32] J. Johnson, A. Alahi, and L. Fei-Fei, “Perceptual losses for real-time style transfer and super-resolution,” in ECCV, 2016.
[33] X. Huang and S. Belongie, “Arbitrary style transfer in real-time with adaptive instance normalization,” in ICCV, 2017.

### Table 13: Results of ownership verification with transformed samples generated by training and testing samples.

| Dataset → | CIFAR-10 | ImageNet |
|-----------|----------|----------|
| Model Stealing | Training Set | p-value | Testing Set | p-value |
| Direct-copy | 0.97 10−7 | 0.96 10−7 | 0.90 10−6 | 0.93 10−7 |
| Distillation | 0.53 10−5 | 0.53 10−5 | 0.61 10−5 | 0.42 10−5 |
| Zero-shot | 0.52 10−5 | 0.53 10−5 | 0.53 10−4 | 0.34 10−3 |
| Fine-tuning | 0.50 10−6 | 0.47 10−6 | 0.60 10−5 | 0.72 10−5 |
| Label-query | 0.52 10−4 | 0.52 10−4 | 0.55 10−3 | 0.40 10−3 |
| Logit-query | 0.54 10−4 | 0.53 10−4 | 0.55 10−4 | 0.48 10−4 |
| Independent | 0.00 1.00 | 0.00 1.00 | 10−9 | 0.99 10−9 | 0.99 10−9 |
[34] X. Chen, Y. Zhang, Y. Wang, H. Shu, C. Xu, and C. Xu, “Optical flow distillation: Towards efficient and stable video style transfer,” in ECCV, 2020.
[35] L. Sachs, Applied statistics: a handbook of techniques. Springer Science & Business Media, 2012.
[36] R. V. Hogg, J. McKean, and A. T. Craig, Introduction to mathematical statistics. Pearson Education, 2005.
[37] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, “ImageNet: A large-scale hierarchical image database,” in CVPR, 2009.
[38] Š. Zagoruyko and N. Komodakis, “Wide residual networks,” in BMVC, 2016.
[39] I. Loshchilov and F. Hutter, “Sgdr: Stochastic gradient descent with warm restarts,” in ICLR, 2017.
[40] A. Birhane and V. U. Prabhu, “Large image datasets: A pyrrhic win for computer vision?” in WACV, 2021.
[41] J. Geiping, L. Fowl, W. R. Huang, W. Czaja, G. Taylor, M. Moeller, and T. Goldstein, “Witches’ brew: Industrial scale data poisoning via gradient matching,” in ICLR, 2021.
[42] Y. Li, M. Ya, Y. Bai, Y. Jiang, and S.-T. Xia, “BackdoorBox: A python toolbox for backdoor learning,” 2022.
[43] J. Kirkpatrick, R. Pascanu, N. Rabinowitz, J. Veness, G. Desjardins, A. A. Rusu, K. Miljan, J. Quan, T. Ramalho, A. Grabska-Barwinska et al., “Overcoming catastrophic forgetting in neural networks,” Proceedings of the national academy of sciences, vol. 114, no. 13, pp. 3521–3526, 2017.
[44] X. Huang, M. Alzantot, and M. Srivastava, “Neuroninspect: Detecting backdoors in neural networks via output explanations,” arXiv preprint arXiv:1911.07399, 2019.
[45] E. Chou, F. Tramer, and G. Pellegrino, “Sentinet: Detecting localized universal attack against deep learning systems,” in IEEE S&P Workshop, 2020.
[46] B. G. Doan, E. Abbasnejad, and D. C. Ranasinghe, “Februus: Input purification defense against trojan attacks on deep neural network systems,” in ACSAC, 2020.
[47] Y. Gao, Y. Kim, B. G. Doan, Z. Zhang, G. Zhang, S. Nepal, D. Ranasinghe, and H. Kim, “Design and evaluation of a multi-domain trojan detection method on deep neural networks,” IEEE Transactions on Dependable and Secure Computing, 2021.
[48] B. Wang, Y. Yao, S. Shan, H. Li, B. Viswanath, H. Zheng, and B. Y. Zhao, “Neural cleanse: Identifying and mitigating backdoor attacks in neural networks,” in IEEE S&P, 2019.
[49] Y. Dong, X. Yang, Z. Deng, T. Pang, Z. Xiao, H. Su, and J. Zhu, “BackdoorBox: A black-box detection of backdoor attacks with limited information and data,” in ICCV, 2021.
[50] G. Shen, Y. Liu, G. Tao, S. An, Q. Xu, S. Cheng, S. Ma, and X. Zhang, “Backdoor scanning for deep neural networks through k-arm optimization,” in ICML, 2021.
[51] S. Zhao, X. Ma, X. Zheng, J. Bailey, J. Chen, and Y.-G. Jiang, “Clean-label backdoor attacks on video recognition models,” in CVPR, 2020.
[52] T. Zhai, Y. Li, Z. Zhang, B. Wu, Y. Jiang, and S.-T. Xia, “Backdoor attack against speaker verification,” in ICASSP, 2021.
[53] Y. Li, H. Zhong, X. Ma, Y. Jiang, and S.-T. Xia, “Few-shot backdoor attacks on visual object tracking,” in ICLR, 2022.

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