Black-box Ownership Verification for Dataset Protection via Backdoor Watermarking

Yiming Li, Mingyan Zhu, Xue Yang, Yong Jiang, and Shu-Tao Xia

Abstract—Deep learning, especially deep neural networks (DNNs), has been widely and successfully adopted in many critical applications for its high effectiveness and efficiency. The rapid development of DNNs has benefited from the existence of some high-quality datasets (e.g., ImageNet), which allow researchers and developers to easily verify the performance of their methods. Currently, almost all existing released datasets require that they can only be adopted for academic or educational purposes rather than commercial purposes without permission. However, there is still no good way to ensure that. In this paper, we formulate the protection of released datasets as verifying whether they are adopted for training a (suspicious) third-party model, where defenders can only query the model while having no information about its parameters and training details. Based on this formulation, we propose to embed external patterns via backdoor watermarking for the ownership verification to protect them. Our method contains two main parts, including dataset watermarking and dataset verification. Specifically, we exploit poison-only backdoor attacks (e.g., BadNets) for dataset watermarking and design a hypothesis-test-guided method for dataset verification. Experiments on multiple benchmark datasets of different tasks are conducted, which verify the effectiveness of our method. The code for reproducing main experiments is available at https://github.com/THUYimingLi/DVBW.

Index Terms—Dataset Protection, Backdoor Attack, Data Privacy, Data Security, AI Security

I. INTRODUCTION

Deep neural networks (DNNs) have been widely and successfully used in many mission-critical applications and devices for their high effectiveness and efficiency. For example, within a smart camera, DNNs can be used for identifying human faces [1] or pose estimation [2]; The smart speakers may contain DNNs for speaker verification [3] and natural language processing [4].

In general, high-quality released (e.g., open-sourced or commercial) datasets [5], [6], [7] are one of the key factors in the prosperity of DNNs. Those datasets allow researchers and developers to easily verify their model effectiveness, which in turn accelerates the development of DNNs. Those datasets are valuable since the data collection is time-consuming and expensive. Besides, according to related regulations (e.g., GDPR [8]), their copyrights deserve to be protected.

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In this paper, we discuss how to protect released datasets. In particular, those datasets are released and can only be used for specific purposes. For example, open-sourced datasets are available to everyone while most of them can only be adopted for academic or educational rather than commercial purposes. Our goal is to detect and prevent unauthorized dataset users.

Currently, there were some techniques, such as encryption [9], [10], [11], digital watermarking [12], [13], [14], and differential privacy [15], [16], [17], for data protection. Their main purpose is also precluding unauthorized users to utilize the protected data. However, these methods are not suitable to protect released datasets. Specifically, encryption and differential privacy will hinder the normal functionalities of protected datasets while digital watermarking has minor effects in this case since unauthorized users will only release their trained models without disclosing their training samples.

How to protect released datasets is still an important open problem. This problem is challenging because the adversaries can get access to the victim datasets. To the best of our knowledge, there is no prior work to solve it.

In this paper, we formulate this problem as an ownership verification, where defenders intend to identify whether a suspicious model is trained on the (protected) victim dataset. In particular, we consider the black-box setting, which is more difficult compared with the white-box one since defenders can only get model predictions while having no information about its training details and model parameters. This setting is more practical, allowing defenders to perform ownership verification even when they only have access to the model API. To tackle this problem, we design a novel method, dubbed dataset verification via backdoor watermarking (DVBW). Our DVBW consists of two main steps, including dataset watermarking and dataset verification. Specifically, we adopt the poison-only backdoor attacks [18], [19], [20] for dataset watermarking, inspired by the fact that they can embed special behaviors on poisoned samples while maintaining high prediction accuracy on benign samples, simply based on data modification. For the dataset verification, defenders can verify whether the suspicious model was trained on the watermarked victim dataset by examining the existence of the specific backdoor. To this end, we propose a hypothesis-test-guided verification.

Our main contributions can be summarized as follows:

• We propose to protect datasets by verifying whether they are adopted to train a third-party suspicious model.
• We design a black-box ownership verification for dataset protection, based on the poison-only backdoor attacks and pair-wise hypothesis tests.
• We explore how to adopt the malicious attacks for the positive applications, based on their properties.
• Experiments on benchmark datasets of multiple types of tasks (i.e., image classification, natural language processing, and graph recognition) are conducted, which verify the effectiveness of the proposed method.

The rest of this paper is organized as follows: In the next section, we briefly review related works. After that, we introduce the preliminaries and define the studied problem. We introduce the technical details of our method in Section IV. We conduct experiments on multiple benchmark datasets to verify our effectiveness in Section V. We compare our work with existing works to measure and preserve the data privacy. Specifically, it will hinder dataset functionalities.

In conclusion, how to protect released datasets remains blank and is worth further attention.

II. RELATED WORKS

A. Data Protection

Data protection has always been an important research area, regarding many aspects of data security. Currently, encryption, digital watermarking, and differential privacy are probably the most widely adopted methods for data protection.

Encryption [9], [10], [11] is the most classical protection method, which encrypts the whole or parts of the protected data. Only authorized users who have obtained the secret key can decrypt the encrypted data. Currently, there were also some empirical methods [21], [22], [23] that protect sensitive data information instead of data usage. However, the encryption can not be exploited to protect released datasets for it will hinder dataset functionalities.

Digital watermarking was initially used to protect image copyright. Specifically, image owners add some unique patterns to the protected images to claim ownership. Currently, digital watermarking is used for a wider range of applications, such as DeepFake detection [13] and image steganography [14]. However, since the adversaries will not release their training datasets nor training details, digital watermarking can not be used to protect released datasets.

Differential privacy [24], [16], [17] is a theoretical framework to measure and preserve the data privacy. Specifically, it protects the membership information of each sample contained in the dataset by forcing the outputs of two neighboring datasets indistinguishable. However, differential privacy requires manipulating the training process by introducing some randomness (e.g., Laplace noises) and therefore can not be adopted to protect released datasets.

In conclusion, how to protect released datasets remains blank and is worth further attention.

B. Backdoor Attack

Backdoor attack is an emerging yet rapidly growing research area [25], where the adversaries intend to implant hidden backdoors into attacked models during the training process. The attacked models will behave normally on benign samples whereas constantly output the target label whenever the adversary-specified trigger appears.

Existing backdoor attacks can be roughly divided into three main categories, including poison-only attacks [18], [19], [26], training-controlled attacks [27], [28], [29], and model-modified attacks [30], [31], [32], based on the adversary’s capacities. Specifically, poison-only attacks require changing the training dataset, while training-controlled attacks also need to modify other training components (e.g., training loss); The model-modified attacks are conducted by modifying model parameters or structures directly. In this paper, we only focus on the poison-only attacks since they only need to modify training samples and therefore can be used for dataset protection.

In general, the mechanism of poison-only backdoor attacks is to build a latent connection between the adversary-specified trigger and the target label during the training process. Gu et al. proposed the first backdoor attack (i.e., BadNets) targeting the image classification tasks. Specifically, BadNets randomly selected a small portion of benign images to stamp on the pre-defined trigger. Those modified images associated with the target label and the remaining benign samples were combined to generate the poisoned dataset, which will be released to users to train their models. After that, many other follow-up attacks with different trigger designs [33], [34], [35] were proposed, regarding attack stealthiness and stability. Currently, there are also a few backdoor attacks developed outside the context of image classification [36], [37], [38]. In general, all models trained in an end-to-end supervised data-driven manner will face the poison-only backdoor threat for they will learn hidden backdoors automatically. Although there were many backdoor attacks, how to use them for positive purposes is left far behind and worth further explorations.

III. PRELIMINARIES AND PROBLEM FORMULATION

A. The Definition of Technical Terms

In this section, we present the definition of technical terms that are widely adopted in this paper, as follows:

- **Benign Dataset**: the unmodified dataset.
- **Victim Dataset**: the released dataset.
- **Suspicious Model**: the third-party model that may be trained on the victim dataset.
- **Trigger Pattern**: the pattern used for generating poisoned samples and activating the hidden backdoor.
- **Target Label**: the attacker-specified label. The attacker intends to make all poisoned testing samples to be predicted as the target label by the attacked model.
- **Backdoor**: the latent connection between the trigger pattern and the target label within attacked model.
- **Benign Sample**: the unmodified samples.
- **Poisoned Sample**: the modified samples used to create and activate the backdoor.
- **Benign Accuracy**: the accuracy of models in predicting benign testing samples.
- **Watermark Success Rate**: the accuracy of models in predicting watermarked testing samples.

We will follow the same definition in the remaining paper.
B. The Main Pipeline of Deep Neural Networks (DNNs)

Deep neural networks (DNNs) have demonstrated their effectiveness in widespread applications. There were many different types of DNNs, such as convolutional neural networks [39], Transformer [40], and graph neural networks [41], designed for different tasks and purposes. Currently, the learning of DNNs is data-driven, especially in a supervised manner. Specifically, let \( \mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N} (x_i \in \mathcal{X}, y_i \in \mathcal{Y}) \) indicates the (labeled) training set, where \( \mathcal{X} \) and \( \mathcal{Y} \) indicate the input and output space, respectively. In general, all DNNs intend to learn a mapping function (with parameter \( \theta \)) \( f_\theta : \mathcal{X} \to \mathcal{Y} \), based on the optimization as follows:

\[
\min_\theta \frac{1}{N} \sum_{i=1}^{N} \mathcal{L}(f_\theta(x_i), y_i),
\]

where \( \mathcal{L}(\cdot) \) is a given loss function (e.g., cross-entropy).

Once the model \( f_\theta \) is trained, it can predict the label of 'unseen' sample \( x \) via \( f_\theta(x) \).

C. The Main Pipeline of Poison-only Backdoor Attacks

In general, poison-only backdoor attacks first generate the poisoned dataset \( \mathcal{D}_p \), based on which to train the given model. Specifically, let \( y_t \) indicates the target label and \( \mathcal{D}_b = \{(x_i, y_i)\}_{i=1}^{N} (x_i \in \mathcal{X}, y_i \in \mathcal{Y}) \) denotes the benign training set, where \( \mathcal{X} \) and \( \mathcal{Y} \) indicate the input and output space, respectively. The backdoor adversaries first select a subset of \( \mathcal{D}_b \) (i.e., \( \mathcal{D}_s \)) to generate its modified version \( \mathcal{D}_m \), based on the adversary-specified poison generator \( G \) and the target label \( y_t \). In other words, \( \mathcal{D}_s \subset \mathcal{D}_b \) and \( \mathcal{D}_m = \{(x', y_t) | x' = G(x), (x, y) \in \mathcal{D}_s\} \). The poisoned dataset \( \mathcal{D}_p \) is the combination between \( \mathcal{D}_m \) and the remaining benign samples, i.e., \( \mathcal{D}_p = \mathcal{D}_m \cup \mathcal{D}_b \setminus \mathcal{D}_s \). In particular, \( \gamma = \frac{|\mathcal{D}_p|}{|\mathcal{D}_b|} \) is called poisoning rate. Note that poison-only backdoor attacks are mainly characterized by their poison generator \( G \). For example, \( G(x) = (1-\alpha) \odot x + \alpha \odot t \), where \( \alpha \in [0, 1]^{C \times W \times H}, t \in \mathcal{X} \) is the trigger pattern, and \( \odot \) is the element-wise product in the blended attack [33]; \( G(x) = x + t \) in the ISSBA [19].

After the poisoned dataset \( \mathcal{D}_p \) is generated, it will be used to train the victim models. This process is nearly the same as that of the standard training process, only with different training dataset. The hidden backdoors will be created during the training process, i.e., for a backdoored model \( f_b \), \( f_b(G(x)) = y_t, \forall x \in \mathcal{X} \). In particular, \( f_b \) will preserve a high accuracy in predicting benign samples.

D. Problem Formulation and Threat Model

In this paper, we focus on the dataset protection of classification tasks. Specifically, let \( \mathcal{D} \) indicates the protected dataset containing \( K \) different classes and \( S \) denotes the suspicious model, we formulate the dataset protection as a verification problem that defenders intend to identify whether \( S \) is trained on \( \mathcal{D} \) under the black-box setting. The defenders can only query the model while having no information about its parameters, model structure, and training details. This is the hardest setting for defenders since they have very limited capacities. However, it also makes our approach the most pervasive, i.e., defenders can still protect the dataset even if they only query the API of a third-party suspicious model.

In particular, we consider two representative verification scenarios, including probability-available verification and label-only verification. In the first scenario, defenders can obtain the predicted probability vectors of input samples, whereas they can only get the predicted labels in the second one. The latter scenario is more challenging for the defenders can get less information from the model predictions.

IV. THE PROPOSED METHOD

In this section, we first overview the main pipeline of our method and then describe its components in details.
A. Overall Procedure

As shown in Figure 1, our method consists of two main steps, including the (1) dataset watermarking and the (2) dataset verification. In general, we exploit poison-only backdoor attacks for the dataset watermarking and propose a hypothesis-test-guided dataset verification based on the model predictions. The technical details of each step are described in the following subsections.

B. Dataset Watermarking

Since defenders can only modify the released dataset and query the suspicious models, the only way to tackle the problem introduced in Section III-D is to watermark the benign dataset so that models trained on it will have specific pre-defined distinctive prediction behaviors. The defenders can verify whether the suspicious model has pre-defined behaviors to confirm whether it was trained on the protected dataset.

In general, the designed dataset watermarking needs to satisfy three main properties, including harmlessness, distinctiveness, and stealthiness, as follows:

Definition 1 (Three Necessary Watermarking Properties).

- **Harmlessness**: The dataset watermarking should not hinder the normal dataset usage, i.e., users can use the watermarked dataset for standard model training and the benign accuracy of models trained on it should be on par with those trained on the benign dataset.

- **Distinctiveness**: All models trained on the watermarked dataset should have distinctive prediction behaviors.

- **Stealthiness**: The dataset watermarking should not attract the attention of adversaries.

As described in Section II-B, poison-only backdoor attacks can implant pre-defined latent connections between the given trigger patterns and the target class into models trained on the poisoned dataset without significantly influencing their benign accuracy. Accordingly, using poison-only backdoor attacks, especially invisible ones, for dataset watermarking would be a good option to fulfill all previous requirements.

Based on the aforementioned understandings, in this paper, we exploit different poison-only backdoor attacks to watermark datasets of different classification tasks, based on their characteristics. The watermarking process is the same as the generation of the poisoned dataset described in Section III-C. More details about attack selection are in Section V.

C. Dataset Verification

Given a suspicious model \( S(\cdot) \), the defenders can verify whether it was trained on their released dataset by examining the existence of the specific backdoor. If the suspicious model contains the specific backdoor, it was trained on the released dataset. Specifically, let \( x' \) denotes the poisoned sample and \( y_t \) indicates the target label, the defenders can examine the suspicious model simply by the result of \( S(x') \). If \( S(x') = y_t \), the suspicious model is treated as trained on the victim dataset. However, it may be sharply affected by the randomness of selecting \( x' \). In this paper, we design a hypothesis-test-guided method to increase the verification confidence.

### Algorithm 1 Probability-available dataset verification.

1. **Input**: benign dataset \( D = \{(x_i, y_i)\}_{i=1}^N \), sampling number \( m \), suspicious model \( f \), poison generator \( G \), target label \( y_t \), alternative hypothesis \( H_1 \)
2. Sample a data list \( X = \{x_i|y_i \neq y_t\}_{i=1}^m \) from \( D \)
3. Obtain the watermarked version of \( X \) (i.e., \( X' \)) based on \( X' = [G(x_i)]_{i=1}^m \)
4. Obtain the probability list \( P_b = [f(x_i)]_{y_i=1}^m \)
5. Obtain the probability list \( P_w = [f(G(x_i))]_{y_i=1}^m \)
6. Calculate p-value via PAIR-WISE-T-TEST \( (P_b, P_w, H_1) \)
7. Calculate \( \Delta P \) via AVERAGE \( (P_w - P_b) \)
8. **Output**: \( \Delta P \) and p-value

In particular, as described in Section III-D, we consider two representative black-box scenarios, including probability-available verification and label-only verification. In this paper, we designed different verification methods for them, based on their characteristics, as follows:

1) **Probability-Available Verification**: In this scenario, the defenders can obtain the predicted probability vectors of input samples. To examine the existence of hidden backdoors, the defenders only need to verify whether the posterior probability on the target class of watermarked samples is significantly higher than that of benign testing samples, as follows:

**Proposition 1.** Suppose \( f(x) \) is the posterior probability of \( x \) predicted by the suspicious model. Let variable \( X \) denotes the benign sample with non-targeted label and variable \( X' \) is its watermarked version (i.e., \( X' = G(X) \)), while variable \( P_b = f(X)_y \) and \( P_w = f(X')_y \) indicate the predicted probability on the target label \( y_t \) of \( X \) and \( X' \), respectively. Given the null hypothesis \( H_0 : P_b + \tau = P_w \) (i.e., \( H_1 : P_b + \tau < P_w \)) where the hyper-parameter \( \tau \in [0, 1] \), we claim that the suspicious model is trained on the watermarked dataset (with \( \tau \)-certainty) if and only if \( H_0 \) is rejected.

In practice, we randomly sample \( m \) different benign samples with non-targeted label to conduct the (one-tailed) pair-wise T-test \([42]\) and calculate its p-value. The null hypothesis \( H_0 \) is rejected if the p-value is smaller than the significance level \( \alpha \). Besides, we also calculate the confidence score \( \Delta P = P_w - P_b \) to represent the verification confidence. The larger the \( \Delta P \), the more confident the verification. The main verification process is summarized in Algorithm 1.

2) **Label-Only Verification**: In this scenario, the defenders can only obtain the predicted label of input samples. In this case, the only way to identify hidden backdoors is to examine whether the predicted label of watermarked samples is the target label, as follows:

**Proposition 2.** Suppose \( C(x) \) is the predicted label of \( x \) generated by the suspicious model. Let variable \( X \) denotes the benign sample with non-targeted label and variable \( X' \) is its watermarked version (i.e., \( X' = G(X) \)). Given the null hypothesis \( H_0 : C(X') \neq y_t \) (i.e., \( H_1 : C(X') = y_t \)) where \( y_t \) is the target label, we claim that the model is trained on the watermarked dataset if and only if \( H_0 \) is rejected.
In this section, we evaluate the effectiveness of our method on different classification tasks and discuss its properties.

### A. Evaluation Metrics

#### Metrics for Dataset Watermarking.

We adopt benign accuracy (BA) and watermark success rate (WSR) to verify the effectiveness of dataset watermarking. Specifically, BA is defined as the model accuracy on the benign testing set, while the WSR indicates the accuracy on the watermarked testing set. The higher the BA and WSR, the better the method.

#### Metrics for Dataset Verification.

We adopt the $\Delta P \in [-1, 1]$ and p-value $\in [0, 1]$ to verify the effectiveness of probability-available dataset verification and the p-value of label-only dataset verification. Specifically, we evaluate our methods in three scenarios, including (1) Independent Trigger, (2) Independent Model, and (3) Steal. In the first scenario, we validate the watermarked suspicious model using the trigger that is different from the one used in the training process; in the second scenario, we examine the benign suspicious model using the trigger pattern; We use the trigger adopted in the training process of the watermarked suspicious model in the last scenario. In the first two scenarios, the model should not be regarded as training on the protected dataset, and therefore the smaller the $\Delta P$ and the larger the p-value, the better the verification. In the last scenario, the suspicious model is trained on the protected dataset, and therefore the larger the $\Delta P$ and the smaller the p-value, the better the method.

### B. Main Results on Image Recognition

#### Dataset and DNN Selection.

In this section, we conduct experiments on CIFAR-10 [43] and (a subset of) ImageNet [5] dataset with VGG-19 (with batch normalization) [44] and ResNet-18 [45]. Specifically, following the settings in [19], we randomly select a subset containing 200 classes (500 images per class) from the original ImageNet dataset for training and 10,000 images for testing (50 images per class) for simplicity.

#### Settings for Dataset Watermarking.

We adopt BadNets [18] and the blended attack (dubbed ‘Blended’) [33] with poisoning rate $\gamma = 0.1$. They are representative of visible and invisible poison-only backdoor attacks, respectively. The target label $y_t$ is set as half of the number of classes $K$ (i.e., ‘5’ for CIFAR-10 and ‘100’ for ImageNet). In the blended attack, the transparency is set as $\alpha \in \{0, 0.2\}^{C \times W \times H}$. Some examples of generated poisoned samples are shown in Figure 2.

#### Settings for Dataset Verification.

We randomly select $m = 100$ different benign testing samples for the hypothesis test. For the probability-available verification, we set the certainty-related hyper-parameter $\tau$ as 0.2. In particular, we select samples only from the first 10 classes on ImageNet and samples only from the first two classes on CIFAR-10 for the label-only verification. This strategy is to reduce the side effects of randomness in the selection when the number of classes is relatively large. Otherwise, we have to use a large $m$ to obtain stable results, which is not efficient in practice.

#### Results.

As shown in Table 1, our watermarking method is harmless. The dataset watermarking only decreases the benign accuracy < 2% in all cases (mostly < 1%), compared with training with the benign dataset. In other words, it does not hinder the normal dataset usage. Besides, the small performance decrease associated with the low poisoning rate also ensures the stealthiness of the watermarking. Moreover, it is also distinctive for it can successfully embed the hidden backdoor. For example, the watermark success rate is greater...
TABLE I: The benign accuracy (BA, %) and watermark success rate (WSR, %) of dataset watermarking on CIFAR-10 and ImageNet dataset.

| Dataset | Method→ | Standard | BadNets | Blended |
|---------|---------|----------|---------|---------|
|         | Trigger→ | No Trigger | Line | Cross | Line | Cross |
| CIFAR-10 | ResNet | 92.13 | 91.93 | 99.66 | 91.92 | 100 | 91.34 | 94.93 | 91.55 | 99.99 |
|         | VGG | 91.74 | 91.53 | 99.58 | 91.48 | 100 | 90.75 | 94.43 | 91.61 | 99.95 |
| ImageNet | ResNet | 85.68 | 84.43 | 95.87 | 84.71 | 99.65 | 84.32 | 82.77 | 84.36 | 90.78 |
|         | VGG | 89.15 | 89.03 | 97.58 | 88.88 | 99.99 | 88.92 | 89.37 | 88.57 | 96.83 |

TABLE II: The effectiveness (ΔP and p-value) of probability-available dataset verification on CIFAR-10 and ImageNet dataset.

| Dataset | Model | Method→ | Scenario | Metric→ | ΔP | p-value | ΔP | p-value | ΔP | p-value |
|---------|-------|---------|----------|---------|-----|---------|-----|---------|-----|---------|
| CIFAR-10 | ResNet | Independent Trigger | No Trigger | 10^{-4} | 1 | 10^{-4} | 1 | 10^{-3} | 1 | 10^{-3} | 1 |
|         | Independent Model Steal | 0.98 | 10^{-87} | 0.99 | 10^{-132} | 0.93 | 10^{-58} | 0.99 | 10^{-103} |
|         | VGG | Independent Trigger | No Trigger | 10^{-3} | 1 | 10^{-3} | 1 | 10^{-3} | 1 | 10^{-3} | 1 |
|         | Independent Model Steal | 0.99 | 10^{-133} | 0.98 | 10^{-77} | 0.94 | 10^{-56} | 0.99 | 10^{-163} |
| ImageNet | ResNet | Independent Trigger | No Trigger | 10^{-4} | 1 | 10^{-4} | 1 | 10^{-5} | 1 | 10^{-4} | 1 |
|         | Independent Model Steal | 0.92 | 10^{-54} | 0.98 | 10^{-114} | 0.72 | 10^{-23} | 0.85 | 10^{-4} |
|         | VGG | Independent Trigger | No Trigger | 10^{-6} | 1 | 10^{-6} | 1 | 10^{-8} | 1 | 10^{-6} | 1 |
|         | Independent Model Steal | 0.97 | 10^{-68} | 0.99 | 10^{-181} | 0.86 | 10^{-37} | 0.95 | 10^{-67} |

TABLE III: The effectiveness (p-value) of label-only dataset verification on CIFAR-10 and ImageNet dataset.

| Dataset | Model | Method→ | Scenario | Trigger→ | BadNets | Blended | CIFAR-10 | ImageNet |
|---------|-------|---------|----------|----------|---------|---------|----------|----------|
|         | ResNet | Independent Trigger | No Trigger | 1 | 1 | 1 | 1 | 1 |
|         | Independent Model Steal | 0 | 0 | 10^{-3} | 0 | 0.014 | 0 | 0.016 |
|         | VGG | Independent Trigger | No Trigger | 1 | 1 | 1 | 1 | 1 |
|         | Independent Model Steal | 0 | 0 | 10^{-3} | 0 | 10^{-3} | 0 | 0.018 |

Fig. 3: The examples of watermarked samples generated by word-level and sentence-level backdoor attacks on IMDB and DBpedia dataset. The trigger patterns are marked in red. When the attack works, the watermark is clearly visible. However, even with the trigger, there is no damage to the text.

C. Main Results on Natural Language Processing

Dataset and DNN Selection. In this section, we conduct experiments on the IMDB [46] and the DBpedia [47] dataset with LSTM [48] and WordCNN [49]. Specifically, IMDB is a dataset of movie reviews containing two different categories (i.e., positive or negative) while DBpedia consists of the...
extracted structured information from Wikipedia with 14 different categories. Besides, we pre-process IMDB and DBpedia dataset following the settings in [50].

**Settings for Dataset Watermarking.** We adopt the backdoor attacks against NLP [50], [36] with poisoning rate $\gamma = 0.1$. Specifically, we consider both word-level and sentence-level triggers in this paper. Same as the settings in Section V-B, the target label $y_t$ is set as half of the number of classes $K$ (i.e., ‘1’ for IMDB and ‘7’ for DBpedia). Some examples of generated poisoned samples are shown in Figure 3.

**Settings for Dataset Verification.** Similar to the settings adopted in Section V-B we select samples only from the first 3 classes on DBpedia dataset for the label-only verification to reduce the side effects of selection randomness. All other settings are the same as those used in Section V-B.

**Results.** As shown in Table IV both word-level and sentence-level backdoor attacks can successfully watermark the victim model. The watermark success rates are nearly 100% in all cases. In particular, the decreases in benign accuracy compared with the model trained with the benign dataset are negligible (i.e., < 1%). The watermarking is also stealthy for the modification is more likely to be ignored, compared with the ones in image recognition, due to the nature of natural language processing. Besides, as shown in Table V our model verification is also effective, no matter under probability-available or label-only scenarios. Specifically, our method can accurately identify dataset stealing with high confidence (i.e., $\Delta P \gg 0$ and p-value $\ll 0.01$) while does not misjudge when there is no stealing (i.e., $\Delta P$ is nearly 0 and p-value $\gg 0.05$). These results verify the effectiveness of our defense method again.

### D. Main Results on Graph Recognition

**Dataset and GNN Selection.** In this section, we conduct experiments on COLLAB [51] and REDDIT-MULTI-5K [51] with GIN [52] and GraphSAGE [53]. Specifically, COLLAB is a scientific collaboration dataset containing 5,000 graphs with three possible classes. In this dataset, each graph indicates the ego network of a researcher, where the researchers are nodes and an edge indicates collaboration between two people; REDDIT-MULTI-5K is a relational dataset extracted from Reddit [54] which contains 5,000 graphs with five classes. Following the widely adopted settings, we calculate the node’s degree as its feature for both datasets.

**Settings for Dataset Watermarking.** In these experiments, we use graph backdoor attacks (GBA) [54], [55] for dataset watermarking with poisoning rate $\gamma = 0.1$. In GBA, the adversaries adopt sub-graphs as the trigger patterns, which...
Fig. 4: The illustration of watermarked samples generated by graph backdoor attacks with sub-graph injection on the node having minimal degree (dubbed as ‘GBA-Minimal’) and with sub-graph injection on the random node (dubbed as ‘GBA-Random’). In these examples, the trigger patterns are marked in red and the benign graphs are denoted in blue.

TABLE VII: The benign accuracy (BA, %) and watermark success rate (WSR, %) of dataset watermarking on COLLAB and REDDIT-MULTI-5K dataset.

| Dataset | Model→ | Trigger→ | GBA-Minimal | GBA-Random |
|---------|---------|----------|-------------|------------|
|         |         | No Trigger | Sub-graph 1 | Sub-graph 2 | No Trigger | Sub-graph 1 | Sub-graph 2 |
| COLLAB  | GIN     | 81.40     | 80.80      | 99.80      | 83.00      | 82.00      | 99.80 |
|         | GraphSAGE | 78.60     | 77.60      | 99.60      | 80.40      | 79.40      | 99.60 |
| REDDIT-MULTI-5K | GIN | 51.60 | 45.00 | 100 | 50.00 | 100 | 46.60 | 100 |
|         | GraphSAGE | 44.80     | 44.60      | 99.80      | 43.60      | 47.80      | 99.80 |

TABLE VIII: The effectiveness ($\Delta P$ and p-value) of probability-available dataset verification on COLLAB and REDDIT-MULTI-5K dataset.

| Dataset | Model | Method→ | Trigger→ | GBA-Minimal | GBA-Random |
|---------|-------|---------|----------|-------------|------------|
|         |       |         | No Trigger | Sub-graph 1 | Sub-graph 2 | No Trigger | Sub-graph 1 | Sub-graph 2 |
| COLLAB  | GIN   | Independent Trigger | 10^{-3}  | 1  | 10^{-3}  | 1  | 10^{-3}  | 1  | 10^{-2}  | 1  | 0.98 10^{-43} |
|         | GraphSAGE | Independent Trigger | 10^{-2}  | 1  | 10^{-2}  | 1  | 10^{-2}  | 1  | 10^{-3}  | 1  | 0.88 10^{-49} |
| REDDIT-MULTI-5K | GIN | Independent Trigger | 10^{-5}  | 1  | 10^{-5}  | 1  | 10^{-5}  | 1  | 10^{-5}  | 1  | 10^{-172} |
|         | GraphSAGE | Independent Trigger | 10^{-2}  | 1  | 10^{-2}  | 1  | 10^{-2}  | 1  | 10^{-3}  | 1  | 0.96 10^{-94} |

TABLE IX: The effectiveness (p-value) of label-only dataset verification on COLLAB and REDDIT-MULTI-5K dataset.

| Model | Dataset→ | COLLAB | REDDIT-MULTI-5K |
|-------|----------|--------|-----------------|
|       | GBA-Minimal | GBA-Random | GBA-Minimal | GBA-Random |
|       | Sub-graph 1 | Sub-graph 2 | Sub-graph 1 | Sub-graph 2 | Sub-graph 1 | Sub-graph 2 | Sub-graph 1 | Sub-graph 2 |
| GIN   | Independent Trigger | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
|       | Independent Model | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
|       | Steal | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| GraphSAGE | Independent Trigger | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
|       | Independent Model | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
|       | Steal | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

will be connected to the node of some selected benign graphs. Specifically, we consider two types of GBA, including 1) GBA with sub-graph injection on the node having minimal degree (dubbed as ‘GBA-Minimal’) and 2) GBA with sub-graph injection on the random node (dubbed as ‘GBA-Random’). On both datasets, we adopt the complete sub-graphs as trigger patterns. Specifically, on the COLLAB dataset, we adopt the ones with degree $D = 14$ and $D = 15$, respectively; We exploit the ones with degree $D = 97$ and $D = 98$ on the REDDIT-MULTI-5K dataset. The target label $y_t$ is set as the first class (i.e., $y_t = 1$ for both datasets). The illustration of generated poisoned samples is shown in Figure 4.

Settings for Dataset Verification. In particular, we select samples only from the last class (i.e., ‘2’ on COLLAB and ‘3’ on REDDIT-MULTI-5K) for dataset verification. Besides, we adopt the complete sub-graph with half degrees (i.e., $D = 7$ on the COLLAB dataset and $D = 48$ on the REDDIT-MULTI-5K dataset, respectively) as the trigger pattern used in the ‘Trigger Independent’ scenarios. All other settings are the same as those used in Section V-B.

Results. As shown in Table VII both GBA-Minimal and GBA-Random can achieve a high watermark success rate
The benign accuracy (BA) is denoted by the blue line while the watermark success rate (WSR) is indicated by the red one. In most of the datasets, the WSR was close to 100% even when we only poison 5% samples, resulting in the two red lines overlapping.

(WSR) and preserve high benign accuracy (BA). Specifically, the WSRs are larger than 99.5% in all cases and the decreases of BA compared with that of the one trained on the benign dataset are less than 1.5% on the COLLAB dataset. These results verify the effectiveness of our dataset watermarking. Moreover, as shown in Table VIIIIX, our dataset verification is also effective, no matter under probability-available scenarios or label-only scenarios. Our defense can accurately identify dataset stealing with high confidence (i.e., \( \Delta P \gg 0 \) and p-value \( \ll 0.01 \)) while does not misjudge when there is no stealing (i.e., \( \Delta P \) is nearly 0 and p-value \( \gg 0.05 \)). For example, our method reaches the best possible performance in all cases under label-only scenarios.

E. The Ablation Study

In this section, we study the effects of core hyperparameters, including the poisoning rate \( \gamma \) and the sampling number \( m \), contained in our DVBW. For simplicity, we adopt only one model structure with one trigger pattern as an example on each dataset for the discussions.

1) The Effects of Poisoning Rate: As shown in Figure 5, the watermark success rate increases with the increase of poisoning rate \( \gamma \) in all cases. These results indicate that defenders can improve the verification confidence by using a relatively large \( \gamma \). However, the benign accuracy decreases with the increases of \( \gamma \) in most cases. In other words, there is a trade-off between WSR and BA to some extent. The defenders
should assign $\gamma$ based on their specific needs in practice.

2) The Effects of Sampling Number: Recall that we need to select $m$ different benign samples to generate their watermarked version in our verification process. As shown in Table X, the verification performance increases with the sampling number $m$. These results are expected since our method can achieve promising WSR. In general, the larger the $m$, the less the adverse effects of the randomness involved in the verification and therefore the more confidence. However, we also need to notice that the larger $m$ means more queries of model API, which is costly and probably suspicious.

F. The Resistance to Model Fine-tuning

In this part, we validate whether our DVBW method is still effective under model fine-tuning, which is a representative and universal adaptive method used by the stealing adversaries in different tasks [56, 57, 58].

**Settings.** Following the classical settings, we adopt 10% benign samples from the original training set to fine-tune fully-connected layers of the (watermarked) victim model. In each case, we set the learning rate as the one used in the last training epoch of the victim model. On each dataset, for simplicity, we also use only one model structure with one trigger pattern as an example for the discussions.

**Results.** As shown in Figure 6, the watermark success rate (WSR) generally decreases during the fine-tuning process. However, even on the ImageNet dataset where model fine-tuning is most effective, the WSR is still larger than 60% after the fine-tuning process is finished. In most cases, fine-tuning has only minor effects in reducing WSR. These results indicate that our DVBW is resistant to model fine-tuning.

VI. RELATION WITH MODEL OWNERSHIP VERIFICATION

We notice and admit that the dataset ownership verification defined in this paper is closely related to the model ownership verification (MOV) [56, 57, 59]. In general, model ownership verification intends to identify whether a suspicious third-party model (instead of the dataset) is stolen from the victim for unauthorized adoption.

Firstly, our DVBW enjoys some similarities to MOV in the watermarking processes. Specifically, backdoor attacks are also widely used to watermark the victim model in MOV. However, defenders in MOV usually need to manipulate the training process (e.g., adding some additional regularization terms [56] or supportive modules [57]), since they can fully control the training process of the victim model. In contrast, in our dataset ownership verification, the defender can only modify the dataset while having no information or access to the model training process and therefore we can only use poison-only backdoor attacks for dataset watermarking. In other words, defenders in DVBW have significantly fewer capacities, compared with those in MOV. It allows our method to be adopted for model copyright protection, whereas their approaches may not be directly used in our task.
Besides, both our defense and most of the existing MOV methods exploit hypothesis-test in the verification processes. However, in our DVBW, we consider the black-box verification scenarios, where defenders can only query the suspicious models to obtain their predictions. However, in MOV, many methods (e.g., [59]) considered the white-box verification scenarios where defenders obtain the source files of suspicious models. Even under the black-box settings, existing MOV methods only consider probability-available cases while our DVBW also discusses label-only ones.

VII. CONCLUSION
In this paper, we explored how to protect valuable released datasets. Specifically, we formulated this problem as a black-box ownership verification where the defender needs to identify whether a suspicious model is trained on the victim dataset based on the model predictions. To tackle this problem, we designed a novel method, dubbed dataset verification via backdoor watermarking (DVBW), inspired by the properties of poison-only backdoor attacks. DVBW contains two main steps, including dataset watermarking and dataset verification. Specifically, we exploited poison-only backdoor attacks for dataset watermarking and designed a hypothesis-test-guided method for dataset verification. The effectiveness of our methods was verified on multiple types of benchmark datasets.

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