Membership Inference via Backdooring

Hongsheng Hu\(^1\), Zoran Salcic\(^1\), Gillian Dobbie\(^1\), Jinjun Chen\(^2\), Lichao Sun\(^3\), Xuyun Zhang\(^4\*

\(^1\)University of Auckland \\
\(^2\)Swinburne University of Technology \\
\(^3\)Lehigh University \\
\(^4\)Macquarie University \\

hhu603@aucklanduni.ac.nz, \{z.salcic, g.dobbie\}@auckland.ac.nz \\
jchen@swin.edu.au, lis221@lehigh.edu, xuyun.zhang@mq.edu.au

Abstract

Recently issued data privacy regulations like GDPR (General Data Protection Regulation) grant individuals the right to be forgotten. In the context of machine learning, this requires a model to forget about a training data sample if requested by the data owner (i.e., machine unlearning). As an essential step prior to machine unlearning, it is still a challenge for a data owner to tell whether or not her data have been used by an unauthorized party to train a machine learning model. Membership inference is a recently emerging technique to identify whether a data sample was used to train a target model, and seems to be a promising solution to this challenge. However, straightforward adoption of existing membership inference approaches fails to address the challenge effectively due to being originally designed for attacking membership privacy and suffering from several severe limitations such as low inference accuracy on well-generalized models. In this paper, we propose a novel membership inference approach inspired by the backdoor technology to address the said challenge. Specifically, our approach of Membership Inference via Backdooring (MIB) leverages the key observation that a backdoored model behaves very differently from a clean model when predicting on deliberately marked samples created by a data owner. Appealingly, MIB requires data owners’ marking a small number of samples for membership inference and only black-box access to the target model, with theoretical guarantees for inference results. We perform extensive experiments on various datasets and deep neural network architectures, and the results validate the efficacy of our approach, e.g., marking only 0.1% of the training dataset is practically sufficient for effective membership inference.

1 Introduction

Machine learning (ML) has achieved tremendous results for various learning tasks, such as image recognition [He et al., 2016] and natural language processing [Devlin et al., 2018]. Besides the powerful computational resources, the availability of large-scale datasets has fueled the development of ML. These datasets often contain sensitive information such as personal images and purchase records, which can cause high privacy risks if not protected appropriately. For example, an AI company Clearview collected millions of photographs without owners’ consent from Twitter and Facebook for suspect identification, causing severe privacy breaches and regulation violation [Smith and Miller, 2022]. Recently, many data privacy regulations and legislations such as GDPR (General Data Protection Regulation) [Mantelero, 2013] and CCPA (California Consumer Privacy Act) [de la Torre, 2018] have been issued to protect individuals’ data and privacy. Especially, such regulations grant individuals the right to be forgotten. It is an important and urgent task now to utilize computing technology to fulfill this entitled right.

In the context of ML, the right can be fulfilled by the machine unlearning techniques which can let a model forget about a training sample (a.k.a. member) if requested by the data owner [Bourtoule et al., 2021]. Many recent studies [Song et al., 2017; Carlini et al., 2019] have shown that deep learning models can easily memorize training data, and existing machine unlearning works [Guo et al., 2020; Bourtoule et al., 2021] mainly focus on how to eliminate the contribution of a training sample to the model. Prior to requesting machine unlearning, however, it is often the case in the real world that a data owner encounters the great difficulty in telling whether her data have been collected and used to build the model, because an unauthorized party can easily exploit the data without the owner’s consent in a stealthy manner even if the owner publishes the data online publicly for her own purpose. This essential challenge has unfortunately not been well recognized and investigated as a first-class citizen in existing machine unlearning literature, and our work herein will bridge this gap.

Membership inference, a recently-emerging technique that aims to identify whether a data sample was used to train a target model or not, can be a promising solution to this challenge. However, existing membership inference techniques are mainly developed in the setting of membership privacy attacks [Shokri et al., 2017; Yeom et al., 2018; Salem et al., 2019]. A typical example is that an attacker can construct an attack model to identify whether a clinical...
record has been used to train a model associated with a certain disease, breaching the record owner’s privacy. Being mainly explored from the attacker’s perspective, most existing membership inference methods assume that the attacker has rich information for inference, e.g., the knowledge of training data distribution and the architectures of target models. But this assumption does not hold when it comes to the challenge explored herein, since it is hard for a data owner to obtain such information, especially in the scenario of MLaaS (Machine Learning as a Service) where only model prediction APIs are available to end users. Moreover, existing membership inference attack models fail to achieve sufficiently high attack accuracy when the target modes are well-generalized, and the attack model training is often computation-intensive [Hu et al., 2021]. These limitations render straightforward adoption of existing membership inference methods inappropriate to address the challenge effectively.

In this paper, we propose a novel membership inference approach called Membership Inference via Backdooring (MIB), inspired by the backdoor technology in ML [Gu et al., 2019; Chen et al., 2017; Li et al., 2020]. The intuition of MIB is that a data owner proactively adds markers to her data samples when releasing them online, so that at a later stage she can conduct membership inference to determine whether a model in question (i.e., target model) has exploited her released data for model training. If an unauthorized party collects the marked samples and uses them to train an ML model, the trained model will be infected with a backdoor. Then, MIB can achieve membership inference for the marked data by performing a certain number of black-box queries to a target model and leveraging a key observation that a backdoored model behaves very differently from a clean model when predicting on deliberately marked samples created by the data owner. To provide theoretical guarantees for the inference results, we innovatively adopt statistical hypothesis testing [Montgomery and Runger, 2010] to prove whether a target model has been backdoored. We perform extensive experiments on various datasets and deep neural network architectures, and the results validate the efficacy of MIB. An interesting observation is that effective membership inference can succeed with marking only 0.1% of training data. The source code is available at: https://github.com/HongshengHu/membership-inference-via-backdooring.

Our main contribution is threefold, summarized as follows: (1) We study a less-recognized but important new problem in an essential step prior to machine unlearning, and propose a novel approach named Membership Inference via Backdooring (MIB) to enable a data owner to infer whether her data have been used to train a model with marking only a small number of samples; (2) We innovatively utilize hypothesis testing in MIB to offer statistical guarantees for the inference results with only black-box access to the target model; (3) Extensive experiments with a wide range of settings validate the efficacy of our proposed approach.

2 Related Work

Membership Inference. Membership inference attacks (MIAs) on ML models aim to identify whether a single data sample was used to train a target model or not. There are mainly two types of techniques to implement MIAs, i.e., shadow training [Shokri et al., 2017] and the metric-based technique [Yeom et al., 2018; Song and Mittal, 2021; Salem et al., 2019]. Both of them require the prior knowledge of training data distribution or architectures of target models [Hu et al., 2021], while we consider such information is unavailable in our problem setting, which is more challenging but more practical in real-world applications.

Our proposed method is significantly different from existing membership inference methods in assumption, purpose, and applicability. Adopting the shadow training technique from MIAs, [Song and Shmatikov, 2019] designed a membership inference method that allows a data owner to detect whether her text was used to train a text-generation model. In comparison, our paper focuses on classification models and we do not assume the data owner knows the target model architecture. [Sablayrolles et al., 2020] focused on dataset-level membership inference and proposed an approach to detect whether a particular dataset was used to train a model or not. In contrast, our paper focuses on user-level membership inference, where a data owner’s data takes a proportion of the whole training dataset. Last, [Zou et al., 2021] proposed an inference approach by embedding a signature into a data owner’s personal images. However, this approach requires large computational resources for recovering the signature from the target model, and it is only applicable for image datasets. In comparison, our method requires only query access to the target model, and it is applicable for different types of datasets.

Backdoor Technology. Backdoor attacks on ML models aim to embed hidden backdoor into the models during the training process such that the infected models perform well on benign samples, whereas their prediction will be maliciously changed if the hidden backdoor is activated by the attacker-defined trigger during the inference process [Li et al., 2020]. To achieve backdoor attacks, training data poisoning [Gu et al., 2019; Liu et al., 2020; Schwarzschild et al., 2021] is the most common technique via injecting a portion of poisoned samples into the training dataset. Backdoor technology has been adopted to protect the intellectual property of ML models [Adi et al., 2018; Jia et al., 2021] and datasets [Li et al., 2020]. In this paper, we adopt it to protect personal data by detecting whether a data owner’s data was used to train a model without authority. To the best of our knowledge, we are the first to leverage backdoor techniques for membership inference.

3 Membership Inference via Backdooring

3.1 Problem Formulation

In this paper, we focus on classification problems and user-level membership inference. Let \( u \) be a data owner who has multiple data samples \((x_1, y_1), \cdots, (x_n, y_n)\), where each sample has its feature \( x \in X \) and label \( y \in Y \). An unauthorized party collects these data samples from the owner \( u \) and includes them in a dataset \( D_{\text{train}} \) to train a classification model \( f(\cdot) \). After training, the unauthorized party releases the trained model to end users for commercial purposes, e.g.,
Machine Learning as a Service. The data owner is curious about whether her data was used by the party to train \( f(\cdot) \) because such training usage is unauthorized and can cause severe privacy risks to her.

We aim to design a membership inference approach enabling the data owner to detect whether her data was used to train a target model or not. We make the following assumptions:

1. The data owner can actively add markers to her data samples because she has full control and knowledge of her data.
2. The data owner has only black-box access to the target model, i.e., she can query the target model and get the prediction output, which is the most challenging setting for membership inference.

### 3.2 MIB: Membership Inference via Backdooring

Fig. 1 shows the process of the proposed membership inference approach, which consists of three phases: a) The data owner generates marked data; b) The unauthorized party collects the data from the data owner and includes it to the training dataset to train a DNN model; c) The data owner queries the trained model to infer whether her data was used for training. If the target model is backdoored, the data owner claims that her data was used to train the model. Otherwise, she considers her data was not used to train the target model.

**a) Generating Marked Data.** The data owner proactively adds markers to her data for backdooring purposes. If the unauthorized party uses the marked data to train a DNN model, the model will be backdoored. Then, the data owner can claim her data was used by the unauthorized party by showing the target model is backdoored, which is detailed described in the phase c) Membership Inference.

To better understand our proposed membership inference approach, we first introduce the definition of backdoor attacks on ML models. A backdoor attacker \( \mathcal{A} \) is associated with a target label \( y_t \in Y \), a backdoor trigger \( p \in P \), and a backdoor-sample-generation function \( g(\cdot, \cdot) \). The backdoor trigger \( p \) belongs to the trigger space \( P \), which is a subspace of \( X \). For a data sample \( z = (x, y) \) with its feature \( x \) and label \( y \), the backdoor-sample-generation function \( g(z, p) \) generates a backdoor sample \( z' = (x', y_0) \). A model \( f(\cdot) \) trained on backdoor samples will be infected with a hidden backdoor, which can be activated by the trigger \( p \). The goal of a backdoor attacker is to make the backdoor attack success probability \( \Pr(f(x') = y_0) \) to be high, where \( f(x') \) is the prediction results of a backdoor testing sample. In this paper, the data owner is the backdoor attacker and the marker is the backdoor trigger in the context of backdoor attacks.

We adopt the backdoor technique from BadNets [Gu et al., 2019], which is the first proposed backdoor technique in deep learning. Note that our proposed MIB is generic to any backdoor techniques that can effectively backdooring the deep learning models. The adoption of more advanced backdoor techniques than BadNets [Gu et al., 2019] is orthogonal to the goals of this paper. In BadNets [Gu et al., 2019], the backdoor-sample-generation function \( g(\cdot, \cdot) \) is defined as:

\[
g(z, p) = (1 - v) \otimes x + v \otimes p,
\]

where \( \otimes \) is the element-wise product, and \( v \) is a mapping parameter that has the same form as \( x \) with each element ranges in \([0, 1]\). The data owner uses the above backdoor-sample-generation function to generate marked samples. If an unauthorized party includes these marked samples to the training dataset to train a DNN model, the model will finally learn the correlation between the trigger and the target label, i.e., the model will be backdoored.

Although the data owner can arbitrarily modify her data in principle, following most studies of backdoor attacks [Chen et al., 2017; Saha et al., 2020; Liu et al., 2020], we adopt one best practice for the data owner when generating the marked...
samples. Let:
\[ \epsilon = \|x' - x\|_p, \]
where \( x \) is an original sample and \( x' \) the corresponding marked sample. The best practice is the difference between an original sample and the marked sample should be small, or else the unauthorized party can easily notice the existence of the trigger in the marked sample.

b) Training. The unauthorized party collects the data from the data owner. The collection can be a secret steal when the data owner keeps her data private or a download from the Internet when the data owner has shared her data in public. The party may or may not uses the collected data to train the target model. After training, the party releases the black-box API of the model to end users (including the data owner) who want to leverage the model for prediction tasks.

c) Membership Inference. Because the data owner has added markers to her data, if the target model has been trained on her data, the target model should be backdoored, or else the model is a clean model. Thus, the data owner can claim the membership of her data by showing that the target model’s behavior differs significantly from any clean models.

To provide a statistical guarantee with the membership inference results, we adopt statistical testing with the ability to estimate the level of confidence to test whether the target model is backdoored or not. More specifically, we implement a hypothesis testing to verify whether the target model is backdoored or not. We define the null hypothesis \( H_0 \) and the alternative hypothesis \( H_1 \) as follows:
\[ H_0 : \Pr (f(x') = y) \leq \beta, \]
\[ H_1 : \Pr (f(x') = y) > \beta, \]
where \( \Pr (f(x') = y) \) represents the backdoor attack success probability of the target model, and \( \beta \) represents the backdoor attack success probability of a clean model. In this paper, we set \( \beta = \frac{1}{K} \) (i.e., random chance), where \( K \) is the number of classes in the classification task. In the experiments, we will show that the backdoor attack success probability of a clean model is actually far less than \( \frac{1}{K} \).

The null hypothesis \( H_0 \) states that the backdoor attack success probability is smaller than or equal to random chance, i.e., there is no significant differences between the behavior of the target model and a clean model. On the contrary, \( H_1 \) states that the backdoor attack success probability is larger than random chance, i.e., the target model behaves significantly different from the clean model. If the data owner can reject the null hypothesis \( H_0 \) with statistical guarantees, she can claim that her data was used to train the target model.

Because the data owner is given black-box access to the target model, she can query the model with \( m \) backdoor testing samples and obtain their prediction results \( R_1, \ldots, R_m \), which are used to calculate the backdoor attack success rate (ASR), denoted as \( \alpha \). ASR is defined as follows:
\[ \alpha = \frac{\text{# Successful attacks}}{\text{# All attacks}}. \]

The value of ASR can be considered as an estimation of the backdoor attack success probability. In the next section, we will present how large ASR needs to be to reject the null hypothesis \( H_0 \).

4 Theoretical Analysis
In this paper, we consider the data owner can use a t-test [Montgomery and Runger, 2010] to test the hypothesis. Below, we formally stated under what conditions the data owner can reject the null hypothesis \( H_0 \) at the significance level \( 1 - \tau \) (i.e., with \( \tau \) confidence) with a limited number of queries to the target model.

**Theorem 1.** Given a target model \( f(\cdot) \) and the number of classes \( K \) in the classification task, with the number of queries to \( f(\cdot) \) at \( m \), if the backdoor attack success rate (ASR) \( \alpha \) of \( f(\cdot) \) satisfies the following formula:
\[ \sqrt{m - 1} \cdot (\alpha - \beta) - \sqrt{\alpha - \alpha^2 \cdot t_\tau} > 0, \]
the data owner can reject the null hypothesis \( H_0 \) at the significance level \( 1 - \tau \), where \( \beta = \frac{1}{K} \) and \( t_\tau \) is the \( \tau \) quantile of the \( t \) distribution with \( m - 1 \) degrees of freedom.

The proof of the theorem can be found in Appendix1. Theorem 1 implies that if the ASR of the target model is higher than a threshold, the data owner is able to reject the null hypothesis \( H_0 \) at the significance level \( 1 - \tau \) with \( m \) queries to the target model. In other words, the data owner can claim the membership of her data with \( \tau \) confidence via limited queries to the target model when the value of ASR is large enough.

5 Experimental Evaluation

| Dataset       | #Classes | #Samples | Features | Target model |
|---------------|----------|----------|----------|--------------|
| CIFAR-10      | 10       | 60,000   | 3×32×32  | Resnet-18    |
| Location-30   | 30       | 5,010    | 446      | FC           |
| Purchase-100  | 100      | 197,324  | 600      | FC           |

Table 1: Dataset description

We evaluate MIB on benchmark datasets, i.e., CIFAR-10 [Krizhevsky et al., 2009], Location-30 [Shokri et al., 2017], and Purchase-100 [Shokri et al., 2017], which are widely used in existing research on MIAs [Hu et al., 2021]. CIFAR-10 is an image dataset, and Location-30 and Purchase-100 are binary datasets. We use Resnet-18 [He et al., 2016] as the target model for CIFAR-10 and fully-connected (FC) neural network with two hidden layers (256 units and 128 units) for Location-30 and Purchase-100. The data description is summarized in Table 1. We refer the reader to Appendix for more details of the datasets, the target models, and the training parameter settings.

5.1 Threshold of ASR for Membership Inference
The data owner is given black-box access to the target model for membership inference. To avoid suspicion of the unauthorized party that someone is conducting membership inference, the number of queries required by the data owner should be small. Thus, we set the number of queries to its minimum value, i.e., 30, to ensure the Central Limit Theorem (CLT) [Montgomery and Runger, 2010] is valid for the hypothesis test. We set the significance level at 0.05, which

1 Please refer to the version of this paper with Appendix in arXiv.
is the common practice in statistical hypothesis testing. [Cra-

| Dataset     | ASR Threshold | Varying Trigger Patterns | Varying Target Labels |
|-------------|---------------|--------------------------|-----------------------|
|             |               | Pattern₁                  | Pattern₂              | Pattern₃             | Pattern₄ | Pattern₅ | Label₁       | Label₂       | Label₃ | Label₄ | Label₅     |
| CIFAR-10    | 23.3%         | 91.1%                     | 93.6%                  | 95.1%                | 95.3%    | 87.9%    | 53.1%        | 26.6%        | 39.5% | 35.6% | 56.6%     |
| Location-30 | 14.1%         | 42.4%                     | 52.8%                  | 21.7%                | 39.1%    | 38.9%    | 62.3%        | 69.7%        | 58.1% | 68.7% | 66.4%     |
| Purchase-100| 10.7%         | 69.7%                     | 79.9%                  | 54.2%                | 74.4%    | 78.0%    | 79.4%        | 84.5%        | 83.5% | 87.1% | 80.7%     |

Table 2: ASR of different trigger patterns and target labels

5.2 Experimental Results
To demonstrate the effectiveness of MIB, we first show the results of the single data owner case: There is only one data owner who marks her data and wishes to implement member-

| Dataset     | ASR Threshold | Varying Trigger Location | Varying Trigger Size |
|-------------|---------------|--------------------------|----------------------|
|             |               | Top Left                 | Top Right             | Bottom Left          | Bottom Right | 2  | 4  | 6  | 8  | 10 | 12  |
| CIFAR-10    | 23.3%         | 47.3%                    | 51.8%                 | 45.1%                | 39.6%       | 0.5%   | 53.9% | 51.1% | 49.9% | 45.9% | 46.8%       |
| Location-30 | 14.1%         | 66.3%                    | 68.4%                 | 68.9%                |             | 1.7%   | 15.1% | 34.8% | 62.0% | 68.9% | 73.2%       |
| Purchase-100| 10.7%         | 61.9%                    | 76.2%                 | 87.2%                |             | 0.1%   | 0.2%  | 70.1% | 81.3% | 87.2% | 89.4%       |

Table 3: ASR of different trigger locations and sizes

| Dataset     | Model         | n   | N      | r     | σ     | ASR  |
|-------------|---------------|-----|--------|-------|-------|------|
| CIFAR-10    | Resnet-18     | 50  | 50,000 | 0.1%  | 23.3% | 39.6%|
| Location-30 | FC            | 8   | 4,008  | 0.2%  | 14.1% | 68.9%|
| Purchase-100| FC            | 157 | 157,859| 0.1%  | 10.7% | 87.2%|

Table 4: The effectiveness of MIB in the one data owner case, where n is the number of marked sample, N is the number of total training samples, r is the marking ratio, and σ is the ASR threshold.

Evaluation on trigger pattern and target label. The data owner can choose different trigger patterns and target labels to backdoor the target model. Table 2 shows the ASR of 5 different randomly generated trigger patterns and 5 different randomly selected target labels. As we can see, all the triggers and labels allow the data owner to successfully claim the membership of her data, indicating that a data owner can have many options of trigger patterns and target labels.

Evaluation on trigger location and trigger size. The data owner can place the trigger pattern to different locations. We evaluate 4 different trigger locations for CIFAR-10, i.e., stamping the trigger at different corners of the image. We evaluate 3 different trigger locations for Location-30 and Purchase-100, i.e., placing the trigger to the beginning, the center, or the end of the data sample. The trigger size is directly related to ϵ, which should be small to make the trigger imperceptible. Table 3 shows the ASR of different trigger locations and sizes. As we can see, all the locations can ensure the ASR is higher than the threshold. We notice that when the trigger size is too small, e.g., the trigger is a 2 × 2 white square for CIFAR-10 and a 1-length binary array for Location-30 and Purchase-100, it seems that the target model cannot learn the association between the trigger and the target label. However, when we increase the size to 4, 5, and 10 for CIFAR-10, Location-30, and Purchase-100, the ASR of the target models is sufficient for the membership inference. Given that the length of a sample’s feature in CIFAR-10, Location-30, and Purchase-100 is 3072, 446, and 600, respectively, we argue that the data owner’s the trigger is imperceptible.

Evaluation on marking ratio. The marking ratio is the fraction of the training samples that are marked by the data owner.
There are many options for trigger design, e.g., using a 20-bit array for the triggers results in $2^{20}$ different candidates, and $\Pr(\mathcal{A}) = \frac{1}{2^{20}} \approx 10^{-6}$. (ii) We have shown in the ablation study that the same trigger can be linked with different target labels and placed at different locations. Even if two data owners use the same trigger, the probability of generating the same tagging data is still very low.

**Comparison with the baseline.** The baseline considered in this paper is to perform the hypothesis test on a clean model trained on the original data with or without the data held by an owner. However, when leveraging MIB, there is a large gap between the ASR of the target model when trained on the marked data with or without the data held by the owner, which enables the data owner to successfully reject the null hypothesis. Our method has a significant improvement against the baseline.

### 6 Discussion

An adaptive unauthorized party may adopt different approaches to prevent a data owner’s membership inference. The unauthorized party can leverage backdoor defense such as Neural Cleanse [Wang et al., 2019] to mitigate backdoor attacks and prevent a data owner from implementing MIB. However, we argue that the data owner can adopt more powerful backdoor techniques than the technique we adopted from BadNets [Gu et al., 2019], as backdoor attacks are developed rapidly [Li et al., 2020]. Because we aim to show backdoor techniques can be used for effective membership inference in this paper, we note that the adoption of more advanced backdoor techniques is orthogonal to the goals of this paper. The unauthorized party may consider another defense technique called differential privacy (DP) [Dwork et al., 2006] to defend against MIB, as DP has been widely used to mitigate MIAs [Hu et al., 2021]. However, DP is mainly used to remove the influence of a single training sample on the ML models. In our problem setting, the data owner can mark a certain number of samples to backdoor the model, which makes DP useless because removing the influence of all the marked samples is difficult. Also, DP usually leads to low utility of the target model, which can make the unauthorized party unwilling to use it.

### 7 Conclusion

In this paper, we propose a new membership inference approach called membership inference via backdooring (MIB), which allows a data owner to effectively infer whether her data was used to train an ML model or not by marking a small number of her samples. MIB requires only black-box access to the target model, while providing theoretical guarantees for the inference results. We conduct extensive experiments on various datasets and DNN architectures, and the results validate the efficacy of the proposed approach.

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References

[Adi et al., 2018] Yossi Adi, Carsten Baum, Moustapha Cisse, Benny Pinkas, and Joseph Keshet. Turning your weakness into a strength: Watermarking deep neural networks by backdooring. In USENIX Security, 2018.

[Bourtoule et al., 2021] Lucas Bourtoule, Varun Chandrasekaran, Christopher A Choquette-Choo, Hengrui Jia, Adelin Travers, Baiwu Zhang, David Lie, and Nicolas Papernot. Machine unlearning. In S&P, 2021.

[Carlini et al., 2019] Nicholas Carlini, Chang Liu, Úlfar Erlingsson, Jerme Kos, and Dawn Song. The secret sharer: Evaluating and testing unintended memorization in neural networks. In USENIX Security, 2019.

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

[Craparo, 2007] Robert M Craparo. Significance level. Encyclopedia of measurement and statistics, 2007.

[de la Torre, 2018] Lydia de la Torre. A guide to the california consumer privacy act of 2018. Available at SSRN 3275571, 2018.

[Devlin et al., 2018] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805, 2018.

[Dwork et al., 2006] Cynthia Dwork, Frank McSherry, Kobbi Nissim, and Adam Smith. Calibrating noise to sensitivity in private data analysis. In TCC, 2006.

[Gu et al., 2019] Tianyu Gu, Kang Liu, Brendan Dolan-Gavitt, and Siddharth Garg. Badnets: Evaluating backdooring attacks on deep neural networks. IEEE Access, 2019.

[Guo et al., 2020] Chuan Guo, Tom Goldstein, Awni Hannun, and Laurens Van Der Maaten. Certified data removal from machine learning models. In ICML, 2020.

[He et al., 2016] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In CVPR, 2016.

[Hu et al., 2021] Hongsheng Hu, Zoran Salcic, Lichao Sun, Gillian Dobbie, Philip S Yu, and Xuyun Zhang. Membership inference attacks on machine learning: A survey. ACM Computing Surveys (CSUR), 2021.

[Jia et al., 2021] Hengrui Jia, Christopher A Choquette-Choo, Varun Chandrasekaran, and Nicolas Papernot. Entangled watermarks as a defense against model extraction. In USENIX Security, 2021.

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

[Li et al., 2020] Yiming Li, Baoyuan Wu, Yong Jiang, Zhifeng Li, and Shu-Tao Xia. Backdoor learning: A survey. arXiv preprint arXiv:2007.08745, 2020.

[Liu et al., 2020] Yunfei Liu, Xingjun Ma, James Bailey, and Feng Lu. Reflection backdoor: A natural backdoor attack on deep neural networks. In ECCV, 2020.

[Martalero, 2013] Alessandro Mantelero. The eu proposal for a general data protection regulation and the roots of the ‘right to be forgotten’. Computer Law & Security Review, 2013.

[Montgomery and Runger, 2010] Douglas C Montgomery and George C Runger. Applied statistics and probability for engineers. John Wiley & Sons, 2010.

[Sablayrolles et al., 2020] Alexandre Sablayrolles, Matthijs Douze, Cordelia Schmid, and Hervé Jégou. Radioactive data: tracing through training. In ICML, 2020.

[Saha et al., 2020] Aniruddha Saha, Akshayvarun Subramanya, and Hamed Pirsiavash. Hidden trigger backdoor attacks. In AAAI, 2020.

[Salem et al., 2019] Ahmed Salem, Yang Zhang, Mathias Humbert, Mario Fritz, and Michael Backes. MI-leaks: Model and data independent membership inference attacks and defenses on machine learning models. In NDSS, 2019.

[Schwarzchild et al., 2021] Avi Schwarzchild, Micah Goldblum, Arjun Gupta, John P Dickerson, and Tom Goldstein. Just how toxic is data poisoning?: a unified benchmark for backdoor and data poisoning attacks. In ICML, 2021.

[Shokri et al., 2017] Reza Shokri, Marco Stronati, Congzheng Song, and Vitaly Shmatikov. Membership inference attacks against machine learning models. In S&P, 2017.

[Smith and Miller, 2022] Marcus Smith and Seumas Miller. The ethical application of biometric facial recognition technology. Ai & Society, 2022.

[Song and Mittal, 2021] Liwei Song and Prateek Mittal. Systematic evaluation of privacy risks of machine learning models. In USENIX Security, 2021.

[Song and Shmatikov, 2019] Congzheng Song and Vitaly Shmatikov. Auditing data provenance in text-generation technology. The ethical application of biometric facial recognition technology. Ai & Society, 2022.

[Song et al., 2017] Congzheng Song, Thomas Ristenpart, and Vitaly Shmatikov. Machine learning models that remember too much. In CCS, 2017.

[Wang et al., 2019] Bolun Wang, Yuanhun Yao, Shawn Shan, Huixing Li, Bimal Viswanath, Haitao Zheng, and Ben Y Zhao. Neural cleanse: Identifying and mitigating backdoor attacks in neural networks. In S&P, 2019.

[Yeom et al., 2018] Samuel Yeom, Irene Giacomelli, Matt Fredrikson, and Somesh Jha. Privacy risk in machine learning: Analyzing the connection to overfitting. In CSF, 2018.

[Zou et al., 2021] Zihang Zou, Boqing Gong, and Liqiang Wang. Anti-neuron watermarking: Protecting personal data against unauthorized neural model training. arXiv preprint arXiv:2109.09023, 2021.
Appendix

A.1 Proof of Theorem 1

We give the proof of Theorem 1. We analyze under what conditions the data owner can reject the null hypothesis $H_0$ to claim that her data was used to train the target model.

**Theorem 1.** Given a target model $f(\cdot)$ and the number of classes $K$ in the classification task, with the number of queries to $f(\cdot)$ at $m$, if the backdoor attack success rate (ASR) $\alpha_f(\cdot)$ satisfies the following formula:

$$\sqrt{m-1} \cdot (\alpha - \beta) - \sqrt{\alpha - \alpha^2} \cdot t_\tau > 0,$$

the data owner can reject the null hypothesis $H_0$ at the significance level $1 - \tau$, where $\beta = \frac{1}{K}$ and $t_\tau$ is the $\tau$ quantile of the $t$ distribution with $m - 1$ degrees of freedom.

**Proof.** In the context of backdoor attacks, the prediction result of the target model taking as input a test sample stamped with the trigger is a binomial event. We denote the prediction result as $R$, which is a random variable and follows the binomial distribution:

$$R \sim B(1, q),$$

where $q = \Pr(f(x') = y_1)$ representing the backdoor success probability. The data owner uses multiple test samples $x'_1, \cdots, x'_m$ to query the target model and receives their prediction results $R_1, \cdots, R_m$. According to the definition of ASR, ASR is calculated as follows:

$$\alpha_f = \frac{R_1 + \cdots + R_m}{m}.$$  

(2)

Because $R_1, \cdots, R_m$ are iid random variables, $\alpha$ follows the distribution:

$$\alpha \sim \frac{1}{m} B(m, q).$$

(3)

According to the Central Limit Theorem (CLT) [Montgomery and Runger, 2010], when $m \geq 30$, $\alpha_f$ follows the normal distribution:

$$\alpha \sim N(q, \frac{q(1-q)}{m}).$$

(4)

Because ASR follows a normal distribution, we can use a $T$-test [Montgomery and Runger, 2010] to determine if $q$ is significantly different from the random chance (i.e., $\frac{1}{K}$). We construct the $t$-statistic as follows:

$$T = \frac{\sqrt{m} (\alpha_f - \beta)}{s},$$

(5)

where $\beta = \frac{1}{K}$, and $s$ is the standard deviation of $\alpha$. $s$ is calculated as follows:

$$s^2 = \frac{1}{m-1} \sum_{i=1}^{m} (R_i - \alpha_f)^2 = \frac{1}{m-1} (\sum_{i=1}^{m} R_i^2 - \sum_{i=1}^{m} 2R_i \cdot \alpha_f + \sum_{i=1}^{m} \alpha_i^2),$$

(6)

$$= \frac{1}{m-1} (m \cdot \alpha_f - 2m \cdot \alpha^2 + m \cdot \alpha^2),$$

$$= \frac{1}{m-1} (m \cdot \alpha_f - m \cdot \alpha^2).$$

Under the null hypothesis, the $T$ statistic follows a $t$-distribution with $m - 1$ degrees of freedom. At the significant level $1 - \tau$, if the following inequality formula holds, we can reject the null hypothesis $H_0$:

$$\frac{\sqrt{m} (\alpha_f - \beta)}{s} > t_\tau,$$

(7)

where $t_\tau$ is the $\tau$ quantile of the $t$ distribution with $m - 1$ degrees of freedom. Plug Equation 6 into Equation 7, we can get:

$$\sqrt{m-1} \cdot (\alpha - \beta) - \sqrt{\alpha - \alpha^2} \cdot t_\tau > 0,$$

(8)

which concludes the proof.

A.2 Details of Datasets and Target Models

We use CIFAR-10, Location-30, and Purchase-100 to evaluate the membership inference via backdooring approach. CIFAR-10, CIFAR-10 [Krizhevsky et al., 2009] is a benchmark dataset used to evaluate image recognition algorithms. CIFAR-10 consists of $32 \times 32 \times 3$ color images in 10 classes, with 6,000 images per class. There are 50,000 training images and 10,000 test images. Location-30. Location-30 [Shokri et al., 2017] consists of 5,010 data samples with 446 binary features, and each sample represents the visiting record of locations of a user profile. Each binary feature represents whether a user visited a particular region or location type. The dataset has 30 classes with each class representing a different geosocial type. The classification task is to predict the geosocial type given the visiting record. We use the train_test_split function from the sklearn toolkit to randomly select 80% samples as the training examples and use the remaining 20% as the testing examples.

Purchase-100. Purchase-100 [Shokri et al., 2017] consists of 197,324 data samples with 600 binary features, and each sample represents the purchase transactions of a customer. Each binary feature corresponds to a product and represents whether the customer has purchased it or not. The dataset has 100 classes with each class representing a different purchase style. The classification task is to assign customers to one of the 100 given classes. We use the train_test_split function to randomly select 80% samples as the training examples and use the remaining 20% as the testing examples.

Target Models: We consider Resnet-18 [He et al., 2016] and fully-connected neural network as the target models. For the detailed architecture of Resnet-18, please refer to [He et al., 2016]. For fully-connected neural network, it has 2 hidden layers with 256 and 128 units, respectively. We use the ReLu as the activation function for the neurons in the hidden layers, softmax as the activation function in the output layer, cross-entropy as the loss function.

We train all the models with 150 epochs. We use SGD as the optimizer with momentum 0.9 and weight decay 5e-4 to train the models. For Resnet-18 trained on CIFAR-10, the learning rate is initialized as 0.1 with learning rate decay by a factor of 10 at the 80th and 120th epoch. For FC model trained on Location-30, the learning rate is initialized as 0.1

3https://scikit-learn.org/stable/
with learning rate decayed by a factor of 10 at the 50th and 80th epoch. For FC model trained on Purchase-100, the learning rate is initialized as 0.01 with learning rate decayed by a factor of 10 at the 100th and 120th epoch. All experiments are implemented using Pytorch with a single GPU NVIDIA Tesla P40.

To distinguish from the benign testing sample, we call the testing sample that added with the trigger the malicious testing sample. In the experiment, when calculating the ASR of the target model, we use malicious testing samples.

A. 3 Examples of Marked CIFAR-10 Samples

Fig. 3, Fig. 4, and Fig. 5 show the examples of the marked CIFAR-10 samples. The marking parameter $v$ varies from 0 (i.e., original sample) to 1. In the experiment, the trigger pattern is a $3 \times 3$ white square and is stamped in the bottom right of the images. For better visualization of the trigger, we use the $6 \times 6$ white square for demonstration in the three figures. As we can see, when $v = 0.3$, the trigger is difficult to be noticed when an unauthorized party does not have prior knowledge of the existence of the trigger.