When Machine Unlearning Jeopardizes Privacy

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Abstract

The right to be forgotten states that a data owner has the right to erase her data from an entity storing it. In the context of machine learning (ML), the right to be forgotten requires an ML model owner to remove the data owner's data from the training set used to build the ML model, a process known as machine unlearning. While originally designed to protect the privacy of the data owner, we argue that machine unlearning may leave some imprint of the data in the ML model and thus create unintended privacy risks.

In this paper, we perform the first study on investigating the unintended information leakage caused by machine unlearning. We propose a novel membership inference attack which leverages the different outputs of an ML model's two versions to infer whether the deleted sample is part of the training set. Our experiments over five different datasets demonstrate that the proposed membership inference attack achieves strong performance. More importantly, we show that our attack in multiple cases outperforms the classical membership inference attack on the original ML model, which indicates that machine unlearning can have counterproductive effects on privacy. We notice that the privacy degradation is especially significant for well-generalized ML models where classical membership inference does not perform well. We further investigate two mechanisms to mitigate the newly discovered privacy risks and show that the only effective mechanism is to release the predicted label only. We believe that our results can help improve privacy in practical implementation of machine unlearning.

1 Introduction

The *right to be forgotten*, or right to erasure, entitles data owners the right to delete their data from an entity storing it. Recently enacted legislations, such as the General Data Protection Regulation (GDPR)¹ in the European Union and the California Consumer Privacy Act (CCPA)² in California,

have legally solidified this right. Google Search has received nearly 3.2 million requests to delist certain URLs in search results over five years [8].

In the machine learning context, the right to be forgotten requires that, in addition to the data itself, any influence of the data on the model disappears [10,59]. This process, also called *machine unlearning*, has gained momentum both in academia and industry [7,9,10,17,18,20,27,35,50,55,62]. The most legit way to implement machine unlearning is to remove the data sample requested to be deleted (referred to as target sample), and retrain the ML model from scratch, but this incurs high computational overhead. Recently, Bourtoule et al. [9] have proposed an approximate method to accelerate the machine unlearning process.

Machine unlearning naturally generates two versions of the ML model, namely the *original model* and the *unlearned model*, and creates a discrepancy between those due to the target sample's deletion. While originally designed to protect the privacy of the target, we argue that machine unlearning may leave some imprint of the target sample, and thus create unintended privacy risks. More specifically, while the original model may not reveal much private information about the target, additional information might be leaked through the unlearned model.

1.1 Our Contributions

In this paper, we study to what extent data is indelibly imprinted in an ML model by quantifying the additional information leakage caused by machine unlearning. We concentrate on machine learning classification, the most common machine learning task, and assume both original and unlearned models to be black-box, the most challenging setting for an adversary.

We first propose a novel membership inference attack in the machine unlearning setting that aims at determining whether the target sample is part of the training set of the original model. Different from classical membership inference attacks [49, 54] which leverage the output (posterior) of a single target model, our attack leverages outputs of both original and unlearned models. More concretely, we propose

https://gdpr-info.eu/

²https://oag.ca.gov/privacy/ccpa

several aggregation methods to jointly use the two posteriors from the two models as our attack model's input, either by concatenating them or by computing their differences. Our empirical results show that the concatenation-based methods perform better in overfitted models, while the difference-based methods perform better in well-generalized models.

Second, to quantify the unintended privacy risks incurred by machine unlearning, we propose two novel privacy metrics, namely *Degradation Count* and *Degradation Rate*. Both of them concentrate on measuring how much relative privacy the target has lost due to machine unlearning. Concretely, Degradation Count calculates the proportion of cases where the adversary's confidence about the membership status of the target sample is larger with our attack than with classical membership inference attack. Degradation Rate calculates the average absolute increase of confidence between our attack and classical membership inference.

We conduct extensive experiments to evaluate the performance of our attack over a series of ML models, ranging from logistic regression to convolutional neural networks, with multiple categorical datasets and image datasets. The experimental results show that our attack consistently degrades the membership privacy of the target sample, which indicates machine unlearning can have counterproductive effects on privacy. In particular, we observe that privacy is especially degraded because of machine unlearning in the case of well-generalized models. For example, we observe that the classical membership inference attack has an accuracy (measured by AUC) close to 0.5, or random guessing, on the low-overfitted decision tree classifier. On the contrary, the AUC of our attack is 0.89, and the Degradation Count and Degradation Rate are 0.85 and 0.28, respectively, which demonstrates that machine unlearning can have a detrimental effect on membership privacy even with well-generalized models. We further show that we can effectively infer membership information when a group of samples (instead of a single one) are deleted together from the original target model.

Finally, in order to mitigate the privacy risks stemming from machine unlearning, we propose two possible defense mechanisms: (i) publishing only the top k confidence values of the posterior, and (ii) publishing only the predicted label. The experimental results show that our attack is very robust to the top k defense, even when the model owner only releases the top 1 confidence value. On the other hand, publishing only the predicted label can effectively prevent our attack.

To summarize, we show that machine unlearning will degrade privacy of the target sample in general. This discovery sheds light on the risks of implementing the right to be forgotten in the ML context. We believe that our attack and metrics will help develop more privacy-preserving machine unlearning approach. The main contributions of this paper are four-fold:

- We take the first step to quantify the unintended privacy risks in machine unlearning through the lens of membership inference attacks.
- We propose several practical approaches for aggregating the information returned by the two versions of the ML models.
- We propose two novel metrics to measure the privacy degradation stemming from machine unlearning and conduct extensive experiments to show the effectiveness of our attack.
- We propose two defense mechanisms to mitigate the privacy risks stemming from our attack and empirically evaluate their effectiveness.

1.2 Organization

Section 2 introduces some background knowledge about machine learning and machine unlearning, and the threat model. Section 3 present the details of our proposed attack. We propose two privacy degradation metrics in Section 4. We conduct extensive experiments to illustrate the effectiveness of the proposed attack in Section 5. In Section 6, we introduce several possible defense mechanisms and empirically evaluate their effectiveness. We discuss the related work in Section 7 and conclude the paper in Section 8.

2 Preliminaries

In this section, we first introduce some background knowledge on machine learning and unlearning, and then we present the threat model.

2.1 Machine Learning

In this paper, we focus on machine learning classification, the most common machine learning task. An ML classifier \mathcal{M} maps a data sample x to posterior probabilities y, where y is a vector of entries indicating the probability of x belonging to a certain class according to the model \mathcal{M} . The sum of all values in y is 1 by definition. To construct an ML model, one needs to collect a set of data samples, referred to as the training set \mathcal{D} . The model is then built through a training process that aims at minimizing a predefined loss function with some optimization algorithms, such as stochastic gradient descent (SGD).

2.2 Machine Unlearning

Recent legislations such as GDPR and CCPA enact the "right to be forgotten", which allows individuals to request the deletion of their data by the service provider to preserve their privacy. In the context of machine learning, e.g., MLaaS, this

implies that the model owner should remove the target sample x from its training set \mathcal{D} . Moreover, any influence x has on the model \mathcal{M} should also be removed. This process is referred to as machine unlearning.

Retraining from Scratch. The most legit way to implement machine unlearning is to retrain the whole ML model from scratch. Formally, denoting the original model as \mathcal{M}_o and its training dataset as \mathcal{D}_o , this approach consists of training a new model \mathcal{M}_u on dataset $\mathcal{D}_u = \mathcal{D}_o \setminus x$. We call this \mathcal{M}_u the unlearned model. Retraining from scratch is easy to implement. However, when the size of the original dataset \mathcal{D}_o is large and the model is complex, the computational overhead of retraining is too large. To reduce the computational overhead, several approximate approaches have been proposed [7, 10, 27, 50], among which SISA [9] works in an ensemble style and is the most general one.

SISA. The training dataset \mathcal{D}_o in SISA is partitioned into k disjoint parts $\mathcal{D}_o^1, \mathcal{D}_o^2, \cdots, \mathcal{D}_o^k$. The model owner trains a set of original ML models $\mathcal{M}_o^1, \mathcal{M}_o^2, \cdots, \mathcal{M}_o^k$ on each corresponding dataset \mathcal{D}_o^i . When the model owner receives a request to delete a data sample x, it just needs to retrain the sub-model \mathcal{M}_o^i that contains x, which results in unlearning model \mathcal{M}_u^i . Sub-models that do not contain x remain unchanged. Notice that the size of dataset \mathcal{D}_o^i is much smaller than \mathcal{D}_o ; thus, the computational overhead of SISA is much smaller than the "retraining from scratch" method.

At inference time, the model owner aggregates predictions from the different sub-models to provide an overall prediction. The most commonly used aggregation strategy is majority vote and posterior average. In our experiments, we use posterior average as aggregation strategy.

2.3 Threat Model

The objective of the adversary is to perform membership inference towards the target sample, i.e., to determine whether a given target sample x is in the training set of the original model [49, 54]. Knowing that a specific data sample x was used to train a particular model may lead to potential privacy breach. For example, knowing that a certain patient's clinical records were used to train a model associated with a disease (e.g., to determine the appropriate drug dosage or to discover the genetic basis of the disease) can reveal that the patient carries the associated disease. The classical membership inference attack can achieve this objective by exploiting the output (typically posterior distribution over possible classes) returned by the original model. In the machine unlearning setting, the adversary has access to the outputs of both the original model and the unlearned model; thus he can exploit

two versions of posteriors to launch the membership inference attack towards the target sample.

Similar to previous membership inference attacks [49,54], we assume the adversary has black-box access to the models. This means that the adversary can only query these models and obtain their corresponding posteriors. Compared to the white-box setting, where the adversary has direct access to the architecture and parameters of the target model, the black-box setting is more realistic, and more challenging for the adversary [39]. We further assume that the adversary has a shadow dataset which can be used to train a set of shadow models to mimic the behavior of the target model. The shadow models are then used to generate another dataset to train the attack model (see Section 3 for more details). The shadow dataset can either come from the same distribution as the target dataset or from a different one. We evaluate both settings in Section 5.

3 Membership Inference in Unlearning

In this section, we detail our membership inference attack in the machine unlearning setting.

3.1 Attack Pipeline

The general attack pipeline of our attack is illustrated in Figure 1. It consists of three phases: posterior generation, feature construction and (membership) inference.

Posterior Generation. The adversary has access to two versions of the target ML models, the original model \mathcal{M}_o and the unlearned model \mathcal{M}_u . Given a target sample x, the adversary queries \mathcal{M}_o and \mathcal{M}_u , and obtains the corresponding posteriors, i.e., \mathbb{P}_o and \mathbb{P}_u , also referred to as confidence values or levels [54].

Feature Construction. Given the two posteriors \mathbb{P}_o and \mathbb{P}_u , the adversary aggregates them to construct the feature vector \mathcal{F} . There are several alternatives to construct the feature. We discuss them in Section 3.3.

Inference. Finally, the adversary feed obtained \mathcal{F} to the attack model, which is a binary classifier, to determine whether the target sample x is in the training set of the original model or not. We describe how to build the attack model in Section 3.2.

3.2 Attack Model Training

We assume the adversary has a local dataset, which we call the shadow dataset \mathcal{D}^s . The shadow dataset can come from a different distribution than the one used to train the target model. To infer whether the target sample x is in the original model or not, our approach is to train a binary classifier

³Note that we also study the removal of more than one sample in our experimental evaluation, but for simplicity we formalize our problem with one sample only.

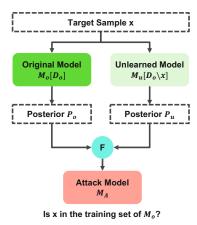


Figure 1: A schematic view of the general attack pipeline.

 \mathcal{M}_A that captures the difference between the two posteriors. The intuition is that, if the target sample x is deleted, the two models \mathcal{M}_o and \mathcal{M}_u will behave differently. Figure 2 illustrates the training process of the attack model, and the detailed training procedure is presented as follows.

Training Shadow Models. To mimic the behavior of the target models, the adversary needs to train a shadow original model and a set of shadow unlearned models. To do this, the adversary first partitions \mathcal{D}^s into two disjoint parts, the shadow negative set \mathcal{D}^s_n and the shadow positive set \mathcal{D}^s_p . The shadow positive set \mathcal{D}^s_p is used to train the shadow original model \mathcal{M}^s_o . The shadow unlearned model \mathcal{M}^s_u is trained by deleting samples from \mathcal{D}^s_p . For ease of presentation, we assume the shadow unlearned model \mathcal{M}^s_u is obtained by deleting exactly one sample. We will show that our attack is still effective for group deletion in Section 5.7. The adversary randomly generates a set of deletion requests (target samples) $\mathcal{R}_p = \{x_p^1, x_p^2, \cdots, x_p^m\}$ and train a set of shadow unlearned models $\mathcal{M}^{s,1}_u, \mathcal{M}^{s,2}_u, \cdots, \mathcal{M}^{s,m}_u$, where shadow unlearned model $\mathcal{M}^{s,i}_u$ is trained on dataset $\mathcal{D}^s_p \setminus x_p^i$.

Obtaining Posteriors. At the posterior generation phase, the adversary feeds each target sample $x_p^i \in \mathcal{R}_p$ to the shadow original model \mathcal{M}_o^s and its corresponding shadow unlearned model $\mathcal{M}_u^{s,i}$, and gets two posteriors \mathbb{P}_o^i and \mathbb{P}_u^i .

Constructing Features. The adversary then uses the feature construction methods discussed in Section 3.3 to construct training cases for the attack model. In classical membership inference, posteriors of $x_p^i \in \mathcal{R}_p$ serve as member cases of the attack model. But in the machine unlearning setting, $x_p^i \in \mathcal{R}_p$ is member of shadow original model \mathcal{M}_o^s and non-member of shadow unlearned model \mathcal{M}_u^s . To avoid confusion, we call the samples related to $x_p^i \in \mathcal{R}_p$ positive cases instead of member cases for the attack model.

To train the attack model, the adversary also needs a set of

negative cases. This can be done by sampling a set of negative query samples \mathcal{R}_n from the shadow negative dataset \mathcal{D}_n^s and query the shadow original model and unlearned model. To get a good model generalization performance, the adversary needs to ensure that the number of positive cases and the number of negative cases of the attack model are balanced, i.e., $|\mathcal{R}_p| = |\mathcal{R}_n|$, where $|\cdot|$ is the cardinality of the sample set.

Improving Diversity. To improve the diversity of the attack model, the adversary obtains multiple shadow original models by randomly sampling multiple subsets of samples from the shadow positive dataset \mathcal{D}_p^s . For each shadow original model, the adversary randomly generates a set of deletion requests and trains a sequence of shadow unlearned models. In Section 5.5, we will conduct empirical experiments to show the impact of the number of shadow original models on the attack performance.

Training Attack Model. Given sets of positive cases with features and negative cases with features, we rely on four standard and widely used classifiers for our attack model: logistic regression, decision tree, random forest, and multilayer perceptron.

3.3 Feature Construction

Given the two posteriors, a straightforward approach to aggregate the information is to concatenate them, i.e., $\mathbb{P}_o||\mathbb{P}_u$, where || is the concatenation operation. This preserves the full information. However, it is possible that the concatenation contains redundancy. In order to reduce redundancy, we can instead rely on the difference between \mathbb{P}_o and \mathbb{P}_u to capture the discrepancy left by the deletion of the target sample. In particular, we make use of the element-wise difference $\mathbb{P}_o - \mathbb{P}_u$ and the Euclidean distance $\|\mathbb{P}_o - \mathbb{P}_u\|_2$.

In order to better capture the level of confidence of the model, one may also sort the posterior before the difference or concatenation operations [16]. Specifically, we sort the original posterior \mathbb{P}_o in descending order and get the sorted original posterior \mathbb{P}_o^s . We then rearrange the order of the unlearned posterior \mathbb{P}_u to align its elements with \mathbb{P}_o , and get the sorted unlearned posterior \mathbb{P}_u^s .

To summarize, we adopt the following five methods to construct the feature for the attack model:

- Direct concatenate (DirectConcat), i.e., $\mathbb{P}_{o}||\mathbb{P}_{u}|$
- Sorted concatenate (SortedConcat), i.e., $\mathbb{P}_o^s||\mathbb{P}_u^s$
- Direct difference (DirectDiff), i.e., $\mathbb{P}_o \mathbb{P}_u$.
- Sorted difference (SortedDiff), i.e., $\mathbb{P}_o^s \mathbb{P}_u^s$.
- Euclidean distance (EucDist), i.e., $\|\mathbb{P}_{o} \mathbb{P}_{u}\|_{2}$

In Section 5.3, we conduct empirical experiments to evaluate the performance of the above methods and summarize a feature choice guidance.

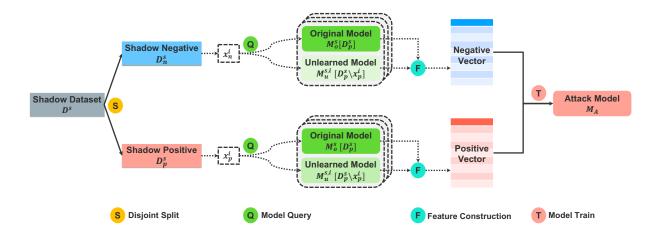


Figure 2: Training process of the attack model. The shadow dataset \mathcal{D}^s is split into disjoint shadow positive dataset \mathcal{D}^s_p and shadow negative dataset \mathcal{D}^s_n . The shadow positive dataset \mathcal{D}^s_p is used to train the shadow original model \mathcal{M}^s_o . The shadow unlearned model $\mathcal{M}^{s,i}_u$ is trained on $\mathcal{D}^s_p \setminus x^i_p$, where $x^i_p \in \mathcal{D}^s_p$. In the inference phase, the adversary first uses target sample x^i_p to query the original and unlearned models simultaneously to generate the positive features. Then she uses a random sample $x^i_n \in \mathcal{D}^s_n$ to query the corresponding models to generate the negative features. Finally, she uses the positive and negative features to train the attack model \mathcal{M}_a .

4 Privacy Degradation Measurement

In this paper, we aim to evaluate to what extent machine unlearning may degrade the membership privacy of an individual whose data sample has been deleted from the training set (we also call this the target sample). Specifically, we want to quantify the additional privacy degradation our attack has over classical membership inference (or the improvement of membership inference) in order to measure the unintended information leakage due to data deletion in machine learning. To this end, we propose two privacy degradation metrics that measure the difference of the confidence levels of our attack and classical membership inference in predicting the right membership status of the target sample.

Given n target samples x^1 to x^n , define p_u^i as the confidence of our attack for classifying x^i as a member, and p_m^i as the confidence of classical membership inference. Let b^i be the true status of x^i , i.e., $b^i = 1$ if x^i is a member, and $b^i = 0$ otherwise. With that, we define the following two metrics:

• **DegCount.** DegCount stands for Degradation Count. It calculates the proportion of target samples whose true membership status is predicted with higher confidence by our attack than by classical membership inference. Formally, DegCount is defined as

$$DegCount = \frac{1}{n} \sum_{i}^{n} \left[b^{i} \mathbb{1}_{p_{u}^{i} > p_{m}^{i}} + (1 - b^{i}) \mathbb{1}_{p_{u}^{i} < p_{m}^{i}} \right]$$

where $\mathbb{1}_P$ is the indicator function which equals 1 if P is true; otherwise equals 0. Higher DegCount means higher privacy degradation level.

DegRate. DegRate stands for Degradation Rate. It calculates the average confidence improvement rate of our attack predicting the true membership status compared to classical membership inference. DegRate can be formally defined as

$$DegRate = \frac{1}{n} \sum_{i}^{n} \left[b^{i} (p_{u}^{i} - p_{m}^{i}) + (1 - b^{i}) (p_{m}^{i} - p_{u}^{i}) \right]$$

Higher DegRate means higher privacy degradation level.

5 Evaluation

In this section, we conduct extensive experiments to evaluate the unintended privacy risks of machine unlearning. We first conduct an end-to-end experiment to validate the effectiveness of our attack on multiple datasets using the most legit unlearning method, i.e., retraining from scratch. Second, we compare different feature construction methods proposed in Section 3.3 and summarize a principle for choosing among them. Third, we evaluate the impact of overfitting and different hyperparameters on our attack. Fourth, we conduct experiments to evaluate dataset and model transferability between shadow model and target model. Finally, we show the effectiveness of our attack against group deletion and SISA unlearning method.

5.1 Experimental Setup

Environment. All algorithms are implemented in Python 3.7 and all the experiments are conducted on a server with

Intel Xeon E7-8867 v3 @ 2.50GHz and 1.5TB memory.

Datasets. We run experiments on two different types of datasets: categorical dataset and image dataset. The categorical datasets are used to evaluate the vulnerability of simple machine learning models, such as logistic regression (LR), decision tree (DT), random forest (RF), and multilayer perceptron (MLP). The image datasets are used to evaluate the vulnerability of state-of-the-art convolutional neural networks, such as ResNet [24]. We use the following datasets in our experiment.

- UCI Adult [1]. UCI Adult is a widely used categorical dataset for classification. It is a census dataset that contains around 50,000 samples with 14 features, including race, gender, occupation, etc. The original classification task is to predict whether the income of a person is over \$50k, which is a binary classification task. To evaluate the performance of multi-class classification, we transform the occupation feature into a label in our experiment, with 12 possible classes for this label. For ease of presentation, we denote these two tasks as two different datasets, namely Adult (income) and Adult (occupation).
- US Accident [2]. US Accident is a countrywide traffic accident dataset, which covers 49 states of the United States. This dataset contains around 3M samples. We filter out attributes with too many missing values and obtain 30 valid features. The valid features include temperature, humidity, pressure, etc. The classification task is to predict the accident severity level which contains 3 classes.
- Insta-NY [6]. This dataset contains a collection of Instagram users' location check-in data in New York. Each check-in contains a location and a timestamp; and each location belongs to a category. We use the number of check-ins that happened at each location in each hour on a weekly basis as the location feature vector. The classification task is to predict each location's category among 9 different categories. After filtering out locations with less than 50 check-ins, we get 19,215 locations for Insta-NY dataset. Later in the section, we also make use of check-ins in Los Angeles, namely Insta-LA [6], for evaluating the data transferring attack. This dataset includes 16,472 locations.
- MNIST [3]. MNIST is an image dataset widely use for classification. It is a 10-class handwritten digits dataset which contains 42,000 samples, each being formatted into a 28 × 28-pixel image.
- CIFAR10 [4]. CIFAR10 is the benchmark dataset used to evaluate image recognition algorithms. This dataset contains 60,000 colored images of size 32 × 32, which

are equally distributed on the following 10 classes: airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck. There are 50,000 training images and 10,000 testing images.

Metrics. In addition to the two privacy degradation metrics proposed in Section 4, we also rely on the traditional AUC metric to measure the absolute performance of our attack and classical membership inference. To summarize, we have the following three metrics:

- AUC. It is a widely used metric to measure the performance of binary classification in a range of thresholds [6, 15, 22, 30, 41, 42, 46, 49, 64, 66]. It tells how much the attack model is capable of distinguishing between member and non-member. Higher AUC value implies better ability to predict the membership status. An AUC value equals to 1 shows a maximum performance (true-positive rate of 1 with false-positive rate of 0) while an AUC value of 0.5 shows a performance equivalent to random guessing.
- **DegCount.** It stands for Degradation Count, which is defined in Section 4.
- **DegRate.** It stands for Degradation Rate, which is defined in Section 4.

Experimental Setting. We evenly split each dataset \mathcal{D} into disjoint target dataset \mathcal{D}^t and shadow dataset \mathcal{D}^s . In Section 5.6, we will show that the shadow dataset can come from a different distribution than the target dataset. The shadow dataset \mathcal{D}^s is further split into shadow positive dataset \mathcal{D}^s_p and shadow negative dataset \mathcal{D}_n^s (80% for \mathcal{D}_p^s and 20% for \mathcal{D}_n^s). We randomly sample S_o subsets of samples from \mathcal{D}_n^s , each containing S_r samples, to train S_o shadow original models. Let us denote the training dataset for the shadow original model $\mathcal{M}_o^{s,i}$ as $\mathcal{D}_o^{s,i}$, where $\mathcal{D}_o^{s,i} \subset \mathcal{D}_p^s$. For each shadow original model $\mathcal{M}_o^{s,i}$, we train S_u shadow unlearned models on $\mathcal{D}_o^{s,i} \setminus x$, where x is randomly sampled from $\mathcal{D}_o^{s,i}$. We then follow the procedure in Section 3.2 to construct the training dataset for the attack model, and train the attack model using different classifiers. By default, we set the hyperparameters of the shadow models to $S_o = 20, S_r = 5000, S_u = 100$.

Similarly, the target dataset \mathcal{D}^t is split into target positive dataset \mathcal{D}^t_p and target negative dataset \mathcal{D}^t_n . Following the same procedure as for the shadow dataset, we train T_o target original models, each containing T_r samples and generating T_u unlearned models. The data generated by the shadow models serve as training data for the attack model, while the data generated by the target models serve as testing data. By default, we set the hyperparameters of the target models to $T_o = 20, T_r = 5000, T_u = 100$. The model parameter settings of logistic regression, decision tree, random forest and multilayer perceptron are listed in Appendix B.

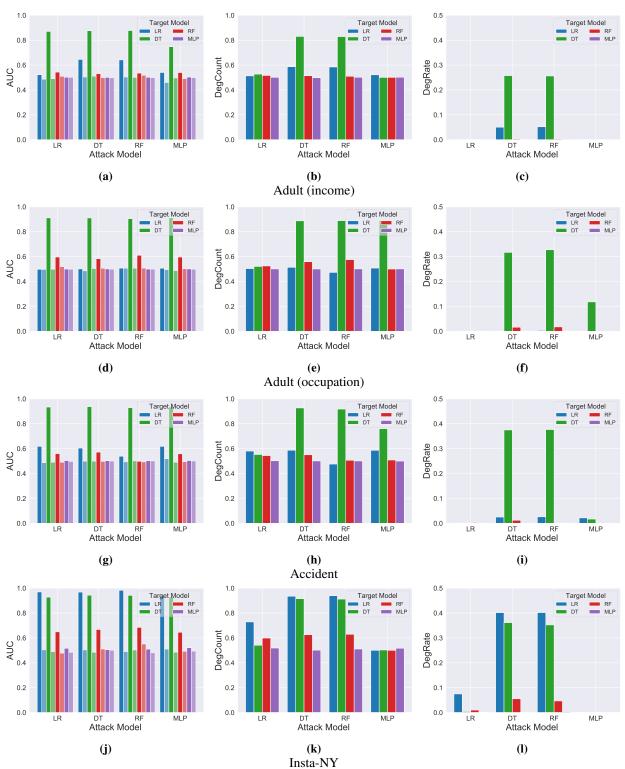


Figure 3: [Higher means greater privacy degradation for the three metrics] Privacy degradation level on Scratch method for categorical datasets. Rows stand for different datasets, columns stand for different metrics. In each subfig, the groups in x-axis represent the different attack models, and the legends (in different colors) represent the different target models. For the AUC metric, the right bars (transparent ones) stand for the AUC value of classical membership inference.

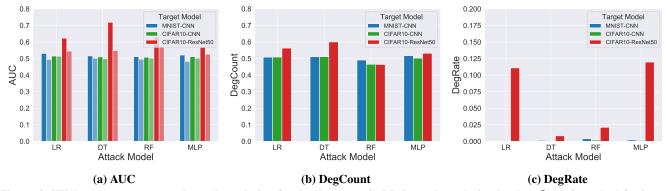


Figure 4: [Higher means greater privacy degradation for the three metrics] Privacy degradation level on Scratch method for image datasets. In each subfig, the groups in x-axis stand for different attack models, the legends (in different colors) stand for different datasets and the corresponding target models. For the AUC metric, the right bars (transparent ones) stand for the AUC value of classical membership inference.

5.2 Evaluation of the Scratch Method

In this subsection, we conduct end-to-end experiment to evaluate our attack against the most legit unlearning approach of retraining the ML model from scratch. We start by considering the scenario where only one sample is deleted for each unlearned model. The scenario where multiple samples are deleted before the ML model is retrained will be evaluated in Section 5.7. We conduct the experiment on both categorical datasets and image datasets with three evaluation metrics, namely AUC, DegCount, DegRate.

Figure 3 shows the performance for categorical datasets. We evaluate the performance on multiple target models and multiple attack models. Specifically, we use four standard classifiers for both target models and attack models, resulting in 16 combinations. The groups on the *x*-axis represent the attack models and the color bars (see the legend) represent the target models. We report here the results with the optimal features as explained in Section 5.3.

The experimental results show that our attack performs consistently better than classical membership inference on all datasets, target models, attack models, and metrics. Compared to classical membership inference, our attack achieves up to 0.48 improvement of the AUC. The best DegCount and DegRate values are of 0.94 and 0.40, respectively. This indicates that our attack indeed degrades membership privacy of the target sample in the machine unlearning setting. Comparing the performance of different target models, we observe that decision tree is the most vulnerable ML model.

Figure 4 illustrates the performance for the image datasets. We use a simple convolutional neural network (CNN), whose architecture is described in Appendix A, as the target model for both MNIST and CIFAR10 datasets. We further use ResNet50 for the CIFAR10 datasets. As for the attack model, we use four standard classifiers, same as in the categorical datasets. The groups in the *x*-axis represent the attack mod-

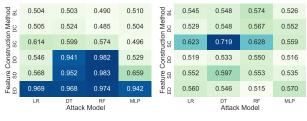
els and the color bars (see the legend) represent the datasets and their corresponding target models. The experimental results show that CIFAR10 trained with ResNet50 is the most vulnerable case. The reason behind is that the overfitting level of CIFAR10 trained with ResNet50 is the largest. From Table 1, we observe that the overfitting level of CIFAR10 trained with ResNet50 is 0.260, while both MNIST and CIFAR10 trained with simple CNNs have an overfitting level smaller than 0.05.

5.3 Finding Optimal Features

Figure 5 illustrates the attack AUC of different feature construction methods. We compare two different types of target models: (a) the well-generalized model logistic regression (trained on Insta-NY dataset), and (b) the overfitted model ResNet50 (trained on CIFAR10 dataset). The readers can refer to Table 1 for the overfitting values, and we will further discuss the impact of overfitting in Section 5.4. We then apply the 5 different feature construction methods proposed in Section 3.3 to 4 different attack models, resulting in 20 combinations. For comparison, we also include the classical membership inference as a baseline.

Concatenation vs. Difference. Concatenation-based methods (DirectConcat, SortedConcat) directly concatenate the two posteriors to preserve the full information, while difference-based methods capture the discrepancy between two versions of posteriors. We use two approaches to capture this discrepancy: element-wise difference (DirectDiff, SortedDiff) and Euclidean distance (EucDist).

Overall, Figure 5 shows that, on the one hand, concatenation-based methods perform better on the overfitted model, i.e., ResNet50. On the other hand, the difference-based methods perform better on the well-generalized model, i.e., logistic regression.



(a) LR + Insta-NY

(b) ResNet50 + CIFAR10

Figure 5: Attack AUC for different feature construction methods for target models (a) logistic regression (trained on Insta-NY dataset) and (b) ResNet50 (trained on CIFAR10 dataset). DC, SC, DD, SD, ED stand for DirectConcat, SortedConcat, DirectDiff, SortedDiff, EucDist, respectively. BL stands for the baseline, i.e., classical membership inference.

The reason behind this is that the concatenation-based methods exploit similar information as classical membership inference, namely the plain posterior information. We can observe from Figure 5b that, classical membership inference performs well on an overfitted target model, which is consistent with the conclusion of previous studies [49, 54]. Thus, our attack should also perform well on an overfitted target model by using similar type information, i.e., the plain posterior information. Our attack outperforms classical membership inference on the overfitted target model essentially because of the additional posterior it uses from the unlearned model. On the other hand, instead of using plain posterior information, the difference-based methods capture the discrepancy between two versions of the posterior due to the deletion of the target sample, i.e., the imprint of the target sample. Therefore, these methods, such as EucDist, can achieve more than 0.95 AUC on the well-generalized model (regardless of the attack model), while the corresponding AUC of classical membership inference is close to 0.5, i.e., equivalent to random guessing.

Sorted vs. Unsorted. Comparing DirectConcat to SortedConcat and DirectDiff to SortedDiff in Figure 5, we observe that attack AUC of both concatenation-based method and difference-based method are clearly better after sorting. These results confirm our conjecture that sorting could improve the confidence level of the adversary.

Feature Selection Summary. Our empirical comparison provides us with the following rules for the feature construction methods: (1) use concatenation-based methods on overfitted models; (2) use difference-based methods on well-generalized models; (3) sort posteriors before the concatenation and difference operations.

Table 1: Attack AUC in different overfitting levels. Values in the parentheses stand for the AUC value of classical membership inference. Due to space limitation, we use Adult (inc) and Adult (occ) to denote Adult (income) and Adult (occupation), respectively.

Dataset	Target Model	Overfitting AUC	
Adult (inc)	LR	0.013	0.600 (0.505)
	DT	0.017	0.882 (0.497)
	RF	0.009	0.544 (0.509)
Adult (occ)	LR	0.016	0.507 (0.506)
	DT	0.017	0.903 (0.506)
	RF	0.043	0.611 (0.507)
Accident	LR	0.022	0.538 (0.494)
	DT	0.025	0.929 (0.501)
	RF	0.026	0.572 (0.497)
Insta-NY	LR	0.096	0.983 (0.490)
	DT	0.024	0.941 (0.503)
	RF	0.081	0.685 (0.551)
MNIST	CNN	0.018	0.511 (0.496)
CIFAR10	CNN	0.036	0.507 (0.502)
	ResNet50	0.260	0.719 (0.548)

5.4 Impact of Overfitting

Overfitting measures the accuracy gap between training and testing datasets. Previous studies [54, 63] have shown that overfitted models are more susceptible to classical membership inference attacks, while well-generalized models are almost immune to them. In this subsection, we want to revisit the impact of overfitting on our attack.

Table 1 depicts the attack AUC for different overfitting levels. We use random forest as attack model, use SortedDiff and SortedConcat as feature construction method for well-generalized and overfitted target model, respectively. The experimental results show that **our attack can still correctly infer the membership status of the target sample in well-generalized models**. For example, when the target model is a decision tree, the overfitting level in Adult (income) dataset is 0.017, thus decision tree can be regarded as a well-generalized model. While the performance of classical membership inference on this model is equivalent to random guessing (AUC = 0.497), our attack performs very well, with an AUC of 0.882. In general, we observe that our attack performance is relatively independent of the overfitting level.

5.5 Hyperparameter Sensitivity

We now evaluate the impact of different hyperparameters on the performance of our attack. Specifically, we want to know the impact of the number of shadow original models S_o , the number of samples S_r per shadow original model and the number of unlearned models S_u per shadow original model. The corresponding hyperparameters of the target models are fixed (as defined at the end of Section 5.1), since only the hy-

Table 2: Attack AUC for dataset and model transfer. Names in the left of arrows stand for configurations of shadow model. Values in the parentheses stand for the attack AUC of the classical membership inference. Columns stand for dataset transfer, rows stand for model transfer.

Shadow→Target	NY→NY	NY→LA		
$\mathbf{DT} \rightarrow \mathbf{DT}$ $\mathrm{DT} \rightarrow \mathrm{LR}$	0.944 (0.491) 0.964 (0.494)	0.931 (0.503) 0.974 (0.513)		
$\begin{matrix} \textbf{LR} \rightarrow \textbf{LR} \\ \textbf{LR} \rightarrow \textbf{DT} \end{matrix}$	0.986 (0.505) 0.927 (0.502)	0.982 (0.511) 0.926 (0.508)		

perparameters of the shadow models can be tuned to launch the attack.

We conduct the experiments on Adult (income) dataset with decision tree as target model. Following our findings in Section 5.3, we evaluate the attack AUC of different combination of attack models, i.e., decision tree, random forest and logistic regression, and difference-based feature construction methods, i.e., DirectDiff, SortedDiff, EucDist.

Number of Shadow Original Models S_o . Figure 6a depicts the impact of S_o , which varies from 1 to 100. The figure shows that the attack AUC sharply increases when S_o increases from 1 to 5, but remains quite stable for greater values of S_o . This indicates that setting $S_o = 5$ is enough for the diversity of shadow original model.

Number of Samples S_r **per Shadow Original Model.** Figure 6b illustrates the impact of $S_r \in \{500, 1000, 2000, 5000, 10000\}$. When S_r increases from 500 to 1000, the attack AUC with SortedDiff increases from 0.67 to 0.83, while the attack AUC with EucDist increases from 0.73 to 0.86, except for logistic regression. However, adding more than 1000 samples does not help improve the attack performance further.

Number of Unlearned Models S_u per Shadow Original Model. Figure 6c illustrates the impact of S_u , which varies from 1 to 100. The experimental result shows that S_u has negligible impact on the attack AUC. This indicates that using a few unlearned models is sufficient to achieve a high attack performance.

5.6 Attack Robustness

In this subsection, we conduct experiments to validate the dataset and model transferability between shadow model and target model. That is, we evaluate whether the adversary can use a different dataset and model architecture than the target model to train the shadow models.

We use Insta-NY and Insta-LA datasets to perform the dataset transferring attack. As described in Section 5.1, these two datasets contain check-in data from different cities, thus have different distributions. We use Insta-NY dataset to train

the shadow models and Insta-LA dataset to train the target model. We evaluate the dataset transferability for two target models (decision tree and logistic regression) with logistic regression as the attack model. The results are given in Table 2. We break the table into two parts: the upper two rows gives results when the shadow model is the decision tree; and the lower two rows are for logistic regression. Within each part, the lower row indicates results for model transfer, and the right column is for dataset transfer.

Dataset Transferability. Comparing the AUC values of the transfer setting with that of the non-transfer setting, we only observe a small performance drop for all target models. For instance, when the target model is decision tree, the attack AUC of transfer setting and non-transfer setting are 0.944 and 0.931, respectively. The attack AUC only drops by 1%.

Model Transferability. For model transferring attack, we evaluate the pairwise transferability among target models decision tree and logistic regression. In Table 2, unbold rows in column NY→NY illustrate the performance of model transfer. The experimental results show that model transfer only slightly degrade the attack performance of our attack. For example, when the shadow model and target model are both logistic regression, the attack AUC equals to 0.986. When we change the target model to decision tree, the attack AUC is still of 0.927.

Dataset and Model Transferability. Unbold rows of column $NY \rightarrow LA$ in Table 2 show the attack AUC when we transfer both the dataset and the model simultaneously. Even in this setting, our attack can still achieve pretty good performance. This result shows that our attack is robust to both different dataset distribution and different model architecture.

5.7 Evaluation of Group Deletion

So far, we have focused on the scenario where only one sample was deleted for each unlearned model. However, there could exist cases where a group of samples are deleted before generating the unlearned model. This can happen when multiple data owners request the deletion of their data at the same time, or when the model owner caches the deletion requests and updates the model only when he has received numerous requests to save computational resources.

In this subsection, we conduct experiments to show the performance of our attack in the group deletion scenario. We randomly delete 10 data samples from each original model to generate the unlearned model. We evaluate our attack on the Insta-NY dataset with three metrics, four different target models, and four different attack models. For each attack model, we select the best features following the principles described in Section 5.3.

The experimental results in Figure 7 show that our attack is still effective, even though the attack performance of group deletion is slightly worse than single sample deletion (see

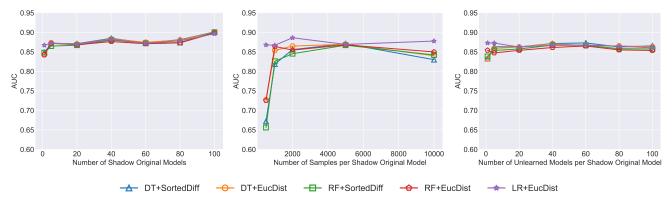


Figure 6: Impact of different hyperparameters on Adult (income) dataset with decision tree as target model. The legends stand for 5 combinations of attack models and feature construction methods.

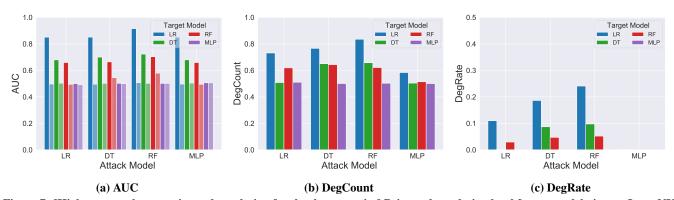


Figure 7: [Higher means larger privacy degradation for the three metrics] Privacy degradation level for group deletion on Insta-NY dataset. In each subfig, the groups in x-axis stand for different attack models, the legends (in different colors) stand for different target models. For the AUC metric, the right bars (transparent ones) stand for the AUC value of classical membership inference.

Figure 3). For example, when the target model is logistic regression and attack model is random forest, the attack AUC of single deletion and group deletion are 0.983 and 0.914, respectively. The reason is that a single sample could be hidden among the group of deleted samples, thereby preserving its membership information. This result reveals that conducting group deletion could mitigate, to some extent, the impact of our attack.

5.8 Evaluation of the SISA Method

The unlearning algorithm we focused on so far is retraining from scratch, which can become computationally prohibitive for large datasets and complex models. Several *approximate* unlearning algorithms have been proposed to accelerate the training process. In this subsection, we evaluate the performance of our attack against the most general approximate unlearning algorithm, SISA [9].

We remind the readers that the main idea of SISA is to split the original dataset into k disjoint shards and train k sub-models. In the inference phase, the model owner aggre-

gates the prediction of each sub-model to produce the global prediction using some aggregation algorithm. In this experiment, we set k=5 and use posterior average as aggregation algorithm.

Figure 8 illustrates the performance of SISA. The experiment is conducted on the Insta-NY dataset with three metrics reported. We report the experimental results of four different target models and four different attack models. For each attack model, we select the best features following the principles described in Section 5.3.

The experimental results show that our attack performance drops compared to the Scratch algorithm. Now, only the target model LR is prone to a significant drop in privacy due to unlearning. One possible reason is that the aggregation algorithm of SISA reduces the influence of a specific sample on its global model.

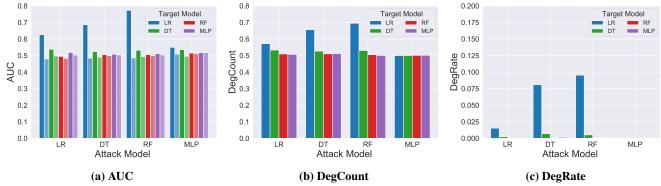


Figure 8: [Higher means larger privacy degradation for the three metrics] Privacy degradation level for SISA method on Insta-NY dataset. In each subfig, groups in x-axis stand for different attack models, the legends (in different colors) stand for different target models. For AUC metric, the right bars (transparent ones) stand for AUC values of classical membership inference.

6 Possible Defenses

This paper takes the first step to investigate the privacy risks stemming from machine unlearning. Extensive experiments have demonstrated that publishing unlearned model could degrade the membership privacy of a target whose data has been deleted. In this section, we present two possible defense mechanisms and empirically evaluate their effectiveness. The main idea of both mechanisms is to reduce the information accessible to the adversary [54].

Publishing the Top-k **Confidence Values.** This defense reduces attacker's knowledge by only publishing the top k confidence values of the posteriors returned by both original and unlearned models. Formally, we denote the posterior vector as $\mathbb{P} = [p_1, p_2, \cdots, p_\ell]$, where ℓ is the number of classes of the target model and p_i is the confidence value of class i. When the target model receives a query, the model owner calculates posterior \mathbb{P} and sorts it in descending order, resulting in $\mathbb{P}^s = [p_1^s, p_2^s, \cdots, p_\ell^s]$. The model owner then publishes the first k values in \mathbb{P}^s , i.e., $[p_1^s, p_2^s, \cdots, p_k^s]$.

In the machine unlearning setting, the top k confidence values of the original model and the unlearned model may not correspond to the same set of classes. To launch our attack, the adversary constructs a pseudo-complete posterior vector for both original model and unlearned model. The pseudo-complete posterior takes the published confidence value for their corresponding classes, and evenly distributes the remaining confidence value to other classes, i.e., for $j \in \{k+1,\ldots,\ell\}$, $p_j^s = \frac{1-(p_1^s+p_2^s+\cdots+p_k^s)}{\ell-k}$. The adversary can then launch our attack using the pseudo-complete posterior.

Table 3 shows the experimental results of Top-1, Top-2 and Top-3 defenses. We conduct experiment on Insta-NY dataset and Adult (occupation) datasets. For Adult (occupation) dataset, we report the results of decision tree as target model; for Insta-NY dataset, we report the results of decision

tree and logistic regression as target model. For each dataset, we report the performance of 4 different attack models, each selecting the best feature following the principle described in Section 5.3. The results show that publishing top k confidence value cannot significantly mitigate our attack.

Publishing the Label Only. This defense further reduces the information accessible to the adversary by only publishing the predicted label instead of confidence values (posteriors). To launch our attack, the adversary also needs to construct the pseudo-complete posterior for both original model and unlearned model. The main idea is to set the confidence value of the predicted class as 1, and set the confidence value of other classes as 0.

Table 3 illustrates the performance of the "label only" defense. The experimental setting is similar to Top-*k* defense. The experimental results show that the "label only" defense can effectively mitigate our attack in all cases. The reason is that deleting one sample is unlikely to change the output label of a specific target sample.

We leave the in-depth exploration of effective defense mechanisms against our attack as a future work.

7 Related Work

Machine Unlearning. The notion of machine unlearning was first proposed in [10], which is the application of the right to be forgotten in the machine learning context. The most legit approach to implement machine unlearning is to remove the revoked samples from the original training dataset and retrain the ML model from scratch. However, retraining from scratch incurs very high computational overhead when the dataset is large and when the revoke requests happen frequently. Thus, most of the previous studies in machine unlearning focus on reducing the computational overhead of the unlearning process [7,9,10,27,50].

Table 3: Attack AUC of the defense mechanisms. No defense stands for the baseline attack without applying any defense mechanisms. Top-1 Top-2, Top-3 stand for publishing the Top-k confidence values. Label stands for the label only defense.

Dataset (Target Model)	Attack Model	No defense	Top-1	Top-2	Top-3	Label
Adult (occupation) (DT)	RF	0.916	0.899	0.906	0.911	0.501
	DT	0.918	0.903	0.906	0.910	0.506
	LR	0.918	0.904	0.907	0.911	0.506
	MLP	0.918	0.904	0.909	0.907	0.493
Insta-NY (DT)	RF	0.937	0.930	0.931	0.942	0.506
	DT	0.938	0.932	0.932	0.943	0.502
	LR	0.928	0.923	0.927	0.926	0.502
	MLP	0.928	0.923	0.927	0.929	0.505
Insta-NY (LR)	RF	0.976	0.947	0.965	0.965	0.546
	DT	0.972	0.946	0.961	0.961	0.546
	LR	0.969	0.948	0.960	0.962	0.546
	MLP	0.970	0.948	0.960	0.966	0.453

Cao and Yang [10] proposed to transform the learning algorithms into summation form that follows statistical query learning, breaking down the dependencies of training data. To remove a data sample, the model owner only needs to remove the transformations of this data sample from the summations that depend on this sample. However, the algorithm in [10] is not applicable to learning algorithms that cannot be transformed into summation form, such as neural networks. Thus, Bourtoule et al. [9] proposed a more general algorithm named SISA. The main idea of SISA is to split the training data into several disjoint shards, with each shard training one sub-model. To remove a specific sample, the model owner only needs to retrain the sub-model that contains this sample. To further speed up the unlearning process, the authors proposed to split each shard into several slices and store the intermediate model parameters when the model is updated by each slice.

Another line of machine unlearning study aims to verify whether the model owner complies with the data deletion request. Sommer et al. [55] proposed a backdoor-based method. The main idea is to allow the data owners to implant a backdoor in their data before training the ML model in the MLaaS setting. When the data owners later request to delete their data, they can verify whether their data have been deleted by checking the backdoor success rate.

The research problem in this paper is orthogonal to previous studies. Our goal is to quantify the unintended privacy risks for deleted samples in machine learning systems when the adversary has access to both original model and unlearned model. To the best of our knowledge, this paper is the first to investigate this problem.

Although quantifying privacy risks of machine unlearning has not been investigated yet, there are multiple studies on quantifying the privacy risks in the general right to be forgotten setting. For example, Xue et al. [62] demonstrate that in search engine applications, the right to be forgotten can enable an adversary to discover deleted URLs when there are

inconsistent regulation standards in different regions. Ellers et al. [13] demonstrate that, in network embeddings, the right to be forgotten enables an adversary to recover the deleted nodes by leveraging the difference between the two versions of the network embeddings.

Membership Inference. Membership inference attacks have been extensively studied in many different data domains, ranging from biomedical data [5, 22, 26] to mobility traces [46]. Shokri et al. [54] presented the first membership inference attack against ML models. The main idea is to use shadow models to mimic the target model's behavior to generate training data for the attack model. Salem et al. [49] gradually removed the assumptions of [54] by proposing three different attack methods. Since then, membership inference has been extensively investigated in various ML models and tasks, such as federated learning [37], white-box classification [39], generative adversarial networks [11, 23], natural language processing [56], and computer vision segmentation [25]. Another line of study focused on investigating the impact of overfitting [31, 63] and of the number of classes of the target model [53] on the attack performance. However, all of the previous studies focus on the classical ML setting where the adversary only has access to a single snapshot of the target model. This is the first work studying membership inference in the machine unlearning context.

To mitigate the threat of membership inference, a plethora of defense mechanisms have been proposed. These defenses can be classified into three classes: reducing overfitting, perturbing posteriors, and adversarial training. There are several ways to reduce overfitting in the ML field, such as L_2 -regularization [54], dropout [49], and model stacking [49]. In [32], the authors proposed to explicitly reduce the overfitting by adding to the training loss function a regularization term, which is defined as the difference between the output distributions of the training set and the validation set. Jia et al. [30] proposed a posterior perturbation method inspired by adversarial example. Nasr et al. [38] proposed an adversar-

ial training defense to train a secure target classifier. During the training of the target model, a defender's attack model is trained simultaneously to launch the membership inference attack. The optimization objective of the target model is to reduce the prediction loss while minimizing the membership inference attack accuracy.

Attacks against Machine Learning. Besides membership inference attacks, there exist numerous other types of attacks against ML models [12, 16, 19, 21, 28, 29, 31, 33, 34, 36, 40, 43–45, 47, 48, 51, 52, 57, 58, 60, 61, 65]. Ganju et al. [16] proposed a property inference attack aiming at inferring general properties of the training data (such as the proportion of each class in the training data). Model inversion attack [14,15] focuses on inferring the missing attributes of the target ML model. A major attack type in this space is adversarial examples [43–45, 57, 65]. In this setting, an adversary adds carefully crafted noise to samples aiming at mislead the target classifier. A similar type of attacks is backdoor attack, where the adversary as a model trainer embeds a trigger into the model for her to exploit when the model is deployed [19, 36, 48, 61]. Another line of work is model stealing, Tramèr et al. [58] proposed the first attack on inferring a model's parameters. Other works focus on inferring a model's hyperparameters [40, 60].

8 Conclusion

This paper takes the first step to investigate the unintended privacy risks in machine unlearning through the lens of membership inference. We propose several feature construction methods to summarize the discrepancy between the posteriors returned by original model and unlearned model. Extensive experiments on five different real-world datasets show that our attack in multiple cases outperform the classical membership inference attack on the target sample, especially on well-generalized models. We further present two mechanisms by reducing the information accessible to the adversary to mitigate the newly discovered privacy risks. We hope that these results will help improve privacy in practical implementation of machine unlearning.

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A Architecture of Simple CNN

Table 4: CNN structure and parameter. For the MNIST dataset, the input_channel C_i equals 1, the image width W and image height H are both equal to 28. For the CIFAR10 dataset, the input_channel C_i equals, the image width W and image height H are both equal to 32. The kernel_size of convolution layer K_c and Max-pooling layer K_m are equal to 3 and 2, respectively.

Layer	Parameters	
Conv2D_1	$(C_i, 32, K_c=3, 1)$	
Relu	-	
Conv2D_2	$(32, H, K_c, 1)$	
Maxpolling2D	$K_m=2$	
Dropout_1	(0.25)	
Flatten	1	
Linear_1	$(H \times (W/2 - K + 1) \times (H/2 - K + 1), 128)$	
Relu	=	
Dropout_2	0.5	
Linear_2	(128, #classes)	
Softmax	dim=1	

B Model Parameter Settings

We use multiple ML models in our experiments. All models are implemented by sklearn version 0.22. For reproduction purpose, we list their parameter settings as follows:

- **Logistic Regression:** We use LBFGS as solver and L_2 penalty for regularization, and set other parameters as default.
- Decision Tree: We use Gini index as criterion, set parameter max_leaf_nodes as 10, and set other parameters as default.
- Random Forest: We use Gini index as criterion, use 100 estimators, set min_samples_leaf=30, and set other parameters as default.

• Multi-layer Perceptron: We use SGD as solver, use ReLu as activation function. The hidden layer size is

128, the learning rate is 0.001, the L_2 regularizer is 0.0001.