# ML-Leaks: Model and Data Independent Membership Inference Attacks and Defenses on Machine Learning Models

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Abstract—Machine learning (ML) has become a core component of many real-world applications and training data is a key factor that drives current progress. This huge success has led Internet companies to deploy machine learning as a service (MLaaS). Recently, the first membership inference attack has shown that extraction of information on the training set is possible in such MLaaS settings, which has severe security and privacy implications.

However, the early demonstrations of the feasibility of such attacks have many assumptions on the adversary such as using multiple so-called shadow models, knowledge of the target model structure and having a dataset from the same distribution as the target model's training data. We relax all 3 key assumptions, thereby showing that such attacks are very broadly applicable at low cost and thereby pose a more severe risk than previously thought. We present the most comprehensive study so far on this emerging and developing threat using eight diverse datasets which show the viability of the proposed attacks across domains.

In addition, we propose the first effective defense mechanisms against such broader class of membership inference attacks that maintain a high level of utility of the ML model.

### I. INTRODUCTION

Machine learning (ML) has become a core component of many real-world applications, ranging from image classification to speech recognition. The success of ML has recently driven leading Internet companies, such as Google and Amazon, to deploy machine learning as a service (MLaaS). Under such services, a user uploads her own dataset to a server and the server returns a trained ML model to the user, typically as a black-box API.

Despite being popular, ML models are vulnerable to various security and privacy attacks, such as model inversion [15], adversarial examples [19] and model extraction [30], [40]. In this paper, we concentrate on one such attack, namely *membership inference attack*. In this setting, an adversary aims to determine whether a data item (also referred to as a data point) was used to train an ML model or not. Successful membership inference attacks can cause severe consequences. For instance, if a machine learning model is trained on the data collected from people with a certain disease, by knowing that a victim's data belong to the training data of the model, the attacker can immediately learn that this victim carries the

disease. Previously, membership inference has been successfully conducted in many other domains, such as biomedical data [7] and mobility data [35].

Shokri et al. [36] present the first membership inference attack against machine learning models. The general idea behind this attack is to use multiple machine learning models (one for each prediction class), referred to as *attack models*, to make membership inference over the *target model*'s output, i.e., posterior probabilities. Given that the target model is a black-box API, Shokri et al. propose to construct multiple *shadow models* to mimic the target model's behavior and derive the data necessary, i.e., the posteriors and the ground truth membership, to train attack models.

There are two main assumptions made in [36]. First, the attacker needs to establish multiple shadow models with each one sharing the same structure as the target model. This is achieved by using the same MLaaS that trains the target model to build the shadow models. Second, the dataset used to train shadow models comes from the same distribution as the target model's training data, this assumption holds for most of the evaluation in [36]. The authors of [36] further propose synthetic data generation to relax this assumption. However, this approach can only be applied to datasets containing binary features for efficiency reasons.

The two assumptions in [36] are rather strong, which largely reduce the scope of membership inference attacks against ML models. In this paper, we gradually relax these assumptions in order to show that far more broadly applicable attack scenarios are possible. Our investigation shows that indeed, membership inference in ML can be performed in an easier way with fewer assumptions than previously considered. To remedy this situation, we further propose two effective defense mechanisms.

#### A. Membership Inference Attack

We study three different types of adversaries based on the design and training data of shadow models. As Table I illustrates, we hereby gradually relax the assumptions of [36] until we arrive at model and data independent adversary.

Adversary type	Shadow r	Target model's	
	No. shadow models	Target model structure	training data distribution
Shokri et al. [36]	multiple	✓	<b>√</b>
Our adversary 1	1	-	$\checkmark$
Our adversary 2	1	-	-
Our adversary 3	-	-	-

TABLE I: An overview of the different types of adversaries. ✓ means the adversary needs the information, - indicates the information is not necessary.

**Adversary 1.** For the first adversary, we assume she has a dataset that comes from the same distribution as the target model's training data. Here, we concentrate on relaxing the assumptions on the shadow models.

We start by using only one instead of multiple shadow models to mimic the target model's behavior. As shadow models are established through MLaaS, which implements the pay-by-query business model, using one shadow model notably reduces the cost of performing the membership inference attack.

Extensive experimental evaluation (we use a suite of eight different datasets ranging from image to text under multiple types of machine learning models) shows that with one shadow model and one attack model, the adversary can achieve a very similar performance as reported in [36]. For instance, when the target model is a convolutional neural network (CNN) trained on the CIFAR-100 dataset [1], our simplified attack achieves a 0.95 precision and 0.95 recall while the attack with 10 shadow models and 100 attack models (as in [36]) has a 0.95 precision and 0.94 recall.

Then, we relax the assumption that the shadow model is constructed in the same way as the target model, In particular, we show that training the shadow model with different architectures and parameters still yields comparable attack performance. Moreover, we propose a new approach for shadow model training, which frees the adversary from even knowing the type of classifiers used by the target model.

**Adversary 2.** For this adversary, we assume she does not have data coming from the same distribution as the target model's training data. Also, the adversary does not know the structure of the target model. This is a more realistic attack scenario compared to the previous one.

We propose a *data transferring attack* for membership inference in this setting. Concretely, we train our single shadow model with a different dataset. This means the shadow model here is not used to mimic the target model's behavior but only to capture the membership status of data points in a machine learning training set.

The main advantage of our data transferring attack is that the adversary does not need any query to the target model for synthetic data generation. In contrast, the method proposed in [36], requires 156 queries on average to generate a single data point. This means our data transferring attack is much more efficient, less costly, and harder to be detected by the MLaaS provider.

Experimental results show that the membership inference attack still achieves a strong performance, with only a few percentage drop compared to the first adversary. More interestingly, we show that our data transferring attack even works between datasets belonging to totally different domains. For example, by training a shadow model with the 20 Newsgroups text dataset [23], we are able to get a 0.94 precision and 0.93 recall for attacking a target model trained on the CIFAR-100 image dataset.

**Adversary 3.** This adversary works without any shadow model, i.e., the attack only relies on the posteriors (outcomes) obtained from the target model when querying it with target data points. No training procedure is required at all. Instead, we utilize several statistical measures, such as entropy and maximum over the target model's posteriors to infer membership.

Experiments show that such a simple attack can still achieve effective inference over multiple datasets. For example, executing this attack on the CIFAR-10 dataset results in a 0.81 precision and 0.82 recall, respectively.

All these experimental results show that membership inference can be performed in a much simpler and more efficient way, which further demonstrates the severe risks of ML models.

#### B. Defense

To mitigate the membership inference risks, we propose two defense mechanisms, namely *dropout* and *model stacking*.

**Dropout.** The reason behind membership inference attacks' effectiveness is the inherent overfitting nature of machine learning models. When an ML model faces a data point that it was trained on, it returns a high posterior for one class compared to others. Therefore, to defend against membership inference, we use a classical approach adopted in deep learning, namely dropout, which aims at preventing overfitting. Dropout randomly deletes in each training iteration a fixed proportion of edges in a fully connected neural network model.

Experiments on multiple datasets show that dropout can be a very effective countermeasure against membership inference. On the CIFAR-100 dataset, dropout (with 0.5 dropout ratio) decreases the performance of membership inference from 0.95 precision and 0.95 recall to 0.61 and 0.60, respectively. Moreover, it almost preserves the same utility as the initial target model: the target model's prediction accuracy only drops from 0.22 to 0.21 (CIFAR-100). As dropout serves as

a regularizer, we observe that, for several learning problems, e.g., the Purchase-100 dataset [36], the target model's accuracy even improves after applying dropout. Therefore, these models improve in performance *and* resilience in membership inference attacks.

Model Stacking. Although the dropout mechanism is effective, it is specific to deep neural networks. For target models using other machine learning classifiers, we propose a second defense mechanism, namely model stacking. Model stacking is a major class of ensemble learning. In model stacking, multiple ML models are organized in a hierarchical way to prevent overfitting. In our case, we construct the target model with three different machine learning models. Two models are placed in the first layer directly taking the original training data as input, while the third model is trained with the posteriors of the first two models.

Through extensive experiments, we show that model stacking is able to significantly reduce the membership inference's performance. For instance, both precision and recall of the attack drop by more than 30% on the CIFAR-100 dataset trained with model stacking. Meanwhile, the target model's prediction performance stays almost the same.

In summary, we make the following contributions:

- We broaden the class of membership inference attacks by substantially relaxing the adversarial assumptions.
- We evaluate membership privacy threat under three different adversarial setups on eight diverse datasets, ultimately arriving at a model and data independent adversary.
   Experimental evaluations demonstrate the severe membership privacy threat for machine learning models.
- We propose two defense mechanisms, namely dropout and model stacking, and we demonstrate their effectiveness experimentally.

**Organization.** The rest of the paper is organized as the following. Section II introduces the definition of membership inference against ML models and datasets used in the paper. Section III, Section IV and Section V present the threat models, attack methodologies, and evaluations of our three different types of adversaries, respectively. In Section VI, we introduce the two defense mechanisms. Section VII discusses the related work and Section VIII concludes the paper.

# II. PRELIMINARIES

In this section, we first define membership inference attack in the machine learning setting. Then, we introduce the datasets used for our evaluation.

# A. Membership Inference Against Machine Learning Models

In this paper, we concentrate on machine learning classification, as it is the most common ML application. An ML classifier is essentially a function  $\mathcal{M}$  that maps a data point  $\mathcal{X}$  (a multidimensional feature vector) to a output vector  $\mathcal{Y}$ . The length of  $\mathcal{Y}$  is equal to the number of classes considered. For most of the classification models, the output vector  $\mathcal{Y}$ 

can be interpreted as a set of posterior probabilities over all classes, and the sum of all the values in  $\mathcal{Y}$  is 1. The parameters of an ML model are learned on a training dataset (denoted by  $\mathcal{D}_{Train}$ ) containing multiple data points following a predefined learning object.

Membership inference attack in the ML setting emerges when an adversary aims to find out whether her target data point is used to train a certain ML model. More formally, given a target data point  $\mathcal{X}_{Target}$ , a trained machine learning model  $\mathcal{M}$ , and external knowledge of an adversary, denoted by  $\mathcal{K}$ , a membership inference attack (attack model) can be formalized as the following function.

$$\mathcal{A}: \mathcal{X}_{Target}, \mathcal{M}, \mathcal{K} \rightarrow \{0, 1\}$$

Here, 0 means  $\mathcal{X}_{Target}$  is not a member of  $\mathcal{M}$ 's training dataset  $\mathcal{D}_{Train}$  and 1 otherwise. The machine learning model  $\mathcal{M}$  that the adversary is targeting on is also referred to as the *target model*. As in [36], we assume the adversary only has blackbox access to the target model, such as an MLaaS API, i.e., the adversary is only able to submit a data point to  $\mathcal{M}$  and the obtain the probabilistic output, i.e.,  $\mathcal{M}(\mathcal{X}_{Target})$ .

The attack model  $\mathcal{A}$  is essentially a binary classifier. Depending on the assumptions, it can be constructed in different ways, which will be presented in later sections.

#### B. Datasets Description

We utilize 8 different datasets in this paper to conduct our experiments. Among them, 6 datasets<sup>1</sup> are the same as the ones used in [36], i.e., MNIST [4], CIFAR-10 [1], CIFAR-100 [1], Location [43], [44], Purchase<sup>2</sup>, Adult [5]. We preprocess all these dataset as described in [36].

In particular, the Purchase dataset does not contain any prediction classes. Following [36], we adopt a clustering algorithm, namely K-means, to manually define classes. The numbers of classes we choose include 2, 10, 20, 50, and 100, therefore, we extend the Purchase dataset into 5 datasets. For instance, Purchase-100 represents the Purchase dataset with 100 different classes.

Moreover, we adopt two other datasets, namely News and Face, in our evaluation. We give a brief introduction about them in the following.

**News.** The News dataset (20 Newsgroups) introduced in [23] is one of the most common datasets used for text classification and clustering. The dataset consists of 20,000 newsgroup documents categorized into 20 classes. The number of data points belonging to each class is very similar, i.e., the dataset has a balanced class distribution. We preprocess the News dataset by first removing headers, footers, and quotes from the documents. Then, we build the TF-IDF matrix out of the raw documents as in [23].

**Face.** The Face dataset (Labeled Faces in the Wild [2]) consists of about 13,000 images of human faces crawled from

<sup>&</sup>lt;sup>1</sup>We excluded *Texas hospital stays* dataset, as there is not enough information provided in [36] for preprocessing it.

<sup>&</sup>lt;sup>2</sup>https://www.kaggle.com/c/acquire-valued-shoppers-challenge/data

the web. It is collected from 1,680 participants, with each participant having at least two distinct images in the dataset. In our evaluation, we only consider people with more than 40 images, which leaves us with 19 people's data, i.e., 19 classes. The Face dataset is challenging for facial recognition, as the images are taken from the web and not under a controlled environment, such as a lab. It is also worth noting that this dataset is unbalanced.

# III. TOWARDS MODEL INDEPENDENT MEMBERSHIP INFERENCE ATTACKS (ADVERSARY 1)

In this section, we describe the first adversary considered for membership inference attack. For this adversary, we mainly relax the assumption on her shadow model design. In consequence, membership inference attack can be performed in a much more efficient and less costly way.

We start by defining the threat model. Then, we describe our first simplification, i.e., using one shadow model instead of multiple. In the end, we propose our second simplification which frees the adversary from knowing the target model's structure.

# A. Threat Model

Similar to [36], we model our attack model  $\mathcal{A}$  as a supervised ML classifier with binary classes (member or non-member). To train  $\mathcal{A}$ , the adversary needs to derive the labeled training data. i.e., the ground truth membership. As mentioned in Section II, the adversary only has black-box access to the target model, i.e., she is not able to extract the membership status from the target model. Therefore, the adversary trains a shadow model [36] to mimic the behavior of the target model, and relies on the shadow model to obtain the ground truth membership to train  $\mathcal{A}$ .

To train the shadow model, we assume that the adversary has a dataset, denoted by  $\mathcal{D}_{Shadow}$ , that comes from the same underlying distribution as the training data for the target model. Note that most of the evaluations in [36] make the same assumption.

We further assume that the shadow model uses the same ML algorithm and has the same hyperparameters as the target model. To achieve this in practice, the adversary can either rely on the same MLaaS provider which builds the target model, or perform model extraction to approximate the target model [40]. Later in this section, we show this assumption can be relaxed as well.

#### B. One Shadow Model

#### Methodology

The adversary's methodology can be organized into three stages, i.e., shadow model training, attack model training and membership inference.

Shadow Model Training. The adversary first splits her dataset, i.e.,  $\mathcal{D}_{Shadow}$ , into two disjoint set, namely  $\mathcal{D}_{Shadow}^{Train}$  and  $\mathcal{D}_{Shadow}^{Out}$ . Then, she uses  $\mathcal{D}_{Shadow}^{Train}$  to train her only shadow model, denoted by  $\mathcal{S}$ .

Attack Model Training. The adversary uses the trained shadow model S to perform prediction over all data points in  $\mathcal{D}_{Shadow}$  (consisting of  $\mathcal{D}_{Shadow}^{Train}$  and  $\mathcal{D}_{Shadow}^{Out}$ ), and obtain the corresponding posterior probabilities. For each data point in  $\mathcal{D}_{Shadow}$ , she takes its three largest posteriors (ordered from high to low) as its *feature vector*. A feature vector is labeled as 1 (member), if its corresponding data point is in  $\mathcal{D}_{Shadow}^{Train}$ , and as 0 (non-member) otherwise. All the generated feature vectors and labels are then used to train the attack model A.

Membership Inference. To perform the attack on whether  $\mathcal{X}_{Target}$  is in  $\mathcal{D}_{Train}$ , the adversary queries  $\mathcal{M}$  with  $\mathcal{X}_{Target}$  to obtain the corresponding posteriors. Then, she picks the 3 maximal posteriors, again ordered from high to low, and feed them into  $\mathcal{A}$  to obtain the membership prediction.

It is important to note that our adversary only uses one shadow model and one attack model in her attack, while the approach in [36] adopts multiple shadow models as well as multiple attack models (one for each class). In particular, as each shadow model is established through MLaaS [36], this strategy will largely reduce the cost of her membership inference attack.

#### **Evaluation**

Experimental Setup. We evaluate our attack over all datasets. For each dataset, we first split it by half into  $\mathcal{D}_{Shadow}$  and  $\mathcal{D}_{Target}$ . Following the attack strategy, we split  $\mathcal{D}_{Shadow}$  by half into  $\mathcal{D}_{Shadow}^{Train}$  and  $\mathcal{D}_{Shadow}^{Out}$ .  $\mathcal{D}_{Target}$ , on the other hand, is used for attack evaluation, it is also split by half: one is used to train the target model, i.e.,  $\mathcal{D}_{Train}$ , and serves as the members of the target model's training data, while the other serves as the non-member data points.

For image datasets, i.e., MNIST, CIFAR-10, CIFAR-100 and Face, we use convolutional neural network (CNN) to build the target model. Our CNN is assembled with two convolutional layers and two pooling layers with one hidden layer containing 128 units in the end. For the other datasets, we use multilayer perceptron (neural network) with one hidden layer (128 units) as the target model. Each shadow model's structure is the same as its corresponding target model, following the assumption that the adversary knows the target model's structure. The attack model is established with another multilayer perceptron (a 64-unit hidden layer and a softmax output layer). All our experiments are implemented in Python with Lasagne [3]. For reproducibility purposes, our code will be made available.

We compare our attack against the attack in [36]. Following the authors' code's original configuration,<sup>3</sup> we train 10 shadow models, and multiple attack models (one for each class).

As membership inference is a binary classification, we adopt precision and recall as our evaluation metric. Formally, let *TP*, *TN*, *FP*, and *FN* denote true positives, true negatives, false

<sup>&</sup>lt;sup>3</sup>https://github.com/csong27/membership-inference

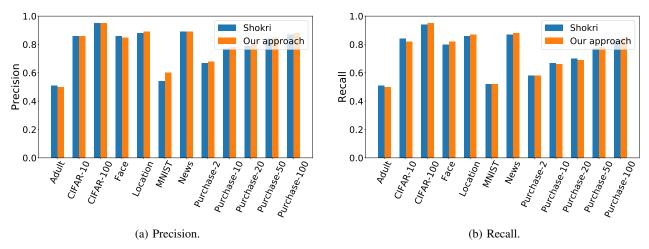


Fig. 1: Comparison of our approach with Shokri's using different datasets. The first figure compares the precision and the second figure compares the recall values for the different datasets.

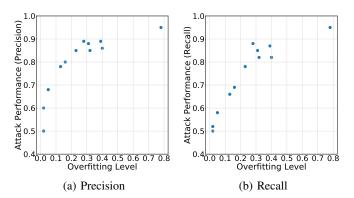


Fig. 2: The relation between the overfitting level (x-axis) and membership inference attack performance (y-axis), (a) precision, (b) recall.

positives and false negatives, respectively. Precision and recall are defined as the following.

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

Moreover, we use accuracy to measure the target model's prediction performance.

Results. Figure 1 depicts the first adversary's performance. In general, we observe that our attack has a very similar membership inference as the one in [36]. For instance, our attack on the CIFAR-100 dataset achieves 0.95 for both precision and recall, while the attack in [36] has a 0.95 precision and 0.94 recall. More interestingly, on multiple datasets, our attack even performs better. In particular, we have around 10% performance gain on the MNIST dataset for precision with a very similar recall.

We also observe variations of the attack performance on different datasets. We relate this to the overfitting level of ML models on different datasets. We quantify the overfitting level of a target model as the difference between its prediction accuracy on the training set and testing set. Through investigation, we discover that if an ML model is more overfitted, then it is more vulnerable to membership inference attack. For instance, our attack on the Adult dataset achieves a relatively weak performance (around 0.5 precision and recall), and there is only a 2% difference between the target model's training and testing accuracy. On the other hand, the membership inference attack achieves a 0.95 precision and recall on the CIFAR-100 dataset. Meanwhile, the corresponding target model provides a much better prediction performance on the training set than on the testing set, i.e., 78% difference. Figure 2 depicts the relation between the overfitting level and attack performance.

Another factor which also affects our attack's performance is the number of classes in the dataset. Both CIFAR-10 and CIFAR-100 are images datasets with different number of classes (10 vs 100), it turns out that our membership inference attack on the latter dataset achieves a 10% better performance than on the former dataset. The similar results can be observed from all the Purchase datasets.

For our attacks, we use only the 3 highest posterior probabilities (in descending order) as the features for our attack. We test the effect of using more posteriors on the CIFAR-100, Location, MNIST and News datasets. The result in Figure 3 shows that this factor does not have a significant effect on the attack's performance for most of the datasets. Generally, 3 posteriors achieves the best performance, especially on the MNIST dataset.

A major difference between our attack and the one in [36] is the number of shadow models used for the attack. We further study this factor's influences on the attack's performance. Figure 4 shows the corresponding results on the Purchase-100, Purchase-50, Adult and Location datasets. By varying the

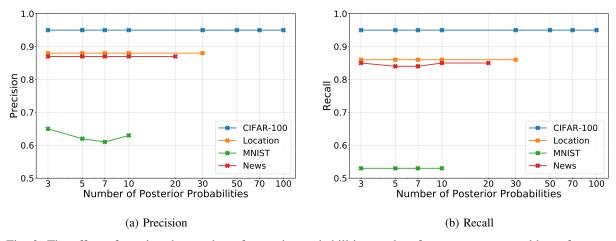


Fig. 3: The effect of varying the number of posterior probabilities used as features on our attack's performance.

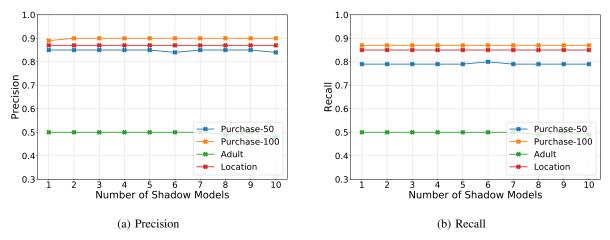


Fig. 4: The effect of varying the number of shadow models used on our attack's performance.

number of shadow models from 1 to 10, we do not observe a significant performance difference for both precision and recall. This means increasing the number of shadow models does not improve the attack's performance.

#### **Evaluation on MLaaS**

All the above experiments are conducted in a local setting. We further evaluate our attack with a real-world MLaaS. In particular, we use Google's MLaaS, namely Google Cloud Prediction API. Under this service, a user can upload her own data and get the black-box ML API trained by Google. A user cannot choose which classifier to use, so as the corresponding structures and parameters. We perform our attack following the same methodology in Section III-B. We construct both target model and shadow model with Google's MLaaS, and build our attack model locally.

We use the Purchase-100 and Location datasets for evaluation. We observe that the attack's performance is even stronger than our previous local evaluation. For the Purchase-100

dataset, our attack on Google's MLaaS has a 0.90 precision and a 0.89 recall, while our local evaluation has a 0.89 precision and a 0.86 recall. For the Location dataset, the precision is 0.89 and the recall is 0.86, which is almost similar to our local evaluation (0.88 precision and 0.86 recall).

#### C. Target Model Structure

One of the above attack's assumptions is that the adversary knows the target model's algorithm and hyperparameters, and implements her shadow model in the same way. Next, we show how to relax this assumption. We first concentrate on target model's hyperparameters, then, the type of classifiers it uses.

# Hyperparameter

We assume that the adversary knows the target model is a neural network, but does not know the details of the model. We first train the shadow model with half of the training parameters of the target model. More precisely, we reduce the batch size, hidden units and regularization parameters to half. On the Purchase-100 dataset, our attack achieves a 0.86 precision and 0.83 recall, which is almost the same as the one reported in Figure 1. We also revert the settings to

<sup>&</sup>lt;sup>4</sup> Google's Cloud prediction API is deprecated on April 20th, 2018 (https://cloud.google.com/prediction/), the new MLaaS provided by Google is called Cloud Machine Learning Engine.

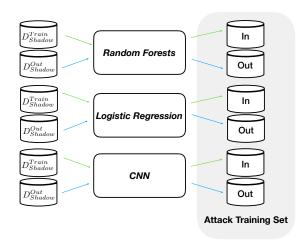


Fig. 5: The architecture of the combining attack on generating data for training the attack model.

test the case when the shadow model has double number of parameters than the target model. The performance drops a bit to 0.82 precision and 0.80 recall, but it is still quite close to our original attack. We also perform evaluation over other datasets, and observe the same results. This evaluation shows the flexibility of the membership inference attack: an adversary with no knowledge about the model's hyperparameters can still get good performance.

# Target Model's Algorithm

We further assume that the adversary has no knowledge on what classification algorithm is adopted by the target model. In this setting, our first attempt is to use any classifier, such as random forests, as the shadow model, and attack the target model that is (very likely to be) different from the shadow model, such as CNN. However, the experimental results are not very promising.

To improve the attack with no knowledge of the target model, we construct a set of ML models, each with a different classification algorithm, and combine them together as one shadow model. Each single single ML model is referred to as a *sub-shadow model*. This is achievable as the types of classifiers are limited. This attack, also referred to as the combining attack, can learn the behavior of the different classifiers and therefore can attack an unknown target model based on the assumption that there is a sub-shadow model which is trained with the same classifier as the target model.

Concretely, we use the same methodology as in Section III-B to train multiple sub-shadow models as illustrated in Figure 5, with each sub-shadow model being a different classifier. The data each sub-shadow model is trained on is the same. All the generated features by all sub-shadow models are stacked together, i.e., the attack model  $\mathcal A$  is trained with a larger dataset. In this new dataset, each data point in  $\mathcal D_{Shadow}$  is represented multiple times with respect to different sub-shadow models' outputs.

We run a local experiment on the Purchase-100 dataset

Classifier	With target model structure		Combining attack	
	Precision	Recall	Precision	Recall
Multilayer perceptron	0.86	0.86	0.88	0.85
Logistic regression	0.90	0.88	0.90	0.88
Random forests	1.0	1.0	0.94	0.93

TABLE II: The performance of building an attack model for every classifier versus a single attack model for all classifiers.

to evaluate this attack. Three popular ML classifiers, i.e., multilayer perceptron, random forests (with 1,000 tree) and logistic regression are adopted as sub-shadow models. The target model for the Purchase-100 dataset is a multilayer perceptron. For a more complete comparison, we further build another two target models that are based on random forests and logistics regression, respectively, and use the same algorithm to build a single shadow model as in Section III-B. Table II depicts the result. As we can see, our combing attack has a similar performance, when target model is multilayer perceptron and logistics regression. Meanwhile, the attack's performance is relatively worse is when the target model is random forests.

In conclusion, we show that our combining attack can free the attacker from knowing the target model, which further enlarges the scope of membership inference attack.

# IV. TOWARDS DATA INDEPENDENT MEMBERSHIP INFERENCE ATTACKS (ADVERSARY 2)

In this section, we relax the assumption on the adversary having a dataset that comes from the same distribution as the target model's dataset.

We start by explaining the threat model, then describe the adversary's attack methodology. In the end, we present a comprehensive experimental evaluation.

# A. Threat Model

Different from the threat model in Section III, we remove the assumption that the adversary has a dataset  $\mathcal{D}_{Shadow}$  that comes from the same distribution as the training data for the target model. This largely reduces the ability of the adversary. For this scenario, the authors of [36] propose to query the target model multiple times to generate synthetic data to train the shadow model. However, this approach can only be applied when the dataset is assembled with binary features. In contrast, our approach can be applied to attack ML models trained on any kind of data.

### B. Methodology

The strategy of the second adversary is very similar to the one of the first adversary. The only difference is that the second adversary utilizes an existing dataset that comes from a different distribution than the target model's training data to train her shadow model. We refer this attack as the *data transferring attack*.

<sup>&</sup>lt;sup>5</sup>We confirm this with the authors of [36].

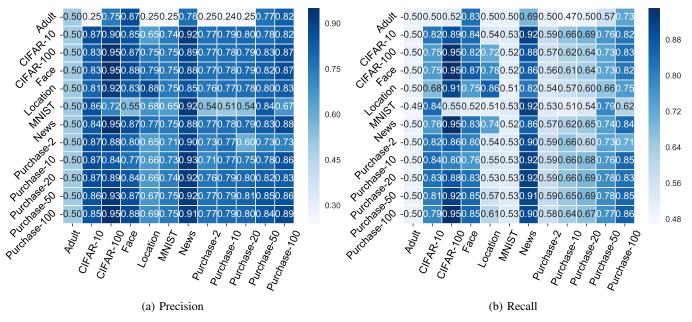


Fig. 6: The performance of our data transferring attack. The x-axis represents the dataset being attacked i.e., the dataset the target model is trained on. The y-axis represents the dataset used for training the shadow model.

Based on the methodology, the shadow model here is not to mimic the target model's behavior, but only to summarize the membership status of a data point in the training set of a machine learning model. As only the three largest posteriors are used for the attack model, we can also neglect the effect brought by datasets with different number of classes.<sup>6</sup>

### C. Evaluation

**Experimental Setup.** We use the same attack model and shadow model setup as presented in Section III, such as data splitting strategy and the types of ML models used. We perform the data transferring attack over all datasets. For evaluation metric, we again use precision and recall.

**Results.** Figure 6 depicts the data transferring attack's performance. The x-axis represents the dataset being attacked, i.e., the dataset the target model is trained on, and the y-axis represents the dataset used for training the shadow model. Compared to the first adversary the attack results of which are listed at the diagonal of Figure 6, the second adversary in multiple cases obtains similar performances. For instance, using the Face dataset to attack the CIFAR-100 dataset results in 0.95 for both precision and recall, while the corresponding results for the first adversary are also 0.95 for both metrics. In several cases, we even observe a performance improvement over the first adversary. For instance, using the Purchase-10 dataset to attack the News dataset achieves a 0.93 precision and 0.92 recall, while the first adversary has a 0.88 precision and 0.86 recall. More interestingly, in many cases, datasets

from different domains can effectively attack each other, e.g., the News dataset and the CIFAR-100 dataset.

For the first adversary, we relax the assumption on shadow model design. This relaxation also applies for the second adversary, as the shadow model and target model are trained with different datasets. For instance, the Purchase-20 dataset is trained with a multilayer perceptron while the CIFAR-100 dataset is trained with a CNN.

One of the major advantages of our data transferring attack lies in its applicability. The synthetic data generation strategy in [36] can not be applied to dataset of any kind, but those with binary features. Even for dataset of binary features, a single synthetic data point requires 156 queries<sup>7</sup> to the target model. Given the large dataset quantity needed for ML models, and MLaaS's pay-per-query business model, this is very costly. Moreover, sending a large amount of queries to an MLaaS API would alert the server, which may not even allow the adversary to finish her synthetic data generation process. Meanwhile, our data transferring attack does not have any of the above constrains.

# D. Evaluation On MLaaS

We also evaluate our data transferring attack on Google's MLaaS. Concretely, we use a shadow model trained on the Location dataset to attack a target model trained on the Purchase-100 dataset. Both models are trained with Google's MLaaS. Experimental results show that we achieve a 0.8 precision and 0.78 recall. We further flip the shadow and target model, i.e., Purchase-100 dataset attacking Location dataset, the membership inference result is also very strong with a 0.87 precision and a 0.82 recall. This shows that our data

<sup>&</sup>lt;sup>6</sup>When the target model is a binary classifier, we take the largest 2 posteriors for our attack.

<sup>&</sup>lt;sup>7</sup>This is the number reported in [36]

transferring attack is not only effective in the local setting, but also in the real-world MLaaS setting.

# V. MODEL AND DATA INDEPENDENT MEMBERSHIP INFERENCE ATTACK WITHOUT TRAINING (ADVERSARY 3)

In this section, we present our third adversary, who does not need to train any shadow model and does not assume knowledge of model or data distribution. We start with the threat model description. Then, we list the attack methodology. In the end, we present the evaluation results.

#### A. Threat Model

We relax the assumption that the adversary needs to train any shadow model to perform her attack. All she could rely on is the target model's output posteriors  $\mathcal{M}(\mathcal{X}_{Target})$  after querying her target data point  $\mathcal{X}_{Target}$ .

#### B. Methodology

The attack model for the third adversary is modeled as an unsupervised binary classification. Concretely, the adversary first obtains  $\mathcal{M}(\mathcal{X}_{Target})$ . Then, she extracts the highest posterior and compare whether this maximum is above a certain threshold. If the answer is yes, then she predicts the data point is in the training set of the target model and vice versa. The reason we pick maximum as the feature follows the reasoning that an ML model is more confident, i.e., one posterior is much higher than others, when facing a data point that it was trained on. In another words, the maximal posterior of a member data point is much higher than the one of a non-member data point.

#### C. Evaluation

**Experimental Setup.** We evaluate the third adversary over all 8 datasets. Note that we do not need to split the dataset as the this adversary does not train any shadow model. Instead, we split each dataset by half, and use one part to train the target model and the others are left out as non-members.

To compare with the previous attacks' performances, we also pick a threshold which results in a similar recall as the first adversary's and report the corresponding precision. As our attack is unsupervised, we further adopt area under the ROC curve, also referred to as the AUC value, as the evaluation metric. Different from making a concrete prediction over a certain threshold, ROC curve plots the relation between false positive rate and true positive rate, over all possible thresholds. Larger AUC indicates stronger prediction. Note that AUC values have been adopted in many privacy attacks as well, such as [8], [16], [35].

**Results.** Table III depicts the third adversary's performance. As we can see, the third adversary also has a good performance, e.g., the attack achieves a 0.96 precision and 0.93 recall on the News dataset. Moreover, in some cases, our attack is comparable with the first adversary. For instance, our attack obtains 0.94 and 0.95 precision and recall, on the target model trained on the CIFAR-100 dataset, while the results for the first adversary is 0.95 for both precision and recall. Meanwhile, in

Dataset	Precision	Recall	Threshold
Adult	0.5	0.5	0.92
CIFAR-10	0.81	0.82	1.0
CIFAR-100	0.94	0.95	0.98
Face	0.77	0.77	0.97
Location	0.84	0.89	0.91
MNIST	0.5	0.54	1.0
News	0.96	0.93	0.9
Purchase-2	0.5	0.58	1.0
Purchase-10	0.54	0.67	1.0
Purchase-20	0.58	0.69	1.0
Purchase-50	0.71	0.78	0.99
Purchase-100	0.83	0.85	0.99

TABLE III: The performance of our third attack on all datasets.

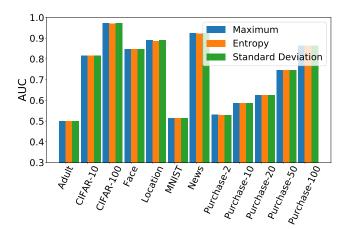


Fig. 7: The attack performance under different statistical metrics.

multiple cases, the previous two adversaries indeed perform better than the third one, e.g., the second adversary has a 0.81 precision on attacking the Purchase-20 dataset, while the third adversary merely has 0.58 precision, given both adversaries obtain the same recall.

We choose the maximal posterior probability as our feature for this attack. We further test the effect of using other statistical metrics, such as standard deviation and entropy. In particular, the entropy of posteriors is defined as the following,

$$-\sum_{p_i \in \mathcal{Y}} p_i \log p_i$$

where  $p_i$  denotes the posterior for the *i*-th class. Different from maximum, we expect the entropy and standard deviation of the member data points to be smaller than those of the non-members. Figure 7 compares the AUC (area under the ROC curve) for using entropy, standard deviation and maximum. As we can see, the AUC score is almost the same for all the features, i.e., standard deviation and entropy can also be used as features for membership inference attack.

From the above analysis, we show that even a weak adversary can achieve a very promising membership inference, this further demonstrates the severe membership privacy risks of ML models.

Threshold	Purchase-100		Location	
	Precision	Recall	Precision	Recall
0.5	0.66	1.0	0.78	0.99
0.6	0.70	1.0	0.83	0.88
0.65	0.74	1.0	0.85	0.70
0.7	0.77	1.0	0.85	0.47
0.8	0.78	0.80	0.76	0.11

TABLE IV: The performance of our third attack (with different thresholds) on target models trained on Google's MLaaS for Purchase-100 and Location datasets.

#### D. Evaluation On MLaaS

We further evaluate the third adversary's performance on Google's MLaaS. We use two datasets, including Purchase-100 and Location, for evaluation. Table IV shows the results. In general, the third attack still has a very good performance, i.e., precision and recall on the Location dataset are above 0.8 (when threshold is above 0.6). Besides, we also observe some interesting differences between Google's MLaaS and our local experiments. On the Location dataset, the attack on Google achieves a similar performance (0.83 precision and 0.88 recall) as our local evaluation (0.84 precision and 0.89 recall). However, we notice the corresponding threshold is quite different (0.6 vs 0.91). This is due to the different model structures between our local setup and Google's MLaaS.

#### VI. DEFENSE

In the previous sections, we have demonstrated the severity of membership inference attacks against machine learning models. To remedy the situation, we propose two defense techniques in this section.

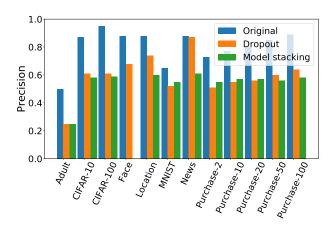
The effectiveness of our membership inference attacks is due to the overfitting nature of ML models. Therefore, our defense techniques are designed to increase ML models' generalizability, i.e., prevent them from being overfitted.

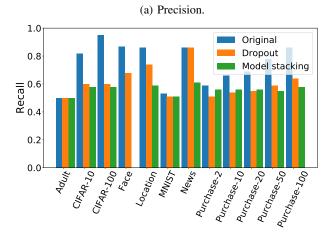
Our first technique is dropout, which is designed for neural network based classifiers. Our second technique is model stacking. This mechanism is suitable for all ML models, independent of the classifier used to build them.

As the first adversary (with one shadow model which shares the same structure as the target model) in general provides the best attack performance, we concentrate on the effectiveness of our defense with respect this adversary in this section. To fully assess the attack's performance under our defense, we further assume the attacker knows the defense technique being implemented and builds her shadow model following the same defense technique.

# A. Dropout

**Methodology.** A fully connected neural network contains a large number of parameters, which is prone to overfitting. Dropout is a very effective method to reduce overfitting based on empirical evidences. Dropout is executed by randomly deleting in each training iteration a fixed proportion (dropout ratio) of edges in a fully connected neural network model. We





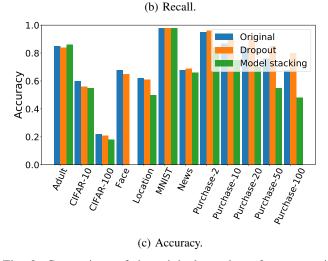


Fig. 8: Comparison of the original attack performance with both of the defense strategies.

apply dropout for both the input layer and the hidden layer (see Section III) of the target model. We set our default dropout ratio to be 0.5 following [38].

# Evaluation.

We test dropout on all datasets. Figure 8a and Figure 8b compare the performance of the attack before and after the

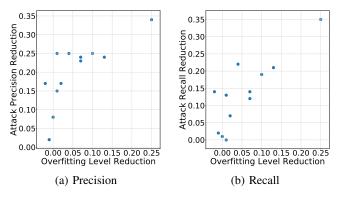


Fig. 9: The relation between the reduction of the overfitting level (x-axis) and the reduction of the membership inference attack performance (y-axis) when applying dropout as the defense mechanism.

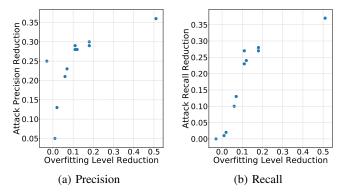


Fig. 10: The relation between the reduction of the overfitting level (x-axis) and the reduction of the membership inference attack performance (y-axis) when applying model stacking as the defense mechanism.

dropout defense. As we can see, the attack performance is reduced in almost all cases. For instance, the precision of the attack on the Purchase-100 dataset drops from 0.89 to 0.64, while the recall drops from 0.86 to 0.63. In another example, the precision and recall on the CIFAR-100 dataset drop by more than 30%. There is only one case where dropout does not help much, i.e., the target model trained on the News dataset.

Figure 8c further shows that original target model's performance (prediction accuracy) after dropout has been applied. We observe that, on more than half of the datasets, the dropout mechanism even increases the target model's prediction performance. For instance, on the Purchase-50 dataset, the target model's accuracy increases from 0.72 to 0.83 after dropout has been applied.

Figure 9 plots the relation between the overfitting level (see Section III) reduction and the attack performance reduction after dropout has been applied. The overfitting level reduction is calculated as the original target model's overfitting level subtracting the dropout-defended target model's overfitting level. As we can see, more effective dropout which results

in larger reduction on overfitting level leads to better defense against membership inference attacks. These results support the argument in [36] that overfitting is the common enemy of membership privacy risks and target model's performance.

So far, we use 0.5 as the dropout ratio, we further test the effect of varying the dropout ratio of our defense. We try different dropout ratios on both input and fully connected layes while monitoring the results on the attack's performance and the target model's accuracy. Figure 11 shows the result on the Purchase-100 dataset. We first observe that higher dropout ratio leads to lower attack performance. For instance, drop ratio 0.75 on both layers reduces the attack's performance to 0.53 precision and recall. On the other hand, both large and small dropout ratio result in the low performance of the target model. This means, the accuracy of the target model is the strongest when dropout ratio is mediate. In conclusion, 0.5 dropout ratio is a suitable choice for this defense technique.

# B. Model Stacking

**Methodology.** The dropout technique is effective, however, it can only be applied when the target model is a neural network. To bypass this limitation, we present our second defense technique, namely model stacking, which works independently of the used ML classifier.

The intuition behind this defense is that if different parts of the target model are trained with different subsets of data, then the complete model should be less prone to overfitting. This can be achieved by using ensemble learning

Ensemble learning is an ML paradigm, where instead of using a single ML model, multiple ML models are combined to construct the final model. There are different approaches to combine these ML models, such as bagging or boosting. For our defense, we focus on stacking the models in a hierarchical way. Figure 12 shows a sample architecture for model stacking.

Concretely, we organize target model in two layers over three ML models. The first layer consists of two ML models (the first and second model). The second layer consists of a single ML model (the third model). As shown in Figure 12, to get the model's output on some data point  $\mathcal{X}$ , we first apply  $\mathcal{X}$  on each of the first two models to have their posteriors  $\mathcal{Y}^1$  and  $\mathcal{Y}^2$ . We then concatenate both outputs, i.e.,  $\mathcal{Y}^1||\mathcal{Y}^2$ , and apply the result to the third model which predicts the final output  $\mathcal{Y}$ .

To maximize the prevention of overfitting, we train the three different models on disjoint sets of data. The intuition behind is that there is no data point seen by more than one model during training.

**Evaluation.** For our evaluation, we use multilayer perceptron or CNN as the first model, random forests as the second model and logistic regression as the third model. We pick this architecture to test the effect of using different machine learning models in the different layers. However, a different selection of models also suffice.



Fig. 11: The performance of our dropout defense using different dropout ratios in different layers. The x-axis represents the input layer, and the y-axis represents the hidden layer.

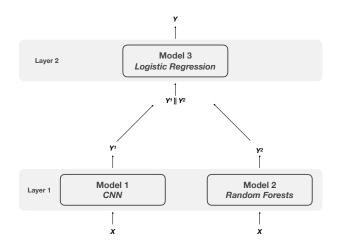


Fig. 12: The architecture of model stacking.

We build both target and shadow models as described, i.e., each model consists of 3 different ML models. To train our target and shadow models, we split the data into 12 disjoint sets. We use the first 6 sets to train and test our target model, and the remaining 6 to train and test the shadow model.

We evaluate this technique on all datasets but the Face dataset as it does not have enough data to have a meaningful result in this setting. Figure 8 shows the result. As we can see, model stacking reduces the attack's performance significantly in all cases. For instance, on the CIFAR-10 dataset, model stacking reduces the attack's precision and recall by more than 30%. Moreover, compared to the dropout defense, model stacking is more effective in some cases. Dropout does not change the attack's performance on the News dataset while model stacking reduces the corresponding precision and recall by 28%. The same result can be observed on the Location dataset. Meanwhile, model stacking affects target model's accuracy more than dropout in multiple cases, e.g., the Purchase datasets. The relation between overfitting level reduction and attack performance reduction for the model stacking technique is very similar to the one for the dropout technique, the results are depicted in Figure 10.

In conclusion, if the target model is not based on neural networks, model stacking is an effective defense technique. Otherwise, dropout is sufficient to mitigate the membership privacy risks.

#### VII. RELATED WORK

**Membership Inference.** Membership inference attack has been successfully performed in many different data domains, ranging form biomedical data [7], [20] to mobility traces [35].

Homer et al. [20] propose the first membership inference attack on genomic data. This attack relies on the  $L_1$  distance between the allele frequencies and the victim's genomic data. Backes et al. [7] generalize this attack to other types of biomedical data. The attack of [7] is based on the likelihoodratio test, the authors theoretically prove its limit on attack success and demonstrate its effectiveness on a large-scale MicroRNA dataset. More recently, the authors of [35] have shown that people's aggregate mobility traces are also prone to membership inference attack. They first formalize membership inference as a distinguishability game. Then, they implement the attack with machine learning classifiers. Largescale evaluation on two real-world datasets has demonstrated their attack's effectiveness. Moreover, the authors of [35] show their framework can easily incorporate different defense mechanisms, such as differential privacy, to allow a comprehensive evaluation of membership inference risks.

Membership Inference Against Machine Learning. Shokri et al. [36] present the first membership inference attack against machine learning models. The key contribution of this work is the proposal of shadow model training, which aims at mimicking the target model's behavior to generate training data for the attack model.

The first adversary in the current paper follows a very similar setting as in [36]. We have shown that one shadow model and one attack model are sufficient to achieve an effective attack compared to the proposal of multiple shadow models and attack models in [36]. Moreover, we show that data transferring attack can bypass the expensive synthetic data generation scheme in [36], and achieves a very similar membership inference attack. Another major contribution of

our paper is the two effective defense mechanisms, such as dropout and model stacking.

Following [36], many recent works have studied membership inference against machine learning from different angles [26], [27], [45].

Attacks Against Machine Learning. Besides membership inference, there exist multiple other types of attacks against ML models. Fredrikson et al. [16] present the model inversion attack in biomedical data setting. In this scenario, an attacker aims to infer the missing attributes of her victim, relying on the output of a trained ML model. The authors of [15] later generalize the model inversion attack to a broader scenario. For instance, they show that it is feasible for an attacker to reconstruct a recognizable face of her victim with model inversion.

Tramèr et al. [40] propose another attack on ML models, namely model extraction attack. This attack aims at stealing the ML model, i.e., the model's learned parameters, through the output of MLaaS API itself. They first propose an equationsolving attack, where an attacker queries MLaaS API multiple times and use the output posteriors to construct a set of equations. By solving these equations, the attacker can obtain the weight of the ML model. The authors of [40] further propose a path-finding algorithm, which is the first practical method to steal decision trees. In the end, Tramèr et al. show that even ML models which do not provide prediction posteriors but only prediction class labels can still be stolen with retraining strategies, such as active learning. It is worth noting that due to the effectiveness of the model extraction attack, we do not consider hiding posteriors as one valid defense mechanism in this paper.

Another major family of attacks against machine learning is adversarial examples [12], [24], [32]–[34], [39], [41], [42]. In this setting, an attacker adds a controlled amount of noise to a data point which aims to fool a trained ML model to misclassify the data point. Adversarial examples can cause severe risks in multiple domains, such as autonomous driving, and voice recognition. On the other hand, researchers have recently shown that adversarial examples can also help to protect users' privacy in online social networks [22], [31], [46].

Privacy Preserving Machine Learning. Another relevant line of work is privacy-preserving machine learning [6], [9]–[11], [13], [14], [17], [18], [25], [29]. Mohassel and Zhang [29] present efficient protocols for training linear regression, logistic regression, neural networks in a privacy-preserving manner. Their protocols fall in the two-server mode where data is distributed over two non-colluding servers. The authors use two-party computation to implement these protocols. The authors of [10] propose a protocol for secure aggregation over high-dimensional data, which is a key component for distributed machine learning. The protocol is also based on multi-party computation, and the authors show that its security under both honest-but-curious and active adversary setting. Large-scale evaluation demonstrates the efficiency of this protocol.

Besides privacy-preserving model training, other works study privacy-preserving classification. Bost et al. [11] design three protocols based on homomorphic encryption. They concentrate on three ML classifiers, such as hyperplane decision, Naive Bayes, and decision trees, and show that their protocols can be efficiently executed. Based on [11], Backes et al. [6] build a privacy-preserving random forests classifier for medical diagnosis.

Besides the above, other recent works on security and privacy in machine learning include [21], [28], [37]

#### VIII. CONCLUSION

Machine learning has been widely adopted in the real world applications and training data is a key factor that drives current progress. However, ML models suffer from membership privacy risks. The existing membership inference attacks have shown effective performance, however, their applicability is limited due to the strong assumption on the threat model.

In this paper, we gradually relax these assumptions towards a more broadly applicable attack scenario. We propose three different types of adversaries which step by step relax assumption on the shadow model's design, knowledge of target model and training data distribution.

Our **first adversary** utilizes only one shadow model. Extensive experiments show that this attack achieves a very similar performance as the previous one which utilizes multiple shadow models. As shadow models are established through MLaaS, our proposal notably reduces the cost of conducting the attack. We further perform the combining attack which does not require knowledge of the type of classifiers used in the target model.

The attack assumption is further relaxed for our **second adversary**, i.e., she does not have a dataset that comes from the same distribution as the training data of the target model. This is a more realistic attack scenario, however, the previously proposed synthetic data generation solution can only be applied in specific cases. In contrast, we propose data transferring attacks, where the adversary utilizes another dataset to build a shadow model and generates the corresponding data to attack the target model. Through experiments, we have discovered that data transferring attack also achieves strong membership inference while being more general, realistic and widely applicable.

The **third adversary** has a minimal set of assumptions, i.e., she does not need to construct any shadow model and her attack is performed in an unsupervised way. We show that even in such a simple setting, membership inference is still effective.

Our **evaluation** is the comprehensive so far and fully demonstrates the severe threat of membership privacy in ML models under those generalized conditions on 8 diverse dataset.

To remedy the situation, we propose **two defense mechanisms**. As we show the connection between overfitting and sensitivity to membership inference attacks, investigate techniques that are designed to reduce overfitting. The first

one, namely dropout, randomly deletes a certain proportion of edges in each training iteration in a fully connected neural network, while the second approach, namely model stacking, organizes multiple ML models in a hierarchical way. Extensive evaluation shows that indeed our defense techniques are able to largely reduce membership inference attack's performance, while maintaining a high-level utility, i.e., the target model's prediction accuracy.

#### REFERENCES

- [1] "Cifar," https://www.cs.toronto.edu/~kriz/cifar.html. 2, 3
- [2] "Labeled Faces in the Wild: A Database for Studying Face Recognition in Unconstrained Environments," http://vis-www.cs.umass.edu/lfw/. 3
- [3] "Lasagne," http://lasagne.readthedocs.io. 4
- [4] "Mnist." 3
- [5] "UCI Machine Learning Repository: Data Sets," http://archive.ics.uci. edu/ml. 3
- [6] M. Backes, P. Berrang, M. Bieg, R. Eils, C. Herrmann, M. Humbert, and I. Lehmann, "Identifying Personal DNA Methylation Profiles by Genotype Inference," in *Proceedings of the 38th IEEE Symposium on Security and Privacy (S&P)*. IEEE, 2017, pp. 957–976. 13
- [7] M. Backes, P. Berrang, M. Humbert, and P. Manoharan, "Membership Privacy in MicroRNA-based Studies," in *Proceedings of the 24th ACM SIGSAC Conference on Computer and Communications Security (CCS)*. ACM, 2016, pp. 319–330. 1, 12
- [8] M. Backes, M. Humbert, J. Pang, and Y. Zhang, "walk2friends: Inferring Social Links from Mobility Profiles," in *Proceedings of the 24th ACM SIGSAC Conference on Computer and Communications Security (CCS)*. ACM, 2017, pp. 1943–1957. 9
- [9] M. Barni, P. Failla, R. Lazzeretti, A.-R. Sadeghi, and T. Schneider, "Privacy-Preserving ECG Classification With Branching Programs and Neural Networks," *IEEE Transactions on Information Forensics and Security*, vol. 6, no. 2, pp. 452–468, 2011. 13
- [10] K. Bonawitz, V. Ivanov, B. Kreuter, A. Marcedone, H. B. McMahan, S. Patel, D. Ramage, A. Segal, and K. Seth, "Practical Secure Aggregation for Privacy-Preserving Machine Learning," in *Proceedings of* the 24th ACM SIGSAC Conference on Computer and Communications Security (CCS). ACM, 2017, pp. 1175–1191. 13
- [11] R. Bost, R. A. Popa, S. Tu, and S. Goldwasser, "Machine Learning Classification over Encrypted Data," in *Proceedings of the 22th Network* and Distributed System Security Symposium (NDSS), 2015. 13
- [12] N. Carlini and D. Wagner, "Towards Evaluating the Robustness of Neural Networks," in *Proceedings of the 38th IEEE Symposium on Security and Privacy (S&P)*. IEEE, 2017, pp. 39–57. 13
- [13] Z. Erkin, M. Franz, J. Guajardo, S. Katzenbeisser, I. Lagendijk, and T. Toft, "Privacy-Preserving Face Recognition," in *Proceedings of 9th International Symposium on Privacy Enhancing Technologies Symposium (PETS)*. Springer, 2009, pp. 235–253. 13
- [14] D. Evans, Y. Huang, J. Katz, and L. Malka, "Efficient Privacy-Preserving Biometric Identification," in *Proceedings of the 17th Network and Distributed System Security Symposium (NDSS)*, 2011. 13
- [15] M. Fredrikson, S. Jha, and T. Ristenpart, "Model Inversion Attacks That Exploit Confidence Information and Basic Countermeasures," in Proceedings of the 22nd ACM SIGSAC Conference on Computer and Communications Security (CCS). ACM, 2015, pp. 1322–1333. 1, 13
- [16] M. Fredrikson, E. Lantz, S. Jha, S. Lin, D. Page, and T. Ristenpart, "Privacy in Pharmacogenetics: An End-to-End Case Study of Personalized Warfarin Dosing," in *Proceedings of the 23rd USENIX Security Symposium (USENIX Security)*. USENIX, 2014, pp. 17–32. 9, 13
- [17] A. Gascón, P. Schoppmann, B. Balle, M. Raykova, J. Doerner, S. Zahur, and D. Evans, "Privacy-Preserving Distributed Linear Regression on High-Dimensional Data," *Proceedings on Privacy Enhancing Technologies*, vol. 2017, no. 1, pp. 345–364, 2017. 13
- [18] R. Gilad-Bachrach, N. Dowlin, K. Laine, K. E. Lauter, M. Naehrig, and J. Wernsing, "CryptoNets: Applying Neural Networks to Encrypted Data with High Throughput and Accuracy," in *Proceedings of the 33rd International Conference on Machine Learning (ICML)*, 2016, pp. 201–210. 13
- [19] I. Goodfellow, J. Shlens, and C. Szegedy, "Explaining and Harnessing Adversarial Examples," in *Proceedings of the 2015 International Con*ference on Learning Representations (ICLR), 2015.

- [20] N. Homer, S. Szelinger, M. Redman, D. Duggan, W. Tembe, J. Muehling, J. V. Pearson, D. A. Stephan, S. F. Nelson, and D. W. Craig, "Resolving Individuals Contributing Trace Amounts of DNA to Highly Complex Mixtures Using High-Density SNP Genotyping Microarrays," PLOS Genetics, vol. 4, no. 8, pp. 1–9, 2008. 12
- [21] T. Hunt, C. Song, R. Shokri, V. Shmatikov, and E. Witchel, "Chiron: Privacy-preserving Machine Learning as a Service," arXiv:1803.05961, 2018. 13
- [22] J. Jia and N. Z. Gong, "AttriGuard: A Practical Defense Against Attribute Inference Attacks via Adversarial Machine Learning," in Proceedings of the 27th USENIX Security Symposium (USENIX Security). USENIX, 2018. 13
- [23] K. Lang, "Newsweeder: Learning to filter netnews," in *Proceedings of the 12th International Conference on Machine Learning (ICML)*, 2, 3
- [24] B. Li and Y. Vorobeychik, "Scalable Optimization of Randomized Operational Decisions in Adversarial Classification Settings," in Proceedings of the 18th International Conference on Artificial Intelligence and Statistics (AISTATS). PMLR, 2015, pp. 599–607.
- [25] J. Liu, M. Juuti, Y. Lu, and N. Asokan, "Oblivious Neural Network Predictions via MiniONN Transformations," in *Proceedings of the 24th ACM SIGSAC Conference on Computer and Communications Security* (CCS). ACM, 2017, pp. 619–631. 13
- [26] Y. Long, V. Bindschaedler, and C. A. Gunter, "Towards Measuring Membership Privacy," arXiv:1712.09136, 2017. 12
- [27] Y. Long, V. Bindschaedler, L. Wang, D. Bu, X. Wang, H. Tang, C. A. Gunter, and K. Chen, "Understanding Membership Inferences on Well-Generalized Learning Models," arXiv:1802.04889, 2018. 12
- [28] L. Melis, C. Song, E. D. Cristofaro, and V. Shmatikov, "Inference Attacks Against Collaborative Learning," arXiv:1805.04049, 2018. 13
- [29] P. Mohassel and Y. Zhang, "SecureML: A System for Scalable Privacy-Preserving Machine Learning," in *Proceedings of the 38th Symposium on Security and Privacy (S&P)*. IEEE, 2017, pp. 19–38. 13
- [30] S. J. Oh, M. Augustin, B. Schiele, and M. Fritz, "Towards Reverse-Engineering Black-Box Neural Networks," in *Proceedings of the 2018 International Conference on Learning Representations (ICLR)*, 2018.
- [31] S. J. Oh, M. Fritz, and B. Schiele, "Adversarial Image Perturbation for Privacy Protection – A Game Theory Perspective," in *Proceedings of the 2017 IEEE International Conference on Computer Vision (ICCV)*. IEEE, 2017, pp. 1491–1500. 13
- [32] N. Papernot, P. D. McDaniel, I. J. Goodfellow, S. Jha, Z. B. Celik, and A. Swami, "Practical Black-Box Attacks Against Machine Learning," in *Proceedings of the 2017 ACM on Asia Conference on Computer and Communications Security (ASIACCS)*. ACM, 2017, pp. 506–519. 13
- [33] N. Papernot, P. D. McDaniel, S. Jha, M. Fredrikson, Z. B. Celik, and A. Swami, "The Limitations of Deep Learning in Adversarial Settings," in *Proceedings of the 1st IEEE European Symposium on Security and Privacy (Euro S&P)*. IEEE, 2015. 13
- [34] N. Papernot, P. D. McDaniel, A. Swami, and R. E. Harang, "Crafting Adversarial Input Sequences for Recurrent Neural Networks," in *Proceedings of the 2016 Military Communications Conference (MILCOM)*. IEEE, 2016, pp. 49–54. 13
- [35] A. Pyrgelis, C. Troncoso, and E. D. Cristofaro, "Knock Knock, Who's There? Membership Inference on Aggregate Location Data," in *Proceedings of the 25th Network and Distributed System Security Symposium* (NDSS), 2018. 1, 9, 12
- [36] R. Shokri, M. Stronati, C. Song, and V. Shmatikov, "Membership Inference Attacks Against Machine Learning Models," in *Proceedings* of the 38th IEEE Symposium on Security and Privacy (S&P). IEEE, 2017, pp. 3–18. 1, 2, 3, 4, 5, 7, 8, 11, 12
- [37] C. Song, T. Ristenpart, and V. Shmatikov, "Machine Learning Models that Remember Too Much," in *Proceedings of the 24th ACM SIGSAC Conference on Computer and Communications Security (CCS)*. ACM, 2017, pp. 587–601. 13
- [38] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: A Simple Way to Prevent Neural Networks from Overfitting," *Journal of Machine Learning Research*, vol. 15, no. 1, pp. 1929–1958, 2014. 10
- [39] F. Tramèr, A. Kurakin, N. Papernot, I. Goodfellow, D. Boneh, and P. McDaniel, "Ensemble Adversarial Training: Attacks and Defenses," in *Proceedings of the 2017 International Conference on Learning Representations (ICLR)*, 2017. 13
- [40] F. Tramèr, F. Zhang, A. Juels, M. K. Reiter, and T. Ristenpart, "Stealing Machine Learning Models via Prediction APIs," in *Proceedings of the* 25th USENIX Security Symposium (USENIX Security). USENIX, 2016, pp. 601–618. 1, 4, 13

- [41] Y. Vorobeychik and B. Li, "Optimal Randomized Classification in Adversarial Settings," in *Proceedings of the 2014 International Conference on Autonomous Agents and Multi-agent Systems (AAMAS)*. International Foundation for Autonomous Agents and Multiagent Systems, 2014, pp. 485–492. 13
- [42] W. Xu, D. Evans, and Y. Qi, "Feature Squeezing: Detecting Adversarial Examples in Deep Neural Networks," in *Proceedings of the 2018* Network and Distributed System Security Symposium (NDSS), 2018.
- [43] D. Yang, D. Zhang, L. Chen, and B. Qu, "NationTelescope: Monitoring and visualizing large-scale collective behavior in LBSNs," *Journal of Network and Computer Applications*, vol. 55, pp. 170–180, 2015.
- [44] D. Yang, D. Zhang, and B. Qu, "Participatory Cultural Mapping Based on Collective Behavior Data in Location-Based Social Networks," ACM Transactions on Intelligent Systems and Technology, vol. 7, no. 3, 2015.
- [45] S. Yeom, M. Fredrikson, and S. Jha, "The Unintended Consequences of Overfitting: Training Data Inference Attacks," arXiv:1709.01604, 2017.
- [46] Y. Zhang, M. Humbert, T. Rahman, C.-T. Li, J. Pang, and M. Backes, "Tagvisor: A Privacy Advisor for Sharing Hashtags," in *Proceedings of the 2018 Web Conference (WWW)*. ACM, 2018, pp. 287–296. 13