Reconciling Utility and Membership Privacy via Knowledge Distillation

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Abstract—Large capacity machine learning models are prone to membership inference attacks in which an adversary aims to infer whether a particular data sample is a member of the target model’s training dataset. Such membership inferences can lead to serious privacy violations as machine learning models are often trained using privacy-sensitive data such as medical records and controversial user opinions. Recently defenses against membership inference attacks are developed, in particular, based on differential privacy and adversarial regularization; unfortunately, such defenses highly impact the classification accuracy of the underlying machine learning models.

In this work, we present a new defense against membership inference attacks that preserves the utility of the target machine learning models significantly better than prior defenses. Our defense, called distillation for membership privacy (DMP), leverages knowledge distillation, a model compression technique, to train machine learning models with membership privacy. We use different techniques in the DMP to maximize its membership privacy with minor degradation to utility. DMP works effectively against the attackers with either a whitebox or blackbox access to the target model.

We evaluate DMP’s performance through extensive experiments on different deep neural networks and using various benchmark datasets. We show that DMP provides a significantly better tradeoff between inference resilience and classification performance than state-of-the-art membership inference defenses. For instance, a DMP-trained DenseNet provides a classification accuracy of 65.3% for a 54.4% (54.7%) blackbox (whitebox) membership inference attack accuracy, while an adversarially regularized DenseNet provides a classification accuracy of only 53.7% for a (much worse) 68.7% (69.5%) blackbox (whitebox) membership inference attack accuracy.

I. INTRODUCTION

The recent breakthroughs in deep learning and computing infrastructure, and the availability of large amounts of data have facilitated the adoption of machine learning (ML) in various domains ranging from recommendation systems to critical health-care management. The quality and quantity of data plays an instrumental role in the performance of machine learning models. Many companies providing ML-as-a-Service computing platforms (e.g., Google API, Amazon AWS, etc.) enable novice data owners to train ML models for different applications. Such models are then released either as a prediction API and accessed in a blackbox fashion, or as a set of parameters and accessed in a whitebox fashion.

The data used for training ML models often contains sensitive user information such as clinical records, location traces, personal photos, etc. [8], [9], [42]; therefore, an ML model trained using sensitive data may pose privacy threats to the data owners by leaking the sensitive training information. This has been demonstrated through various inference attacks [19], [39], [13], [18], [6], [27], most notably the membership inference attack [40] which is the focus of our work. An adversary with just a blackbox access to the target model can mount successful membership inference attack to determine if a given target sample belonged to the training set of the target model or not [30]. The attack performance significantly improves with a whitebox access to the trained models [31]. Membership inference attacks are able to distinguish the members from non-members by learning the behavior of the target model on member versus non-member inputs. They use different features of the target model for this classification, including the entropy of the predictions [40], the input loss, and gradients of the input loss with respect to the model parameters [31]. Membership inference attacks are particularly more impactful against large neural networks [40], [28], [13], [14], [8] because such models can better memorize their training samples.

Recent work has investigated several defenses against membership inference attacks. Early defenses suggest to limit information disclosure by releasing only a subset of the predictions [40], [13]. Such defenses, however, are shown to be ineffective against membership inference attacks [40] and cannot be deployed in the whitebox setting. Another major class of defense mechanisms adds noise to gradients or outputs of the model to provide differential privacy (DP) guarantees [33], [3], [5], [7], [35]. These defenses aim to protect privacy of any training dataset (but not the specific training dataset used to train a given model). Therefore, they add very large amount of noise which significantly hurts the utility of the trained models [45], [33]. Finally, recent work [30] suggests to use adversarial regularization defense targeted to defeat membership leakage by improving the target model’s generalization. Such defenses also suffer from a significant utility loss, and, as we empirically show, cannot provide acceptable trade-offs between membership privacy and utility when evaluated against whitebox or blackbox membership inference attacks [31]. In summary, the existing defenses against membership inference attacks offer poor tradeoffs between model utility and membership privacy.

Our contributions. In this work, we demonstrate a defense against membership inference attacks that provides...
a significantly better tradeoff between privacy and utility compared to the existing defenses. That is, our defense can reduce membership leakage with very little degradation to the classification performance of the target model. Also, unlike some of the previous defenses, our defense works against both blackbox and whitebox adversaries. We call our defense mechanism distillation for membership privacy (DMP), as it uses knowledge distillation [2], [16]. Knowledge distillation (also known as knowledge transfer) is a training paradigm used to reduce the sizes of trained models, therefore enabling their deployment on resource-constrained devices such as mobile phones.

The objective of our defense, DMP, is to train a machine learning model resilient to membership inference attacks with either a blackbox or whitebox access to the model. The first stage of DMP is the pre-distillation phase in which DMP learns an unprotected model by training on the sensitive (private) training data without any privacy mechanism. Next, during the distillation phase, DMP distills (transfers) the knowledge of the unprotected model using a non-private reference data drawn from the same distribution as the sensitive dataset. The final stage of DMP is the post-distillation phase in which DMP trains a protected model on the reference data and its distilled labels. Such protected model is the output of DMP. Note that, unlike conventional uses of knowledge distillation, DMP does not use distillation for model compression; therefore the size of the protected is the same as that of the unprotected model.

We define a membership leakage metric to quantify membership leakage through a trained model’s predictions. Our metric measures the membership leakage about a data sample as the difference in the entropy of predictions of models trained with and without the data sample in their training data. As mentioned above, our DMP defense transfers the knowledge of a (privacy-leaking) trained model using a (non-sensitive) reference dataset which is drawn from the same distribution as the sensitive training dataset. We use our leakage metric to select the (non-sensitive) reference data used by DMP such that it reduces membership leakage. Additionally, DMP uses a softmax layer at an appropriate temperature to make the distribution of prediction vectors close to uniform distribution, and therefore increasing its entropy. We show that increasing the softmax temperature reduces the difference in the entropies of predictions of the models trained with and without the target data sample, and reduces membership leakage about the sample.

DMP’s objective is to preserve the utility of the target model while reducing membership leakage. To do so, DMP trains the protected (i.e., membership-inference resistant) model using Kullback-Leibler divergence as the loss function. This forces the protected model to imitate the behavior of the original, unprotected model on the reference data, therefore, strongly preserves classification accuracy of the model[45, 2, 16]. We show that the use of the softmax layer at high temperatures in the protected model reduces the generalization error of the unprotected model and strengthens its membership privacy. Essentially, DMP leverages the noise due to the uncertainty in predictions of the unprotected model, and provides highly generalized models resistant to inference attacks.

We evaluate DMP extensively on several benchmark classification tasks and show that DMP significantly outperforms existing defenses in terms of the trade-offs between utility and privacy. For example, for CIFAR-100 classification with DenseNet (L=100,k=12), training, test, and inference accuracies of the DMP-trained model are 66.7%, 63.1%, and 53%, respectively, which are significantly better than the adversarially regularized model (77.8%, 58.4%, and 61.9%, respectively) and the unprotected model (99%, 65.2%, and, 72.2%, respectively), in terms of privacy-utility tradeoffs. For a deeper DenseNet (L=140,k=19), to reduce the generalization error by 26% over the unprotected model, DMP incurs 0.2% accuracy loss while an adversarially regularized model incurs a 27% accuracy loss. Evaluating any defense mechanism on small datasets is important, because memorization becomes significant for smaller datasets [6, 27]; our evaluation shows the efficacy of DMP in this setting. Furthermore, the regularization performance of DMP is far more superior than adversarial regularization: DMP reduces generalization error by half for Purchase-100 while for CIFAR-100 the reduction is 10-folds. Membership inference attacks exploit statistical differences between various features of given model on members and non-members of its training dataset; we empirically show the indistinguishability of such features due to DMP training which strengthens membership inference resistance of the model.

Throughout our experiments, we use non-sensitive reference data which has only feature vectors without true labels. However, in the presence of true labels, DMP-trained models outperform the baseline unprotected models (by 3% for Purchase-100 and CIFAR-100 tasks) in terms of classification accuracy, while preserving the membership privacy of the private training data. Note that, we do not claim an information-theoretic privacy using DMP, as promised by differential privacy [10] techniques, instead we demonstrate DMP’s empirical privacy against membership inference attacks for given training datasets.

II. PRELIMINARIES

In this section, we describe some preliminary concepts required to understand the intuition behind our proposed technique. Specifically, we describe the machine learning setting, membership inference attacks, and knowledge distillation.

A. Machine learning setting

In this work, we focus on supervised learning and classification problems. Let $X$ be the $d$-dimensional feature space and $Y$ be the $n$-dimensional output space, where $n$ denotes the total number of prediction classes. The objective of machine learning is to learn a mapping $\theta : X \rightarrow Y$ that outputs an $n$-dimensional vector with each dimension $y \in Y$ representing the probability of input belonging to the corresponding class. Let $Pr(X, Y)$ be the underlying distribution of all data points in the universe $X \times Y$, where $X$ and $Y$ are random variables
for the feature vectors and the classes of data points, respectively. Consider \( \ell(\theta(x), y) \) to be a loss function measuring the deviation of the model’s prediction on input \( x \), and the actual label of \( x \), i.e., \( y \). The objective a machine learning model is to minimize the expected loss over all \((x, y)\):

\[
L(\theta) = \mathbb{E}_{(x, y) \sim \text{Pr}(X, Y)}[\ell(\theta(x), y)]
\]

This minimization is intractable because it is over the entire data population. Therefore, in practice, the loss functions is minimized over a finite set of training samples which is drawn from the population, i.e., \( D_y \subset (X, Y) \). The corresponding optimization problem is:

\[
L_{D_y}(\theta) = \frac{1}{|D_y|} \sum_{(x, y) \in D_y} \ell(\theta(x), y) \tag{1}
\]

\[
\theta^* = \arg\min_{\theta} L_{D_y}(\theta) + \lambda R(\theta) \tag{2}
\]

where \( \theta \) is the model, \( R(\theta) \) is a regularizer whose goal is to generalize the model, and \( \lambda \) is a hyperparameter.

### B. Knowledge distillation

Knowledge distillation was introduced by Hinton et al. [16] with the purpose of model compression that allows the deployment of large models on resource-constrained devices such as mobile phones. The intuition behind distillation is that, the knowledge acquired by models is not only encoded in model parameters but also in model predictions. To perform distillation, a large network, \( \theta \), is trained normally on some data, \( D \). Then a possibly overlapping data, \( D' \), is drawn from the same distribution as \( D \), and the prediction vectors (called soft labels) of \( D' \) are obtained by querying \( \theta \). Finally, the soft labels and features of \( D' \) are used to train another neural network \( \theta' \) with a smaller (compressed) size.

Usually, machine learning models use a softmax layer after their output layer, to produce probabilities over the classes. The functionality of the softmax layer is given by

\[
F(X) = \left[ \frac{\exp(z_i(X)/T)}{\sum_{i=0}^{n-1} \exp(z_i(X)/T)} \right]_{l=0..n-1}
\]

where the \( z(X) \) vector denotes the \( n \)-dimensional output of the last layer of neural network, and \( T \) is a parameter of softmax called temperature. To train the distilled network, \( \theta' \), either of \( z(X) \) or \( F(X) \) can be used.

If the true labels, called hard labels, are available for features of \( D' \), the dataset is called labeled otherwise called unlabeled. If \( D' \) is labeled, the distilled network, \( \theta' \), can be trained with both hard and soft labels. As shown in other domains [34], [45], [2], the accuracy of \( \theta' \) is generally very close to or even better (in case of labeled \( D' \)) than that of \( \theta \). We note that in knowledge distillation the size of second neural network is smaller than that of the network whose knowledge is distilled in \( D' \), however when these two networks have the same size the learning process is also known as knowledge transfer. We use the term ‘knowledge distillation’ in our work, as it does not affect our analysis or results.

### C. Membership inference attack setting

Membership inference is a serious privacy concern for machine learning models [15], [28], [40], [25]. Consider a machine learning model \( \theta \) and a data sample \((x, y)\). The goal of a membership inference adversary is to infer whether \((x, y)\) belongs to the dataset used to train the model \( \theta \). The membership inference attack exploits the memorization of training data by large neural networks by inspecting various features of the target trained model. Therefore, the standard approach for the membership inference adversary is to train an inference model, \( h \), whose goal is to classify data samples into members and non-members.

Let \( \theta \) be the target model and \( h : F(X, Y, \theta) \rightarrow [0, 1] \) be the inference model. For a given data sample \((x, y)\), the inference adversary evaluates \( F(X, Y, \theta) \), which is a combination of different features of \( \theta \) related to \((x, y)\), for instance, \( \theta \)’s prediction on the record \[40], \[30], \[28\], the loss function on the record, the gradients of the loss \[31], \[28\], etc. Based on this input feature vector \( F(X, Y, \theta) \), the output of \( h \) is the probability that \((x, y)\) has been a member of \( \theta \)’s training set. Let \( \text{Pr}_D(X, Y) \) and \( \text{Pr}_{\neg D}(X, Y) \) be the conditional probabilities of the members and non-members, respectively. For the above setting, the expected gain of the inference model can be computed as:

\[
G_{\theta}(h) = 0.5 \times \mathbb{E}_{(x, y) \sim \text{Pr}(D, X, Y)}[\log(h(F(x, y, \theta)))]
+ 0.5 \times \mathbb{E}_{(x, y) \sim \text{Pr}_{\neg D}(D, X, Y)}[\log(1 - h(F(x, y, \theta)))]
\]

In practice [15], [28], [40], [25], [31], [30], the inference adversary only knows a (small) subset of the members \( D \), i.e., she only knows \( D^A \subset D \) and has access to enough non-members \( D'^A \) required to train \( h \). Therefore, the adversary computes an empirical gain as:

\[
G_{\theta, D^A, D'^A}(h) = \frac{1}{|D^A|} \sum_{(x, y) \in D^A} [\log(h(F(x, y, \theta)))]
+ \frac{1}{|D'^A|} \sum_{(x, y) \in D'^A} [\log(1 - h(F(x, y, \theta)))]
\]

which is used to get the inference model:

\[
h = \arg\max_h G_{\theta, D^A, D'^A}(h) \tag{6}
\]

In [5], the two summations compute the empirical gain of inference model on the subset of members and non-members that the adversary has. The empirical gain decreases if the features, \( F(x, y, \theta) \), on the members and non-members are indistinguishable.
III. INTRODUCING DISTILLATION FOR MEMBERSHIP PRIVACY (DMP)

We present Distillation For Membership Privacy (DMP), whose goal is to train ML models that are resilient to membership inference attacks. Our design of DMP is motivated by the poor privacy-utility tradeoffs provided by existing defenses against membership inference discussed in Section VII. DMP leverages knowledge distillation [16], introduced in Section II-B, to train high-utility ML models resistant to membership inference.

A. Notations

We start by introducing the notations used throughout the paper. We consider the data universe \((X \times Y)\) where \(X\) is the exhaustive set of feature vectors and \(Y\) is the set of class labels corresponding to each feature vector in \(X\). \(\Pr(X, Y)\) represents the underlying distribution of \((X \times Y)\), where \(X\) and \(Y\) are random variables representing the feature vectors and the label vectors, respectively. A labeled dataset consists of pairs of feature vectors and labels, i.e., it is a subset of \((X \times Y)\). On the other hand, an unlabeled dataset consists of only feature vectors, i.e., it is a subset of \((X)\).

We use \(D_tr \subset (X \times Y)\) to refer to a private training dataset, i.e., a dataset containing privacy-sensitive information. We call an ML model trained using a private dataset \(D_tr\) as unprotected model, as such a model is susceptible to membership inference attacks. We denote such unprotected model by \(\theta_{up}\). On the other hand, we call an ML model protected and denote it by \(\theta_p\) if it is trained in a way that resists membership inference attacks. Recall that the goal of our DMP technique is to create such protected models.

As described later, DMP creates protected models using the non-sensitive reference dataset (which is disjoint from the sensitive training dataset \(D_tr\)). \(X_{ref}\) represents an unlabeled reference dataset, and \(\bar{Y}_{ref}\) represents the soft labels (prediction vectors) of \(\theta_{up}\) on \(X_{ref}\). Unless stated otherwise, we assume that any model \(\theta\) uses a softmax layer. We use the notation \(\theta_T\) if softmax temperature is to be specified. For instance, \(\theta_{up}^T\) is \(\theta_{up}\) augmented with a softmax layer with a temperature of \(T = 4\).

B. Main intuition of DMP

In this work we focus on large capacity neural networks which memorize their training data [28], [31], [40], [41] and perform significantly differently on the members versus non-members of the training data. This difference facilitates membership inference attacks, and therefore, should be minimized. In the pre-distillation phase, we train an unprotected model, \(\theta_{up}\), on \(D_tr\) without any privacy guarantees. The intuition behind DMP is that, for the data outside of \(D_tr\), the entropies of output distribution of \(\theta_{up}\) trained on \(D_tr\) with or without any particular sample are indistinguishable. That is, such predictions do not provide significant membership information about the particular sample from \(D_tr\).

To make output distributions of \(\theta_{up}\) even more indistinguishable, DMP uses softmax layer in \(\theta_{up}\) at high temperature to label \(X_{ref}\) and smooths distribution of \(\theta_{up}(X_{ref})\). Finally, DMP trains a protected model, \(\theta_p\), on these predictions with reduced membership information. The high prediction entropy acts as noise during the training of \(\theta_p\) and increases resistance of \(\theta_p\) to membership inference. However, due to training on \(\theta_{up}(X_{ref})\) using KL-divergence loss, DMP-trained models perfectly match the performance of \(\theta_{up}\) on the test data, and therefore, have high classification performance.

C. Details of the DMP technique

Here we present the details of the DMP technique, which Algorithm. [1] summarizes. DMP has three main phases, as described below.

1) Pre-distillation phase: In this phase, an unprotected model \(\theta_{up}\) is trained on the sensitive, labeled training data, \(D_tr\). Therefore, the unprotected model \(\theta_{up}\) is obtained using standard training techniques without any privacy enforcement; in particular, we simply use the stochastic gradient descent (SGD) algorithm to train \(\theta_{up}\) with optimized loss on \(D_tr\):

\[
\theta_{up} = \arg\min_{\theta} \frac{1}{|D_tr|} \sum_{(x, y) \in (D_tr)} \sum_{i=0}^{C-1} \mathbb{I}_{y = i} \log(\theta(x))
\]  

(7)
where \( I_{y=x} \) is an indicator function which outputs 1 when \( i \) is the true class of the sample \((x, y)\) and 0 otherwise; \( C \) is the number of classes in the classification task. Note that we use a softmax layer (introduced in Section II-B) as the last layer of our unprotected model. Therefore, \( \theta(x) \) in (9) is the class probability vector obtained by passing the logits of the model’s output through the softmax layer.

2) Distillation phase: In this phase, we first obtain the reference data, \( X_{\text{ref}} \), that is used to transfer the knowledge of \( \theta_{\text{up}} \) in \( \theta_p \). The selection of \( X_{\text{ref}} \) is important to reduce the membership leakage; later, we discuss the selection process in Section IV-A. Note that, the unlabeled \( X_{\text{ref}} \) alone cannot be used for learning due to the unavailability of labels. We label \( X_{\text{ref}} \) using \( \theta_{\text{up}} \) to get \( Y_{\text{ref}} \), where \( Y_{\text{ref}} = \theta_{\text{up}}(X_{\text{ref}}) \). Note that the last layer of \( \theta_{\text{up}} \) is a softmax layer at temperature \( T \). As shown later in Section IV-C, the temperature parameter should be chosen properly to increase resilience to membership inference attacks. Also, we will show that the high entropy (uncertainty) of the predictions, \( Y_{\text{ref}} \), of the unprotected model is the key enabler of membership privacy.

3) Post-distillation phase: In this phase, we train a protected model \( \theta_p \) using the reference data \( (X_{\text{ref}}, Y_{\text{ref}}) \) obtained in the distillation phase. Since the knowledge of \( \theta_{\text{up}} \) is distilled in the soft labels of \( X_{\text{ref}} \), i.e., \( (X_{\text{ref}}, Y_{\text{ref}}) \), we expect \( \theta_p \) to provide a utility close to its corresponding unprotected (sensitive) model \( \theta_{\text{up}} \).

The empirical risk for model \( \theta_p \) on a sample \((x, y)\) in \((X_{\text{ref}}, Y_{\text{ref}})\) is defined using the Kullback-Leibler divergence; here, \( y = \theta_{\text{up}}(x) \). The final \( \theta_p \) is obtained by solving the empirical risk minimization optimization problem given by (9).

\[
\mathcal{L}_{KL}(x, y) = - \sum_{i=0}^{C-1} \theta(x)_i \log \left( \frac{\theta(x)_i}{y_i} \right) \\
\theta_p = \arg\min_{\theta} \frac{1}{|X_{\text{ref}}|} \sum_{(x, y) \in (X_{\text{ref}}, Y_{\text{ref}})} \mathcal{L}_{KL}(x, y) 
\]

Note that, (10) is minimized when \( \theta_{\text{up}}(x) = \theta_p(x) \) for all \((x, y) \in (X_{\text{ref}}, Y_{\text{ref}})\). Hence, \( \theta_p \) perfectly learns the behavior of \( \theta_{\text{up}} \) on the non-member inputs. Hence, in theory, the performance of \( \theta_p \) on the test data is similar to that of \( \theta_{\text{up}} \); this has been empirically observed in many previous works. However, the low confidence (i.e., high entropy) of \( \theta_{\text{up}} \) in the \( Y_{\text{ref}} \) predictions prevents \( \theta_p \) from learning the behavior of \( \theta_{\text{up}} \) on the members; the prediction entropy of \( \theta_p \) on members is very high (Figure 2 middle) unlike that of \( \theta_{\text{up}} \) (Figure 2 left). \( \theta_p \) does not converge to \( \theta_{\text{up}} \); because the latter is trained explicitly to learn the mapping \( f_{\text{up}} : x \rightarrow y \) for \((x, y) \in D_{\text{tr}} \) while the earlier learns the mapping \( f_p : x \rightarrow \bar{y} \) for \((x, y) \in (X_{\text{ref}}, Y_{\text{ref}}) \). Due to this empirical risk minimization, the DMP-trained models do not lose classification performance on the test data while preserving membership privacy; our experiments will confirm this hypothesis.

IV. ANALYSIS OF DISTILLATION FOR MEMBERSHIP PRIVACY

In this section, we analyze and discuss the sources of membership resistance provided by DMP. Specifically, we will show the impact of different components of DMP in reducing membership leakage, and will discuss some of our design choices towards better membership defense.

A. Membership leakage metric

We define a membership leakage metric to quantify membership leakage through a model’s predictions.

Definition 1. (Membership leakage) Consider datasets \( D \sim \text{Pr}(X, Y) \) and \( D' \leftarrow D \setminus (x, y) \) differing in a single sample \((x, y)\), and models \( \theta \) and \( \theta' \) trained on \( D \) and \( D' \), respectively. Then, the membership leakage about \((x, y) \) due to any sample \((x', y') \) \( \sim \text{Pr}(X, Y) \) is directly proportional to the distance \( \mathcal{D} \) between features of \( \theta \) and \( \theta' \) on \((x', y') \) extracted using a function \( \mathcal{F} \), i.e.,

\[
\text{I}^\text{ml}(D, x', y', x, y) = K \cdot \mathcal{D}(\mathcal{F}(\theta, x', y'), \mathcal{F}(\theta', x', y')) \tag{10}
\]

Here, \( K \) is a constant of proportionality. Therefore, \( \text{I}^\text{ml} \) measures membership leakage due to features of \( \theta \) on an input \((x', y')\), for a specific member, \((x, y)\), of a given training set \( D \). Examples of the features, \( \mathcal{F} \), include prediction, prediction entropy, the input loss and gradients of the loss with respect to the model parameters [28, 40, 41]. Potential distance metrics, \( \mathcal{D} \), include \( L_p \) norm and KL-divergence. In DMP, the only source of membership leakage to \( \theta_p \) is the predictions of \( \theta_{\text{up}} \) on unlabeled reference data, \( X_{\text{ref}} \). For concreteness, we use the \( L_1 \) norm of the difference between the entropies of model predictions as the function \( \mathcal{f} \), i.e.,

\[
\text{I}^\text{ml}(D, x', x, y) = K \cdot |H(\theta(x')) - H(\theta'(x'))| \tag{11}
\]

\[
H(\theta(x)) = \sum_{i=0}^{n} \theta(x)_i \log(\theta(x)_i)
\]
Therefore, this $I^{m1}$ captures the effect of training data on the entropy of model predictions.

B. Reference data selection to reduce membership leakage

In this section, we draw connections between membership leakage through the predictions of $\theta_{up}$ and the entropy of these predictions, and give a practical approach of measuring membership leakage. We then justify the utility of our approach to select $X_{ref}$ used to transfer the knowledge of $\theta_{up}$.

The intuition behind $I^{m1}$ stems from the significantly different behavior of deep neural networks on members and non-members of their training data. Therefore, $I^{m1}$ is not an absolute metric, but a relative measure of the sensitive membership information content. We explain this statement for our setting. For any training sample $(x, y) \in D_{tr}$, the entropy $H(\theta_{up}(x))$ will be low, because $(x, y)$ is memorized by $\theta_{up}$. But, $H(\theta_{up}(x))$ will be high, because $\theta_{up}$ is not trained on $(x, y)$. Therefore, the predictions of $(x, y)$ using $\theta_{p}$ trained on $(x, \theta_{up}(x))$ versus $(x, \theta'_{up}(x))$ in the post-distillation phase will have low and high entropies, respectively. This difference in entropies will facilitate membership leakage for $(x, y)$ through $\theta_{p}$. This entropy difference primarily arises due to training $\theta_{p}$ on the data for which the predictions of $\theta_{up}$ have very low entropies. Such low entropy predictions are characteristic of the data similar to the training data of the target neural networks, and convey the sensitive membership information.

On the other hand, both $H(\theta_{up}(x'))$ and $H(\theta'_{up}(x'))$ are high for $(x', y') \notin D_{tr}$, because none of the $D_{tr}$ samples significantly influences these predictions. Note that, if $H(\theta_{up}(x'))$ is high, $H(\theta'_{up}(x'))$ will also be high. This is quite intuitive, because a model cannot learn more by removing samples from its training dataset, assuming there are no malicious data that increase the entropy due to their presence in the training data. Consequently, $\theta_{p}$ trained on $(x', \theta_{up}(x'))$ versus $(x', \theta'_{up}(x'))$ will have high entropy (low confidence) on the $(x, y)$ in both the cases, which reduces the membership inference risk to the $(x, y)$. Therefore, high entropy predictions result in lower membership leakage than low entropy predictions.

Computing $I^{m1}$ is not practical as it requires repetitive training; therefore, in the rest of the paper, we use the entropy of predictions to represent membership leakage, since it is inversely proportional to $I^{m1}$ as discussed above. We validate this in Figure 2 using AlexNet trained on CIFAR-100 data. We distill the knowledge of $\theta_{up}$ using the feature vectors of $X_{ref}$, $(\frac{1}{2}D_{tr} + \frac{1}{2}X_{ref})$ and $D_{tr}$. As can be seen, reducing the proportion of $D_{tr}$ in the data used for distillation increases the per class entropy of $\overline{Y}_{ref}$ (Figure 2 (Left)). Next, we train three $\theta_{p}$ on the three different sets of feature vectors and corresponding predictions. We observe that, when $\theta_{p}$ is trained on the predictions with higher entropy, its predictions on members and non-members of $D_{tr}$ (Figure 2 (Right)) become more indistinguishable. The difference is maximum for $\theta_{p}$ trained on $D_{tr}$ itself, i.e., when the entropy of predictions is 0. The difference is minimum for $\theta_{p}$ trained on $\theta_{up}(X_{ref})$, i.e., on the predictions with maximum entropy. The indistinguishable entropy of $\theta_{p}$ on members and non-members of $D_{tr}$ are shown in Figure 2 (Middle). This indistinguishability mitigates the membership inference risk. Therefore, for effective reduction of membership leakage, we select reference data for which the predictions of $\theta_{up}$ have high entropy. Note that, the predictions with high entropy do not leak sensitive membership information, but the vice versa need not be true.

Finally, note that the larger the size of $X_{ref}$, the more the membership leakage via the predictions, $\overline{Y}_{ref}$ [33]. However, increasing the reference data also improves the classification accuracy of $\theta_{p}$. We demonstrate the tradeoff between classification accuracy and membership inference risk in Figure 5 of Section VI-B1. Therefore, in DMP, we argue to select the size of reference based on the desired utility-privacy tradeoffs.

In summary, we introduce a membership leakage metric to measure the relative membership information content in the
predictions of a model. We then introduce a more practical approach to measure membership leakage based on the metric and use it to select non-sensitive reference data. We leave investigating the exact membership leakage metric to future work, and focus in this work on demonstrating the efficacy of DMP using randomly sampled $X_{ref}$ from available data.

Figure 3: Role of softmax $T$ in DMP in reducing the membership leakage about $D_{tr}$. (Top): Shows the difference in per class average entropies of predictions of $\theta_{up}^T$ on $D_{tr}$ and $D_{ref}$, for $T \in \{1, 1.5, 2\}$. Increasing the softmax $T$ makes the predictions of $\theta_{up}$ more indistinguishable and reduces the membership leakage about $D_{tr}$. (Bottom): Shows this difference for three different $\theta_{up}$’s trained on $\{X_{ref}, \theta_{up}^T[X_{ref}]\}$ $T \in \{1, 1.5, 2\}$. As the softmax $T$ in $\theta_{up}^T$ increases, the predictions of corresponding $\theta_{up}$ become more indistinguishable due to reduced membership leakage through $\theta_{up}^T[X_{ref}]$.

C. The impact of softmax on membership leakage and generalization error

As argued above, DMP can better reduce membership leakage by using reference data for which entropy of predictions of the unprotected model is high. In this section, we discuss how DMP uses a softmax layer to further increase the entropy of predictions and reduce membership leakage. At $T = \infty$, softmax output is a uniform distribution with entropy of 1. Note that, entropy is a continuous function and therefore the difference of entropies is also a continuous function. The entropies of $\theta_{up}(x')$ and $\theta_{tr}(x')$ tend to 1 with increase in temperature of softmax in $\theta_{up}$ and $\theta_{tr}$, respectively. That is, their difference continuously reduces to 0 from some finite value. Therefore, increasing the softmax temperature reduces the membership leakage via $\theta_{up}(x')$.

We demonstrate this on a fully connected network trained on Purchase-100 dataset, in Figure 3. The effect of the temperature of softmax layer in $\theta_{up}$ is shown in Figure 3 (Top): With increase in the softmax temperature, the difference in the per-class average entropy of predictions of $\theta_{up}$ on $D_{tr}$ and $D_{ref}$ reduces. As discussed above, this reduction is because the distribution of all of these predictions tends to be uniform. We then train three different $\theta_{up}$’s on different prediction sets which are obtained with the softmax temperature in $\theta_{up}$ set at 1, 1.5, and 2. The predictions of these three $\theta_{up}$’s are shown in Figure 3 (Bottom); the temperature of all of the $\theta_{up}$’s is set at 1. It can be seen that, the difference in the entropy of predictions of $\theta_{up}$ reduces when trained on predictions obtained with higher softmax temperature in $\theta_{up}$. This validates our hypothesis that increasing the softmax temperature reduces the membership leakage through predictions of $\theta_{up}$.

The reason for this is as follows. Increasing the temperature of softmax in $\theta_{up}$ smooths its predictions. This reduces the KL-divergence loss in (8) back-propagated through the parameters of $\theta_{up}$, and therefore, also reduces the magnitude of gradients used to update the parameters of $\theta_{up}$ in each epoch of its training. The small gradients prevent $\theta_{up}$ to learn any information, including the membership information, from $Y_{ref}$.

We note that, appropriately setting the temperature of softmax in $\theta_{up}$ significantly reduces the generalization error of $\theta_{up}$, along with reduction in membership inference risk. This is demonstrated by Figure 4. Increasing the softmax $T$ in $\theta_{up}$ reduces the generalization error (i.e., the gap between the train and test accuracies) of $\theta_{up}$. However, high temperatures also reduce general information about the distribution $Pr(X, Y)$ transferred to $\theta_{up}$. This causes reduction in the classification accuracy of $\theta_{up}$, as we demonstrate in Table 1.

Table I: Data sizes used in DMP training. $D_{tr}$ and $D_{ref}$ are training data and reference data, respectively. $D^{A}$, $D^{X}$ data are adversary’s knowledge of members and non-members of $D_{tr}$. Here, $D^{A}$ and $D_{ref}$ are disjoint.

| Dataset    | $|D_{tr}|$ | $|D_{ref}|$ | $|D^{A}|$ | $|D^{X}|$ |
|------------|----------|----------|----------|----------|
| Purchase-100 | 10000    | 10000    | 5000     | 5000     |
| CIFAR-100   | 25000    | 25000    | 12500    | 8000     |
| CIFAR-10    | 25000    | 25000    | 12500    | 8000     |
Table II: Temperature of softmax layer for different combinations of dataset and network architecture. These are used to produce results of Table III

| Dataset       | Architecture          | Softmax T |
|---------------|-----------------------|-----------|
| Purchase-100  | Fully Connected        | 1.0       |
|               | AlexNet                | 4.0       |
| CIFAR-100     | DenseNet-BC (L=100, k=12) | 4.0      |
|               | DenseNet-BC (L=190, k=40) | 1.0     |
| CIFAR-10      | AlexNet                | 1.0       |

V. EXPERIMENTAL SETUP

A. Datasets

Below, we detail the datasets and neural network architectures used in our experiments.

CIFAR-100. CIFAR-100 is a popular benchmark dataset used to evaluate image recognition algorithms [23]. It contains 60,000 color (RGB) images (50000 for training and 10000 for testing), each of 32 × 32 pixels. The images are clustered into 100 classes based on objects in the images and each class has 500 training and 100 test images.

CIFAR-10. CIFAR-10 has 60,000 color (RGB) images (50000 for training and 10000 for testing), each of 32 × 32 pixels. The images are clustered into 10 classes based on the objects in the images and each class has 5000 training and 1000 test images. In DMP, protected models learn on the knowledge of unprotected model; with large number of classes, predictions of models tend to include more information useful for training [40]. Therefore, We use this dataset to assess the efficacy of DMP when the number of classes is small.

Purchase-100. The Purchase100 dataset contains the shopping records of several thousand online customers, extracted during Kaggle’s “acquire valued shopper” challenge [12]. Each record in the dataset is the shopping history of a single customer. The dataset contains 600 different products, and each user has a binary record which indicates whether she has bought each of the products (a total of 197,324 data records). The records are clustered into 100 classes based on the similarity of the purchases, and our objective is to identify the class of each user’s purchases.

B. Target model architectures

We use same architecture for both the unprotected and the protected models unlike conventional distillation [16]. For CIFAR-100 dataset, we use two state-of-the-art architectures: AlexNet [24] and DenseNet [20]. AlexNet has 2.47M parameters. We use two variants of DenseNet: DenseNet-BC (L=100, k=12) with 5.62M parameters, denoted by Dense19, and DenseNet-BC (L=190, k=40) with 0.77M parameters, denoted by Dense12. We choose these two models to assess the efficacy of DMP technique for models with varying capacities. For CIFAR-10, we use AlexNet architecture. For Purchase100, we used a fully connected network with hidden layers of sizes {1024, 512, 256, 128}. We measure the training (A_{train}) and test (A_{test}) accuracy of these models as the percentage of the training and test data for which the models produce correct labels. The generalization error (E_{general}) is measured as the difference of the training and the test accuracy.

C. Membership inference attack model architectures

We use the state-of-the-art membership inference attack model proposed by Nasr et al. [31] to evaluate the strength of DMP and compare it with the other defenses. For an input, we use its feature vector, label and cross-entropy loss of the target model’s prediction as the features in the blackbox membership inference case. Along with these features, we also use gradients of the loss with respect to last two layer of the target model and outputs of the last two layers of the target model as the features in the whitebox membership inference. Following the previous works [40], [30], [31], we measure the whitebox (A_{wb}) and blackbox (A_{bb}) membership inference risks as the accuracy of corresponding attack model. Attack model outputs member or non-member for a given record, therefore the attack accuracy is measured as the percentage of unknown test data for which the attack model correctly predicts the membership (i.e., member is predicted member and non-member is predicted non-member). We use the same number of members and non-members in the unknown test data.

VI. EXPERIMENTS

We present our evaluation of DMP, performed using the experimental setup described in Section V.

A. Comparing DMP with prior membership inference defenses

In this section, we compare the performance of our DMP technique with two state-of-the-art membership inference defenses: Adversarial regularization [30] and DP-SGD [1]. We use code of adversarial regularization provided by the authors of [30] and use PyTorch implementation of DP-SGD verified by the authors of TensorFlow DP-SGD library [1].

Comparing to Adversarial Regularization. Table III compares DMP with the adversarial regularization defense [30], also showing the results for the corresponding unprotected model. E_{general} are generalization errors, A_{test} are test accuracies of the target ML model and A_{wb}, A_{bb} are whitebox and blackbox membership inference risks. The goal of an effective defense mechanism is to reduce E_{general}, A_{wb} and A_{bb} while keeping A_{test} high. As can be seen, the unprotected models are highly susceptible to blackbox and whitebox membership inference attacks for all the datasets and model architectures. The adversarial regularization defense [30] reduces inference risk at the cost of large decreases in the model’s utility. We use the adversarial regularization parameter, λ, proposed by in the original work [30], i.e., 3 for Purchase-100 and 6
for CIFAR datasets. For Purchase-100, classification accuracy reduces by 5% to improve inference resistance by 20%. However, DMP incurs just 0.6% accuracy reduction to improve the resistance by 25%. For the simple Purchase-100 task, the adversarially regularized model manages descent privacy and utility tradeoff, but for more complex CIFAR-100, it reduces inference risk just by 11-13% and classification accuracy by 5-7%. We observe that at higher $\lambda$ values the defense incurs very high loss in the accuracy and produces unusable models. DMP, on the other hand, maintains the classification accuracy within 2.5% of that of the baseline cases, while also reduces the inference risk by 16% (CIFAR-10 + AlexNet) to 35% (CIFAR-100 + AlexNet). This shows that, DMP reduces the membership inference risk significantly with negligible reduction in the classification accuracy and provides much better tradeoff than adversarial regularization.

Adversarial regularization mitigates the membership inference risk to some extent, due to the adversarial training. The authors of [30] claim that such training effectively regularizes the final models (i.e., reduces their generalization error) over the baseline models, and forces them to perform similarly on members and non-members of the training data. But, the regularization is not significant, especially for the smaller training data sizes, because deep neural networks are harder to prevent from over-fitting to smaller datasets. This can be seen in $E_{\text{generr}}$ column of Table III. Here, the training data sizes are smaller compared to the original work [30], and clearly show the poor regularization performance of adversarial regularization. Note that, this is precisely the reason why adversarially regularized models are also prone to the membership inference attacks we use to evaluate the defenses in this work. The large generalization error due to poor regularization is sufficient to mount membership inference attacks: Accuracy of both the blackbox and whitebox membership inference is more than 60% in all the cases. Furthermore, we note that stronger inference attack models, used to strengthen the membership privacy using adversarial regularization, fail to regularize the final model while also compromising the classification accuracy.

On the other hand, the regularized performance of DMP is far superior than that of adversarial regularization: DMP reduces the generalization error by 10-folds from 34% to 3.6% for CIFAR-100 with Dense12 and 63.2% to 6.5% for AlexNet models, as shown in Table III. DMP’s strong regularization performance is the result of distillation using softmax layer at an appropriate temperature, as shown in Section IV-C. This reduces the membership leakage and prevents $\theta_p$ from learning fine-grained information about $D_q$. This can also be seen from the DMP training progress shown in Figure 4, which implies that DMP-trained $\theta_p$ does not overfit to the training data, due to the reduced membership information leaked to $\theta_p$. The reduction in the membership leakage also reflects in the indistinguishability of various statistics of the protected model, as we demonstrate in Section VI-C. With increasing capacity, models tend to overfit more as they can store fine-grained information about the training data in their parameters. However, even with for the large capacity, DMP-trained Dense19 incurs only 7.3% generalization error and reduces the membership inference risk by 28%, as shown in Table III.

Recall that the risk of membership inference increases for the higher capacity models [31]. We assess the efficacy of DMP on Dense12 and Dense19 architectures which have significantly different capacities. With no defense, both models have similar classification accuracy (~ 65%) and generalization error (~ 35%). However, Dense19 is 9% more susceptible to inference attacks than Dense12, due to the high capacity. The larger capacity of Dense19 also incurs ~ 5% higher generalization error for the DMP-trained Dense19 compared to the DMP-trained Dense12. But, the inference risk to Dense19 is only 1-2% higher than that of Dense12. Also, the low whitebox inference attack accuracy implies that the extra parameters of DMP-trained Dense19 do not contain any extra membership information, and therefore, do not increase the membership inference risk significantly.

In DMP, the empirical risk minimization formulated in [9] to train $\theta_p$ forces it to imitate the behavior of $\theta_{up}$ on non-member data. DMP incorporates the requirement of high accuracy of classification on the test data from the final models in its learning objective and reduces the test accuracy loss compared to the other defenses. In DMP, $\theta_p$ learns from the prediction
vectors, $Y_{\text{ref}}$. Therefore, to understand the efficacy of DMP for the task involving small number of classes, we experiment with AlexNet architecture with CIFAR-10 data. As can be seen, **DMP results in high utility models even with small number of classes**, the classification performance reduces only by 2.5% for CIFAR-10.

**Comparing to DP-SGD.** We compare DMP and DP-SGD defenses in terms of the (empirically observed) tradeoffs between utility and privacy measured as membership inference resistance. Recently, Jayaraman et al. [21] perform similar analysis to find that the differentially private mechanisms offer poor utility-privacy tradeoffs on complex tasks when evaluated using membership and attribute inference attacks. Below, we confirm these findings and show that DMP technique can provide much better tradeoffs against strong membership inference attacks; we leave the evaluation using attribute inference to future work.

DP-SGD provides theoretical differential privacy guarantees by adding DP noise to gradients of loss on training data used to update the model parameters during training. Our motivation is to understand the privacy budget ($\epsilon, \delta$) of DP-SGD required to achieve a reasonable tradeoff between classification performance and the corresponding membership inference risk. Table IV shows the results for AlexNet trained on CIFAR-10 data, averaged over 3 runs of each experiment; $\delta$ is constant at $10^{-6}$. We note that DP-SGD incurs significant (35%) loss in classification performance at lower $\epsilon$. With larger $\epsilon$, the accuracy of DP-SGD trained models improves but at the cost of higher membership inference risk. This risk arises due to poor generalization at high privacy budgets which is sufficient for successful membership inference. More importantly, for a **specific empirical membership inference risk (~51%)**, models trained using DP-SGD incur much higher classification performance loss (15.3%) than those trained using DMP (2.5%), compared to the baseline model.

**Table IV: Tradeoff between utility and empirical membership inference risk for different softmax temperatures. Increase in temperature of softmax layer of $\theta_{\text{up}}$ reduces its sensitivity to input perturbations. This indeed reduces sensitive information, $I^{\text{ml}}$, transferred to $\theta_p$ which results in lower generalization error and lower inference risk as shown.**

| Defense | Softmax T | Training Accuracy | Test Accuracy | Attack Accuracy |
|---------|------------|-------------------|---------------|----------------|
| No defense | n/a | 100 | 67.5 | 77.9 |
| DMP | 100 | 68.1 | 65.0 | 51.3 |
| >100 | 55.8 | 52.2 | 51.7 |
| 50.2 | 37.2 | 36.9 | 50.2 |
| 12.5 | 30.2 | 31.7 | 49.9 |
| 6.8 | 27.8 | 29.4 | 50.0 |

**B. Choice of parameters in DMP**

We demonstrate the impact of various parameters of DMP on its performance.

1) **The size of reference data**: DMP-trained models learn from the knowledge in the predictions of $\theta_{\text{up}}$ on the non-sensitive reference data. The membership leakage, $I^{\text{ml}}$, through the predictions of $\theta_{\text{up}}$ on $X_{\text{ref}}$ increases with the size of $X_{\text{ref}}$ as argued in Section IV A. To validate this hypothesis, we quantify the classification accuracy and the membership inference risk of $\theta_p$ with increasing the amount of $X_{\text{ref}}$ used for distillation. We use Purchase-100 data and vary $|X_{\text{ref}}|$ as shown in Figure 5 in all the experiments, we fix the softmax $T$ of $\theta_{\text{up}}$ at 1.0. For our unprotected model $\theta_{\text{up}}$, it has a train accuracy, test accuracy, and membership inference risk of 100%, 74.9%, and 82.3%, respectively. Initially, the test accuracy of $\theta_p$ increases with $|X_{\text{ref}}|$ due to the useful knowledge transferred. But, beyond the test accuracy of $\theta_{\text{up}}$, its predictions essentially inserts noise in the training data of $\theta_p$, therefore the gain from increasing the size of reference data slows down. Although this noise marginalizes the increase in the test performance of $\theta_p$, it also prevents $\theta_p$ from learning more about $D_{\text{tr}}$ and prevents further inference risk; this is shown by the train accuracy and membership inference risk curves in Figure 5, respectively. Therefore, size of reference data should be selected based on the desired tradeoff between utility and privacy of the final model.

Finally, we note that if the reference data used in DMP is labeled, i.e., if the correct $Y_{\text{ref}}$ are available for $X_{\text{ref}}$, the performance of DMP both in terms of classification accuracy and membership risk due to $\theta_p$ will improve. For CIFAR-100 with Dense12 model, DMP-trained $\theta_p$ with unlabeled $X_{\text{ref}}$ has classification accuracy and membership risk of 63.1% and 53.7%, respectively. For the same dataset and model, with labeled $X_{\text{ref}}$, the classification accuracy and membership risk are 67.2% and 51.8%, respectively. Similarly, for Purchase-100, the classification accuracy increases from 74.3% to 77.2% and the membership risk reduces from 55.5% to 51.4%; the generalization error reduces by half from 12.6% to 6.8%. Therefore, similar to data augmentation, **DMP also serves as a utility improvement technique in the presence of labeled**
C. Reasoning about the effectiveness of DMP

In this section, we present the statistics of different features of the target models, trained with and without defenses, on the members and non-members of their training data. As discussed in Section II-C, the blackbox and whitebox membership inference attacks [31], [40], [28], [12] exploit these statistical differences.

Figure 4 shows the effect of softmax \( T \) on the training accuracy on the private training data, \( D_{tr} \), and test accuracy of \( \theta_p \) as the training progresses. In theory, with increase in \( T \) of softmax layer of \( \theta_{up} \), the generalization error of \( \theta_p \) should decrease due to reduced membership leakage. We observe this in Figure 4. From left to right, the generalization errors of \( \theta_p \) trained with temperatures 2, 4, 6 are 4.7\% (66.3, 61.6), 3.6\% (66.7, 63.1), and 0.8\% (55.7, 54.9), respectively. Parentheses show the corresponding training and test accuracies, respectively. This confirms that increasing softmax \( T \) improves DMP’s reduces membership leakage and strengthens membership resistance (Section IV-C).

In Figure 5 we show the fraction of classes (y-axis) for which the generalization error of the target models is lesser than a particular value (x-axis). Here, closer the line to the line \( x = 0 \), lower the generalization error. We observe that, with the no defense case as baseline, the reduction in the generalization error using DMP is more than twice that using the adversarial regularization. DMP reduces the error by half for Purchase-100 and the reduction is 10-folds for CIFAR-100 dataset. Along with the generalization error, reducing the difference in entropies of predictions of target models on members and non-members of the training data is a necessary condition to mitigate the membership inference attacks. In Figures 2 and 3 we show how increasing the softmax \( T \) and using non-members in the distillation phase reduces the difference in the entropies. Note that adversarial regularization performs well for large training datasets, but we explicitly consider small training datasets as they are harder to prevent from overfitting and therefore from the membership inference.

To assess the efficacy of DMP against the stronger whitebox membership inference attacks [31], [28], we study the

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Table V shows the temperatures used in our experiments for different datasets and models.
gradients of input loss of $\theta_{up}$ versus $\theta_p$ on members and non-members of $D_t$. Figure 7 shows the fraction of members and non-members given on y-axes that fall in a particular range of gradient norm values given on x-axes. Gradients are computed with respect to the parameters of the given model. We note that the distribution of the norms of $\theta_{up}$ (upper figures) is heavily skewed to the left for the members, i.e., towards lower gradient norm values, unlike that for the non-members. This is because $\theta_{up}$ memorizes $D_t$ and therefore the loss and its gradient for the members is very small compared to the non-members. Therefore, non-members are more evenly distributed over a large range of the norm values. However, for the DMP-trained $\theta_p$, both members and non-members are evenly distributed across a large range of gradient norm values. This implies loss of DMP-trained $\theta_p$ on members significantly increases. This implies that DMP significantly reduces the unintended memorization of $D_t$ in the model parameters and makes gradients of members and non-members indistinguishable. This is reflected in the significant reduction (27.6%) in the membership inference risk to the large capacity Dense19 model (Table III). This indistinguishability of different statistics of features of $\theta_p$ on members and non-members mitigates the membership inference risk to $D_t$ with either of blackbox and whitebox access to $\theta_p$.

VII. RELATED WORK

Privacy preserving machine learning is an active area of research. Defenses based on trusted hardware and cryptographic primitives [41], [17], [26], [29] hinder a direct access to sensitive training data during training. However, the final models remain susceptible to various inference attacks through blackbox or whitebox accesses, especially for large capacity neural networks due to their large memorization capacities [12]. Such inference attacks include input inference [13], blackbox and whitebox membership inference [40], [31], [38], attribute inference [6], parameter inference [43], [44], training data embedding attacks [41], and side-channel attacks [46]. In this paper, we focus on the membership inference attacks for adversaries with blackbox and whitebox access to the model.

Several recent defenses have been proposed against membership inference attacks [1], [35], [30], [33]. Unfortunately, such existing defenses do not provide practically acceptable tradeoffs between privacy and utility, i.e., they hurt the model’s prediction accuracy significantly to provide membership privacy. Defenses based on differential privacy (DP) [1], [35], [33], [22], [36] provide rigorous membership privacy guarantees, but at prohibitive costs to the accuracy of the models. For instance, the DP-SGD defense proposed by Abadi et al. incurs significant classification losses and high generalization errors for complex classification tasks, e.g., the accuracy loss and generalization error for training on CIFAR-10 are both $\sim 7\%$ in their original work. Such a high generalization error is sufficient for membership inference [27], [37], [40], [31]. therefore, the membership privacy of such models can be breached. Adversarial regularization [30] is another recent defense that is tailored to membership inference attacks, in

Figure 6: The empirical CDF of the generalization error of models trained with DMP and adversarial regularization (AdvReg), and without defense. The y-axis is the fraction of classes that have generalization error less than the corresponding value on x-axis. The error reduction using DMP is much larger (10-folds for CIFAR-100 dataset and by 2-folds for Purchase-100 dataset) than using AdvReg. Refer to Table III for the specific accuracies.
contrast to DP techniques that are general defenses. As shown in Section VI, the adversarial regularization defense suffers from large accuracy losses for smaller training datasets, and does not converge when stronger inference attack models are used during the adversarial training.

Knowledge distillation has been used in several privacy defenses [33], [22], [36], [32], which perform distillation using the noisy aggregate of predictions of models of multiple data holders. In particular, PATE [33] combines knowledge distillation and DP [1]. In PATE, an input is labeled by an ensemble of teacher models, and the final student model is trained using the noisy aggregates of all labels; finally, the DP noise is added during the aggregation. These approaches add large amounts of noise to provide privacy to any data with the underlying distribution, and in this process incur high accuracy losses [35]. However, due to the targeted motivation to provide membership inference resistance, our technique relies on the noise due to the low confidence of models in the predictions on test data and on the indistinguishability due to reduced sensitivity of predictions due to a softmax layer at an appropriate temperature. PATE requires a large number of teacher models to compensate for the noise added to the individual query responses. Therefore, it requires huge amounts of training data (65M for Glyph character recognition task), availability of which may not be practical for an individual user using some MLaaS platform. Finally, similar to DP-SGD [1], PATE does not evaluate the empirical membership inference risk of its models. Bassily et al. [3] propose similar approach as PATE. The work focuses on providing differential privacy using the sparse vector technique [11] and gives bounds on sample complexity in terms of the VC dimensions of the task. Wang et al. [45] propose RONA, a private model compression technique that adds noise similar to DP-SGD [1] during the training of a student model. Our approach differs from these in that, we do not explicitly add DP noise, and instead, use the inherent noise in knowledge transfer to achieve membership inference resistance (i.e., privacy) for free. Our evaluation is similar to that in [21].

Long et al. [27] investigated membership inference attacks against well-generalized models. Their attack identifies the vulnerable outliers in the sensitive training data of the well-generalized models to infer their membership. In DMP, the outliers can be protected by setting high softmax temperatures, but at the cost of utility degradation. This is similar to previous
defenses: in DP-SGD, privacy budget is reduced and in the adversarial regularization, high regularization factor is set to provide privacy to the outliers. But the important difference is that, in DMP, the expected membership privacy protection to the given sensitive training data is very strong and incurs significantly lower classification accuracy costs compared to previous defenses.

To summarize, all of the existing defenses rely on adding some explicit noise during the training or regularization of the model in different ways. Because of such explicit noise additions, all these defenses suffer from significant utility degradations in terms of classification performance of the final models. By contrast, DMP provides membership inference resistance using various implicit sources of noise due to knowledge distillation. Knowledge distillation presents itself as a promising option for practical utility-privacy trade-offs because of its proven ability to transfer the utility of the cumbersome model to the final model [16].

VIII. CONCLUSIONS
Motivated by the poor tradeoffs between model utility and resistance to membership inference attacks, we introduced distillation for membership privacy (DMP), an effective defense against membership inference attacks on machine learning models. DMP leverages various sources of noise in the knowledge distillation (transfer) process to train models resilient to membership inference and with high classification performance. DMP trains machine learning models that are resistant to whitebox and blackbox membership inference attacks while preserving the utility (e.g., classification accuracy) of the models significantly better than state-of-the-art membership inference defenses. We validate DMP’s superior performance in terms of tradeoff between membership privacy and utility of the models, and in terms of regularization strength through extensive experiments on different deep neural networks and using various benchmark datasets.

IX. ACKNOWLEDGEMENT
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