
Towards the Infeasibility of Membership Inference on Deep Models

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Abstract

Recent studies propose membership inference (MI) attacks on deep models. Despite the moderate accuracy of such MI attacks, we show that the way the attack accuracy is reported is often misleading and a simple blind attack which is highly unreliable and inefficient in reality can often represent similar accuracy. We show that the current MI attack models can only identify the membership of misclassified samples with mediocre accuracy at best, which only constitute a very small portion of training samples. We analyze several new features that have not been explored for membership inference before, including distance to the decision boundary and gradient norms, and conclude that deep models' responses are mostly indistinguishable among train and non-train samples. Moreover, in contrast with general intuition that deeper models have a capacity to memorize training samples, and, hence, they are more vulnerable to membership inference, we find no evidence to support that and in some cases deeper models are often harder to launch membership inference attack on. Furthermore, despite the common belief, we show that overfitting does not necessarily lead to higher degree of membership leakage. We conduct experiments on MNIST, CIFAR-10, CIFAR-100, and ImageNet, using various model architecture, including LeNet, ResNet, DenseNet, InceptionV3, and Xception. Source code: <https://github.com/shrezaei/MI-Attack>.

1 Introduction

There is an extensive recent literature on membership inference (MI) attacks on deep learning models that achieve high MI attack accuracy [16, 15, 8, 18, 9, 20, 10, 21]. These MI attack models often use confidence values of the target model to infer the membership of an input sample. High MI attack accuracy is often justified by claiming that deep learning models are more confident towards the training (member) samples than the samples they have not seen during training¹. Consequently, MI attack accuracy is reported to be highly correlated to model's overfitting or generalization gap [15, 16, 18] because an overfitted model should perhaps behave even more confident towards training samples.

In this paper, we show that the attack accuracy reported in literature is misleading. In general, we find that accuracy of MI attacks on majority of training samples **are not much better than a random guess**. We show that existing MI attack models mostly **distinguish correctly classified samples from misclassified samples, rather than distinguishing train samples from non-train samples**. As a result, the MI attack performance essentially represents the gap between the train accuracy and test accuracy, i.e. generalization gap. To better understand the performance of MI attacks that

¹In this paper, we use training samples and member samples interchangeably. Moreover, we also use non-training, test, and non-member interchangeably.

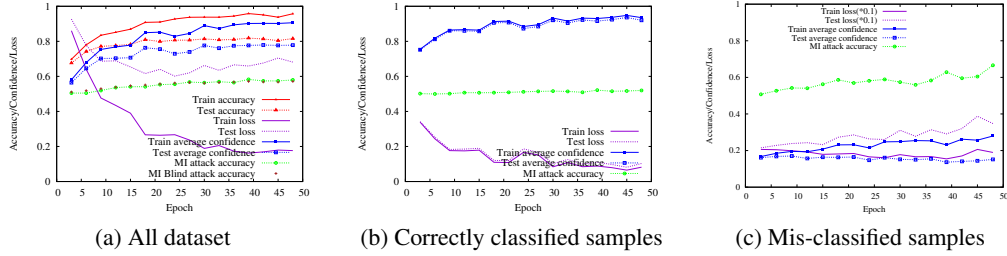


Figure 1: The effect of overfitting on MI attack, where the target model is a simple CNN model with two convolutional blocks and the task is CIFAR-10. (a) By analyzing the entire dataset as a whole, one may conclude that confidence values are distinguishable feature and MI attack accuracy improves when overfitting occurs. (b) For the correctly labeled samples, model behavior is almost similar for training and test set. (c) For the misclassified samples, there exist a noticeable gap in average confidence values between the train and test set, and, hence, the MI attack accuracy is higher.

exploit generalization gap, we introduce a naive and impractical attack, called blind attack. **Blind attack** predicts a sample as *member* if it is correctly labeled by the target model, and predicts it as *non-member* if misclassified. As shown in Figure 1(a), the accuracy of MI attack is almost the same as that of the blind attack. This clearly shows that reporting only the accuracy, shown in Figure 1(a), is misleading because it cannot reveal how much MI attacks exploit the generalization gap instead of learning a representative and effective distinguishable features of train and test samples.

To better demonstrate how current MI attacks work, we separate datasets into two parts: correctly classified samples and misclassified samples. As shown in Figure 1(b) and (c), the MI attack on correctly classified samples barely outperform a random guess, while MI attack on misclassified samples is slightly more effective. In general, we find that membership inference of correctly classified samples, independent of what dataset or model is used, is a more difficult task than the membership inference of misclassified samples.

Interestingly, as target models overfit (starting from epoch 20 in Figure 1(a)), the MI attack accuracy over correctly classified samples barely changes (Figure 1(b)). At the same time, the training accuracy increases, that is, more training samples are correctly classified. Therefore, for the majority of training samples (that are correctly classified), membership inference becomes more difficult. Hence, contrary to common beliefs, overfitting does not necessarily lead to more privacy leakage, although it may hurt the model generalization.

Our contributions are summarized as follows:

- We show that attack accuracy alone is a misleading measure and an unreliable blind attack can generate similar accuracy. Instead, we study the accuracy of correctly classified samples and misclassified samples separately. **We show that membership inference of correctly classified samples, to which the majority of training samples belong, is a very difficult task.**
- We perform MI attack on various datasets (including MNIST, CIFAR-10, CIFAR-100, and ImageNet), and models (LeNet, ResNet, DenseNet, InceptionV3, Xception, etc), some of which are studied for the first time in the MI context. We conduct experiments such that they give a lot more advantages to the attacker than in any previous work. Even in this case, we show that a meaningful membership inference attack with high accuracy is not achievable. Moreover, we show that deeper models does not necessarily memorize and leak more training samples, and in many cases MI attacks are less effective on them.
- In addition to confidence values of the target model, we extensively analyze and use other information available from the target model, including values from intermediate layers, the gradient w.r.t input, gradient w.r.t to model weight, and distance to the decision boundary. These types of information slightly leak more membership status than confidence values, but they still do not suffice for a reliable MI attack in practice. Surprisingly, all evidence suggests that deep models often behave similarly on train and non-train samples across

all these metrics. The only considerable difference appears between correctly classified samples and misclassified samples, not between the train and non-train samples.

In summary, membership inference of correctly classified samples, to which the majority of training samples belong, is a very difficult task. However, we are hesitant to generalize our results to all scenarios and perhaps more research is needed, some of which are as follows:

- We do not extend our conclusion to generative models. High capacity generative models can often memorize training samples, which can be retrieved at inference time, as shown in [1]. However, there is no trivial method to retrieve memorized samples from a discriminative model even if it memorizes training samples.
- We do not extend the conclusion to any attack that can be launched during the training phase, such as data poisoning, model/training manipulation [17], etc. We only study membership inference on naturally trained models and natural datasets. Deep models may behave very differently if any unnatural manipulation appears during the training phase.
- In each dataset, there often exists outliers. The MI attack maybe more successful on these samples [10], whether they are classified correctly or not.

2 Related Work

The first membership inference attack on deep models is proposed by Shokri et al. in [16]. The key idea is to build a machine learning attack model that takes the target model’s output (confidence values) to infer the membership of the target model’s input. To train the attack models, membership dataset containing (x_{conf}, y_{mem}) pairs is needed where x_{conf} represents the confidence values obtained by the target model for each sample and y_{mem} is a binary variable indicating whether the sample is used in target model’s training or not. To build the membership dataset, a set of shadow models are trained for which the training and non-training samples are known. The attack is possible under two assumptions [15]: (a) the shadow models share the same structure as the target model, and (b) the training dataset used to train the shadow models share the same distribution as the one used to train the target model. To mitigate these limitations, Salem et al. [15] relax the second assumption by showing the attack is possible using different datasets and the first assumption by proposing a threshold-based attack that does not require a training procedure. To further relax these assumptions, several studies [8, 18, 9, 20, 10, 21] introduce better dataset generating procedures for shadow models, and extend the experiments to various scenarios and datasets. However, all studies share the same idea of using target model’s output for membership inference. In this paper, we show that the output of deep learning models are often similar for correctly labeled samples, whether they were used in training or not.

3 The Case of Misleading Report

First, we need to shed a light on the issue of misleading reports. Membership inference is a binary classification and, hence, it is commonly compared to a random guess which achieves 50% accuracy. Intuitively, a MI attack that shows a significant accuracy improvement over 50% of the random guess is considered to be an effective MI attack. However, this comparison does not reveal what is learned by the attack model. We show that the blind attack can achieve the same accuracy despite being useless in practice. Hence, a useful MI attack model should considerably outperform blind attack.

Why is the blind attack useless in practice? The goal of membership inference attack in reality is often to correctly identify training (member) samples. The reason is that in practice any given sample input can be assumed to be non-member because the training samples constitute only a very small portion of possible natural inputs. Hence, in reality, the membership inference problem is a highly imbalanced problem where the members class is the minority class. In this case, the blind attack achieves very low accuracy. However, in experimental settings, this is usually reversed because the majority of available samples is used to train the target model. In such unrealistic experimental setting, the blind attack represents high accuracy if the generalization gap is non-negligible. This misleading illusion of high accuracy leads to an unreliable MI attack model if used in reality where the majority of given correctly classified samples do not actually belong to the train set (see more discussions in Appendix A.1). This also explains why current MI attacks report high accuracy.

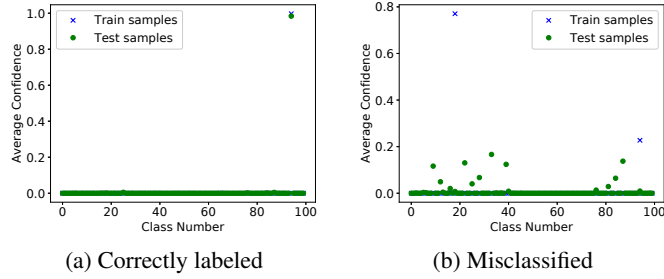


Figure 2: Distribution of average confidence values for CIFAR 100 dataset (ResNet) (class 94)

How can we analyze if an MI attack exploits the generalization gap? Given that the blind attack is useless in practice, a good MI attack must have at least two features to be considered useful: (a) performing significantly better than the blind attack during experimental evaluations, and (b) relying on more informative features than only the correctness/incorrectness of the target model prediction. Reporting MI attack performance metrics alongside the blind attack can solve the first problem. Furthermore, we propose to report the performance of MI attack on correctly labeled samples and misclassified samples separately to solve the both issues. Regardless of the balanced accuracy of the blind attack on the entire dataset, the balanced accuracy of the blind attack on correctly classified samples and misclassified samples are always exactly 50%, when they are reported separately. This separation allows us to use 50% accuracy as a baseline similar to all typical binary tasks informatively. A good MI attack model which exploits target models leakage rather than only correctness/incorrectness of the prediction should achieve reasonable balanced accuracy on correctly labeled samples and misclassified samples separately.

4 Methodology

Threat model and assumptions In this paper, we gives an attacker the most relaxed limitations to show that even in such cases membership inference cannot significantly outperforms a random guess. We assume a white-box access to the model and unlimited number of queries. Moreover, we give the membership status of up to 80% of training samples and test samples to the attackers and we only ask the attack model to predict the membership inference of the remaining samples. Hence, the attack performance we report in this paper is as good as or better than any proposed attack based on shadow models [16, 9] or transferred or synthesized data [8, 15]. In addition to confidence values of the target model, which have been used extensively for membership inference attack in the past, we also study the output of intermediate layers, distance to the decision boundary and a set of gradient norms to better understand if deep models behave differently on training and test samples.

Confidence values Confidence values, or the output of Softmax layer, have been widely used for membership inference [16, 15, 8, 18, 9, 20, 10, 21]. Figure 2 shows the distribution of average confidence for correctly classified samples and misclassified samples of a typical model. As it is shown, misclassified samples often show different distribution for training samples and test samples. However, correctly classified samples often saturate the true class confidence value and zero out other confidence values. We show in Section 5 that membership inference attack models are often fail to considerably outperform a coin toss for correctly labeled samples.

Output of intermediate layers In deep models, first layers often extract general and simple features that are not specific to training samples. As suggested in [13], the last layer and layers close to the last one contain more sample-specific information. Hence, we also use the output of the fully connected layers before the Softmax for membership inference attacks.

Distance to the decision boundary Some research focuses on understanding decision boundary of deep models [11, 7] or geometry and space of deep models [4, 12] to often understand the nature of adversarial examples or to improve robustness. In this paper, we investigate whether the distance to boundary is a distinguishable feature for training and test samples to be used for membership

Table 1: Accuracy of various datasets, target models, and MI attack models

Dataset	MNIST	CIFAR-10	CIFAR-100	CIFAR-100	CIFAR-100	ImageNet	ImageNet
Model	LeNet	CNN2	CNN3	DenseNet	ResNet56	InceptionV3	Xception
Train	99.74%	97.44%	97.38%	88.15%	99.46%	87.91%	87.77%
Test	99.05%	82.07%	55.63%	56.52%	57.36%	79.98%	80.70%
MI Attack	50.04%	57.27%	74.01%	65.23%	74.46%	50.03%	51.18%
Blind Attack	50.07%	57.13%	70.23%	65.68%	71.97%	54.12%	53.37%

inference. To find the distance to the decision boundary, we use FGM [3] optimization procedure to craft an image on the other side of the decision boundary. Then, we perform a binary search to find an instance for which the model’s confidence for two classes are almost equal, that is, the difference between two confidences is smaller than a small threshold, similar to [7]. Finally, we obtain the L_2 distance between the original sample and the crafted samples as a measure of distance to the boundary (See Appendix A.2 for the algorithm).

Gradient norm It has been shown that the gradient of loss with respect to model parameters, $\frac{\partial L}{\partial w}$, is often smaller for training samples than non-training samples [13] and it can be used for membership inference attack in federated learning scenario. In this paper, we study the gradient of loss with respect to model parameters, $\frac{\partial L}{\partial w}$, and also the gradient of loss with respect to model input, $\frac{\partial L}{\partial x}$. The large value for the former indicates that major re-tuning of model parameters is needed for that sample, and hence, it can be an indication of a non-member sample. The large value of the latter indicates that there are input samples with better output in the vicinity of that sample, and hence, it can be an indication of a non-training sample. Both $\frac{\partial L}{\partial w}$ and $\frac{\partial L}{\partial x}$ are extremely high dimensional. Thus, we adopt the seven norms used in [14], originally used for analysis of deep model’s uncertainty, namely L_1 , L_2 , absolute minimum, L_∞ , mean, Skewness, and Kurtosis.

5 Experimental Evidence

Target models and datasets We train various CNN-based models on four image classification tasks: MNIST, CIFAR-10, CIFAR-100, ImageNet. For MNIST, we train LeNet model. For CIFAR-10 and CIFAR-100, we train a shallow CNN-based models with 2 (CNN2) and 3 (CNN3) convolutional blocks with a single fully connected (FC) layer, respectively. Each convolutional block contains two convolution layers with 3×3 receptive fields and a max pooling of size 2×2 . FC layers have 128 and 1024 neurons for CIFAR-10 and CIFAR-100, respectively. Additionally, we train DenseNet [6] and ResNet56 [5] models for CIFAR-100 dataset. For ImageNet, we use pre-trained InceptionV3 [19] and Xception [2] models without any re-training. For ImageNet, we conduct experiments with only 100 classes out of 1000 classes due to the limited computational and time budget. We use Adam optimizer with a learning rate of 0.001. We do not perform any data augmentation or any special weight initialization, such as the one proposed in [5], or extensive hyper parameter tuning.

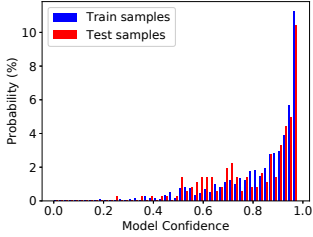
MI attack models In most cases, we fit three types of attack models: FC neural network (NN), random forest (RF), and XGBoost. For the NN model, we train a model with 2 hidden layers of size 128 and 64. For RF and XGBoost, we perform a random search over a large set of hyper-parameters. In this paper, we only report the best MI attack accuracy we achieve over all attack models and hyper-parameters. Note that the goal of this paper is to show the inefficacy of the best possible MI attack, not to show which attack model can marginally outperform the others. The input of attack models varies which is described in each following subsection. The target and MI attack model performances are shown in Table 1. Note that **even the best MI attack models can barely outperform the blind attack**.

5.1 Confidence Values

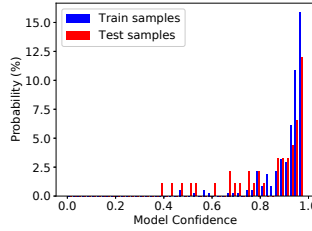
Confidence values are extensively used for MI attacks. As shown in Table 2, the MI attacks are more successful on inferring membership of misclassified samples, which often consist a small portion of training samples. Interestingly, the state-of-the-art target models on ImageNet does not even leak membership status of misclassified samples. The highest MI attack accuracy on correctly classified

Table 2: Membership attack results based on confidence values

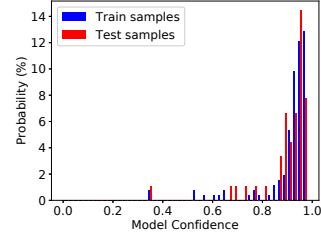
Dataset(Model)	-	Attack Accuracy	Train Confidence	Test Confidence
MNIST	All data	50.04% \pm 0.11	99.61 \pm 4.57	98.90 \pm 9.14
	Correctly classified	49.98% \pm 0.01	99.81 \pm 2.04	99.75 \pm 2.51
	Misclassified	62.30% \pm 17.93	77.61 \pm 16.05	87.09 \pm 15.93
CIFAR-10 (CNN2)	All data	57.27% \pm 3.11	95.09 \pm 13.87	79.49 \pm 34.41
	Correctly classified	50.04% \pm 0.06	96.58 \pm 9.46	94.74 \pm 12.40
	Misclassified	62.14% \pm 7.72	59.15 \pm 17.09	73.64 \pm 21.81
CIFAR-100 (CNN3)	All data	74.0% \pm 7.9	95.73% \pm 10.82	54.93% \pm 42.75
	Correctly classified	58.16% \pm 5.11	96.48% \pm 8.02	89.14% \pm 17.39
	Misclassified	79.39% \pm 24.39	60.42% \pm 15.68	64.68% \pm 22.61
CIFAR-100 (DenseNet)	All data	65.23% \pm 6.43	83.39% \pm 27.61	54.14% \pm 43.36
	Correctly classified	52.24% \pm 2.93	92.17% \pm 13.76	90.07% \pm 16.17
	Misclassified	58.94% \pm 15.22	63.82% \pm 19.47	68.64% \pm 21.87
CIFAR-100 (ResNet)	All data	74.46% \pm 8.12	99.03% \pm 6.57	54.53% \pm 46.19
	Correctly classified	55.35% \pm 4.02	99.43% \pm 3.4	94.9% \pm 11.84
	Misclassified	83.34% \pm 23.46	72.75% \pm 17.14	81.61% \pm 19.62
ImageNet (InceptionV3)	All data	50.03% \pm 0.28	76.03% \pm 25.52	68.62% \pm 29.43
	Correctly classified	50.03% \pm 0.31	83.99% \pm 15.55	81.85% \pm 16.37
	Misclassified	51.5% \pm 8.57	13.57% \pm 11.44	10.8% \pm 9.38
ImageNet (Xception)	All data	51.18% \pm 3.56	73.56% \pm 25.56	66.92% \pm 28.58
	Correctly classified	50.72% \pm 3.57	81.24% \pm 16.81	79.08% \pm 17.18
	Misclassified	51.95% \pm 19.29	13.48% \pm 10.94	11.27% \pm 8.94



(a) CIFAR-10



(b) CIFAR-100 (CNN3)



(c) ImageNet (InceptionV3)

Figure 3: Distribution of the confidence of the true class for correctly labeled samples. The distribution of the target model confidence for the true class is similar across training and test samples. There are some small peaks out of the $[0.8, 1]$ range which can be often detected by MI attack models. That is the reason MI attacks achieve slightly accuracy than a random guess.

samples is observed on CNN3 model trained on CIFAR-100, which is 58.16%. However, this is only slightly better than a random guess which renders it impractical for accurate membership inference.

Note that the balanced accuracy of the blind attack on only correctly classified (or misclassified samples) is always 50% regardless of the accuracy over all samples. Therefore, when reading the accuracy of correctly classified or misclassified samples, the baseline can be considered to be 50%. However, when reading the accuracy over all data, one should compare with the blind attack accuracy (in Table 1).

The table also shows the average confidence value of the training samples and test samples. For correctly classified samples, the average confidence gap between training and test samples are smaller than misclassified samples. Despite the clear difference between average confidence of training samples and test samples, the high variance makes classification unreliable. As shown in Figure 3, the confidence values of training and test samples of correctly labeled samples often show similar distribution. The existence of outliers can often be seen on the histogram that accounts for slight improvement of MI attack accuracy.

Table 3: MI attack accuracy based on the output of intermediate layers. In all following reports, attacks that demonstrate more than 1% percent attack accuracy improvement over confidence value-based attack are marked as bold.

Dataset (Model)	Layer	Correctly classified	misclassified
MNIST	-1	51.03 \pm 4.64	52.50 \pm 0.30
	-2	49.74 \pm 0.14	50.62 \pm 0.41
CIFAR-10	-1	50.22 \pm 0.28	59.89 \pm 4.84
	-2	50.92 \pm 1.60	57.86 \pm 4.40
CIFAR-100 (CNN3)	-1	50.30 \pm 2.19	63.36 \pm 4.20
	-2	50.09 \pm 0.74	58.76 \pm 5.47
CIFAR-100 (DenseNet)	-1	51.59 \pm 4.64	57.21 \pm 7.34
CIFAR-100 (ResNet)	-1	50.96 \pm 3.49	50.28 \pm 5.58
ImageNet (InceptionV3)	-1	50.09 \pm 0.56	50.96 \pm 2.74
ImageNet (Xception)	-1	51.31 \pm 6.03	56.42 \pm 13.93

Table 4: Average L2 distance of an input to decision boundary and MI attack accuracy. C and I represents CIFAR and ImageNet, respectively.

Dataset (Model)	Correctly Classified			Misclassified		
	MI Attack	Average Distance		MI Attack	Average Distance	
	Accuracy	Train	Test	Accuracy	Train	Test
MNIST	50.06% \pm 6.08	1.3726 \pm .4001	1.3714 \pm .4512	49.81% \pm 9.05	0.0103 \pm .0016	0.0108 \pm .0024
C-10	54.44% \pm 6.05	0.2133 \pm .1679	0.1849 \pm .1718	48.7% \pm 5.27	0.0053 \pm .0098	0.0048 \pm .0088
C-100 (CNN3)	58.52% \pm 9.00	0.2467 \pm .1723	0.1911 \pm .1698	59.9% \pm 1.24	0.0015 \pm .0025	0.0034 \pm .0063
C-100 (DenseNet)	53.58% \pm 6.60	0.1512 \pm .1254	0.1692 \pm .1426	47.8% \pm 15.06	0.0044 \pm .0088	0.0041 \pm .0085
C-100 (ResNet)	59.54% \pm 8.39	0.0312 \pm .0264	0.0411 \pm .0285	52.63% \pm 18.60	0.0214 \pm .0111	0.0164 \pm .0124
I (InceptionV3)	51.75% \pm 8.24	212.40 \pm 64.83	218.68 \pm 63.03	44.95% \pm 11.97	215.84 \pm 67.01	215.16 \pm 61.55
I (Xception)	53.01% \pm 9.57	214.51 \pm 64.64	216.23 \pm 61.98	49.29% \pm 13.50	212.42 \pm 67.04	214.76 \pm 64.02

5.2 Output of Intermediate Layers

The attack accuracy based on the output of intermediate layers are shown in Table 3. We only launch an attack on the output of FC or flattened layers. The layer column shows the number of layers we go back from the Softmax layer. Interestingly, as we go back from the last layer, deep learning models leak less membership status, except for Xception model on ImageNet which slightly leaks more membership status on misclassified samples.

5.3 Distance to the Boundary

Since the distance to the decision boundary is one-dimensional, we only fit a logistic regression to the samples. As shown in Table 4, on average, the misclassified samples of train and test sets share almost the same distance to the boundary. Interestingly, for correctly classified samples, a MI attack model based on distance to the decision boundary marginally outperforms attack models based on confidence values across most datasets and model architecture. However, the attack accuracy is still low.

5.4 Gradient Norm

Table 5 shows the accuracy of MI attack model based on gradient norms. For each case, we fit a logistic regression to the 7 norms introduced in Section 4. Gradient norms w.r.t x is more effective for correctly classified samples while the the gradient norms w.r.t w is more effective for misclassified samples. Gradient w.r.t x often leak more membership status than all other metrics for correctly classified samples. Nevertheless, the results are still far away from a reliable MI attack.

Table 5: Accuracy of attack model based on gradient norms with respect to input (x) and weights (w)

Dataset (Model)	Correctly Classified		Misclassified	
	Grad w.r.t w	Grad w.r.t x	Grad w.r.t w	Grad w.r.t x
MNIST	52.06% \pm 3.37	53.19% \pm 3.52	57.84% \pm 26.8	52.02% \pm 22.2
CIFAR-10	50.56% \pm 4.44	51.19% \pm 2.8	61.89% \pm 10.41	52.94% \pm 12.05
CIFAR-100 (CNN3)	61.03% \pm 8.77	61.19% \pm 8.8	61.81% \pm 15.43	61.98% \pm 9.91
CIFAR-100 (DenseNet)	51.13% \pm 7.3	54.9% \pm 7.87	50.58% \pm 12.31	53.71% \pm 11.03
CIFAR-100 (ResNet)	58.91% \pm 8.2	59.19% \pm 8.01	56.07% \pm 15.8	53.33% \pm 17.3
ImageNet (InceptionV3)	49.25% \pm 11.77	52.10% \pm 9.63	58.48% \pm 15.38	50.55% \pm 16.51
ImageNet (Xception)	51.65% \pm 8.23	53.23% \pm 9.15	55.62% \pm 15.52	46.12% \pm 14.4

Table 6: The effect of deep model’s depth on MI attack based on confidence values. The last digit in the model name represents the number of convolutional blocks.

Dataset (Model)	Target Model Accuracy		Blind Attack Accuracy	MI Attack Accuracy		
	Train	Test		All Data	Correctly Classified	Misclassified
CIFAR-10 (CNN1)	95.48%	71.87%	61.94% \pm 3.68	63.08% \pm 3.42	53.17 \pm 1.78	62.06 \pm 1.71
CIFAR-10 (CNN2)	95.82%	81.84%	57.15% \pm 2.92	58.28% \pm 2.82	52.14 \pm 1.19	60.45 \pm 4.59
CIFAR-10 (CNN3)	97.97%	84.76%	56.43% \pm 3.46	57.48% \pm 3.44	51.56 \pm 1.64	58.22 \pm 14.90
CIFAR-100 (CNN1)	99.87%	39.49%	80.24% \pm 8.43	87.08% \pm 7.85	70.13% \pm 9.34	96.93% \pm 11.98
CIFAR-100 (CNN2)	99.55%	51.86%	74.12% \pm 7.23	80.48% \pm 7.85	64.84% \pm 7.63	93.78% \pm 16.36
CIFAR-100 (CNN3)	98.46%	55.61%	70.23% \pm 7.35	74.01% \pm 7.90	58.16% \pm 5.11	79.39% \pm 24.39
CIFAR-100 (CNN4)	96.72%	58.59%	69.05% \pm 7.47	71.84% \pm 7.54	56.67% \pm 4.84	71.29% \pm 24.21

5.5 Effect of Model Depth

We train a set of CNN-based models on CIFAR-10 and CIFAR-100. Table 6 demonstrates the effect of model’s depth on model’s membership leakage. Despite the general intuition that the deeper models tend to memorize training samples, deeper models are more resistant to membership inference attack on both correctly classified samples and misclassified samples. The reason is two-folded: (a) the gap between the train and test accuracy drops as model’s depth increases which degrade the accuracy of attack models relying on generalization gap, and (b) the deeper models behave more similarly across train and test samples, the effect of which is reflected on the reduction of MI attack accuracy on both correctly classified samples and misclassified samples. The MI attack accuracy over training epochs and the effect of overfitting for these models are presented in Appendix A.3 and A.4.

6 Conclusion

In this paper, we show that commonly-used MI attacks based on confidence values of deep models are not practical and reliable as it has been reported before. Throughout exhaustive experimentation on various datasets and deep model architectures, we show that membership inference attacks barely outperform a simple blind attack that predict membership status of a sample based on whether the target model classifies it correctly or not. We demonstrate the problem of reporting attack accuracy on the entire dataset alone, and we report the attack accuracy on correctly classified samples and misclassified samples separately to show how much membership attack improvement over the blind attack is possible. Moreover, we show that deeper models are less prone to membership inference attack and the membership inference of correctly classified samples, to which most training samples belong, is a considerably more difficult task than misclassified samples. Additionally, we analyze several other features of input samples, including the distance to the decision boundary and gradient norms, to further illustrate the infeasibility of reliable membership inference attack on deep models. In summary, we find that naturally trained deep models often behave indistinguishably across training and test samples and, hence, an accurate membership inference attack on all training samples in practice is not possible unless a new revolutionary approach is introduced.

Broader Impact

Membership inference, if possible, can lead to privacy breach of training samples. In many applications, datasets are considered to be sensitive, such as medical data. In this paper, we show that reliable and accurate membership inference of **deep models** is an extraordinary difficult task. Moreover, it becomes almost impossible when input dimension becomes very large. As a result, individuals or organizations who share or provide public access to their models can be more confident that the privacy of their training samples are protected. This benefits, however, comes with a legal challenge when someone wants to show his/her private data has been used without permission. For example, corporations may hold a large amount of private/sensitive data, such Facebook or Google. They are not supposed to use certain part of data under certain regulations. However, if they use such data to train a model, it is hard for users to prove with high confidence that such illegal usage of private data has occurred. Currently, there is no easy solution to such a problem. One possible ideal solution can involve a certificate-based proof which can be used by model trainers to show that certain data has not been used during training, when they are asked. This is still an open problem and we think solving this problem is more important than focusing on privacy preserving approaches for deep models since they do not seem to leak much reliable information about membership of training samples.

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A Appendix

A.1 Misleading Report and Imbalanced Problem in MI in Details

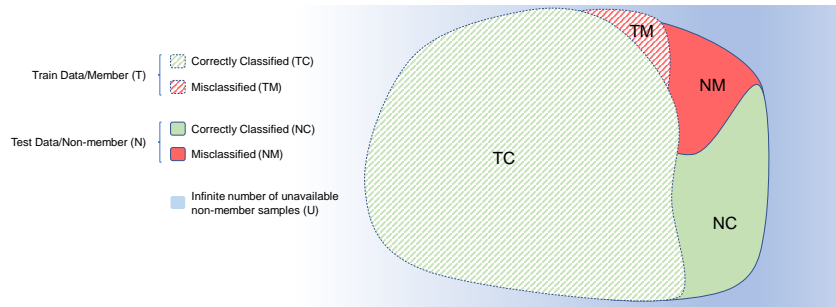


Figure 4: A distribution of member and non-member samples of a typical task. Although T is fixed, N can practically grows to infinity by obtaining samples from U . Typical MI attack models learn to separate green regions from the red regions. However, the true goal of membership inference is to separate solid colored regions from the regions with rotated stripes.

In a typical imbalanced problem, reporting balanced accuracy or precision/recall can reveal the performance of a model. Unfortunately, this approach still does not address the MI attack experiment

issue because MI problem has a unique subtlety in comparison with common imbalanced problems: In MI problem, one class (member) has fixed number of samples and the other class (non-member) has practically infinite number of samples. Ironically, during experimental evaluations, the number of samples available from non-member class is much smaller than the member class. As shown in Figure 4, member samples (T) are limited and known during evaluation, but only a small portion of non-member samples (N) is available during evaluation. The entire non-member samples are represented by $U + N$. For the blind attack, all TC and NC (green regions) samples are inferred to be members and, hence, the precision ($\frac{TC}{TC+NC}$) during evaluation is high. However, in practice, the precision of a random set of samples is almost zero because TC is fixed and NC can grow to infinity. As an example, in CIFAR-10 dataset, T is 50000, and N is 10000 but it can potentially grow to the entire U with almost $o(256^{3072})$ samples. Even if we only consider the naturally occurring images, the difference is still extremely large. However, these samples are not available during the experimental evaluations. This shows that although the blind attack can achieve high accuracy (precision/recall) during evaluation, it is still useless in practice.

A.2 Algorithm to find decision boundary

Algorithm 1 shows the FGM-based method to find the distance to the boundary. It first uses the gradient of loss w.r.t the input to find the direction for which the confidence decreases and changes the input slightly towards that direction. This process continues until the input is changed enough to be labeled as a different class by the target model. This modified sample is considered to be on the other side of the decision boundary. Then, the algorithm uses the binary search to find a new sample between these two last modified samples that reside on different side of the decision boundary. The process stops when a sample is found such that the confidence of the target model for two different classes are very close.

Algorithm 1 FGM-based algorithm to find distance to the decision boundary

Input: S (maximum number of steps), \mathbf{x} (input sample) and y (the sample ground-truth), f_{cls} (an interface to the target model which returns predicted class), f_{conf} (an interface to the target model which returns the confidence value of the predicted class), L (target model loss function), θ (confidence threshold indicating when the algorithm stops optimizing):

```

1: procedure DISTANCE_TO_BOUNDARY( $\mathbf{x}, f$ )
2:    $\mathbf{x}_0 = \mathbf{x}$ 
3:   for  $t$  from 0 to  $S$  do
4:      $\mathbf{x}_{t+1} = \mathbf{x}_t + \varepsilon \frac{\nabla_{\mathbf{x}} L(\mathbf{x}_t, y)}{\|\nabla_{\mathbf{x}} L(\mathbf{x}_t, y)\|_2}$ 
5:     if  $f_{cls}(\mathbf{x}_{t+1}) \neq f_{cls}(\mathbf{x}_t)$  then
6:       while  $|f_{conf}(\mathbf{x}_{t+1}) - f_{conf}(\mathbf{x}_t)| > \theta$  do
7:          $\mathbf{x}_m = \frac{\mathbf{x}_{t+1} + \mathbf{x}_t}{2}$ 
8:         if  $f_{cls}(\mathbf{x}_m) = f_{cls}(\mathbf{x}_t)$  then
9:            $\mathbf{x}_t = \mathbf{x}_m$ 
10:        else if  $f_{cls}(\mathbf{x}_m) = f_{cls}(\mathbf{x}_{t+1})$  then
11:           $\mathbf{x}_{t+1} = \mathbf{x}_m$ 
12:        else
13:          return Error!
  return  $\|\mathbf{x}_0 - \mathbf{x}_t\|_2$ 
return Optimization failed!

```

A.3 CIFAR-10: Effect of model depth and overfitting

In this section, we analyze the accuracy of MI attack models, based on confidence values, over training procedure. We track three CNN models with various depth, that is, CNN1, CNN2, and CNN3, containing one, two, and three convolutional blocks, respectively. The result of MI attack over training epochs are illustrated in Figure 5, 6, and 7. On CIFAR-10 dataset, as the target model gets deeper, the MI attack accuracy drops slightly. Moreover, as target models overfit, MI attack accuracy over misclassified samples slightly increases, but the MI attack accuracy of correctly labeled samples does not change. At the same time, the number of misclassified training samples decreases as target models overfit. Hence, deeper and slightly overfitted models may slightly improve the privacy of training samples for CIFAR-10 dataset.

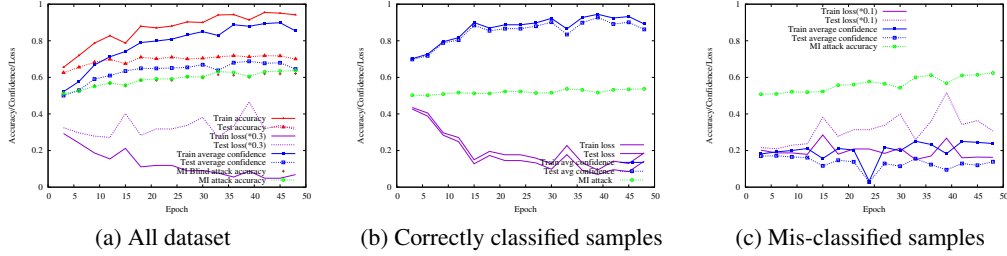


Figure 5: Training progress and MI attack on CIFAR-10 for CNN1 model with 1 convolutional blocks

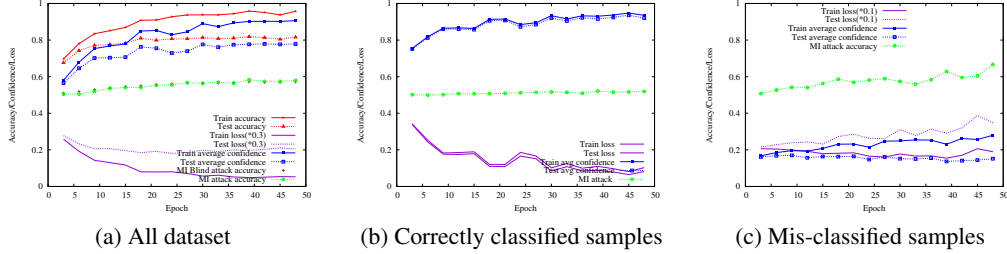


Figure 6: Training progress and MI attack on CIFAR-10 for CNN2 model with 2 convolutional blocks

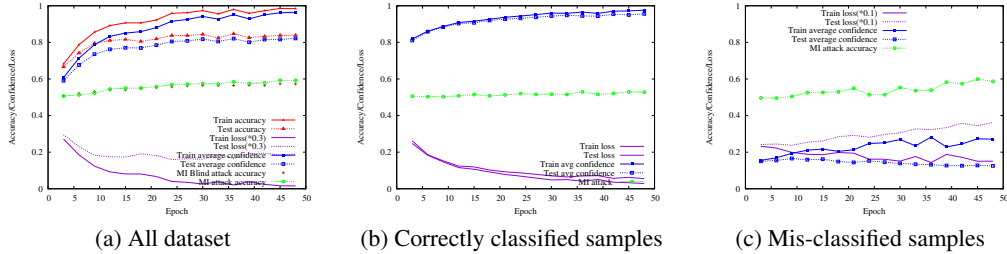


Figure 7: Training progress and MI attack on CIFAR-10 for CNN3 model with 3 convolutional blocks

In general, confidence-based attacks exploit the gap between confidence value of training samples and non-training samples to perform membership inference. However, at the epoch when the model starts overfitting (i.e. test loss stops decreasing), the average confidence value of correctly classified training samples is almost saturated (i.e. becomes almost one). Therefore, overfitting does not significantly increase the average gap between training and non-training samples that are correctly classified. This is clearly depicted in Figure 5 (b), 6 (b), and 7 (b). Nevertheless, this is not true for misclassified samples because the confidence value of misclassified training samples still increase. As the confidence value of misclassified training samples increase, many of them eventually becomes correctly classified. Hence, only a small portion of the misclassified training samples remain misclassified for which the membership inference is a relatively easy task. This is shown in Figure 5 (c), 6 (c), and 7 (c).

A.4 CIFAR-100: Effect of model depth and overfitting

We conduct a similar experiment on CIFAR-100 as in Appendix A.3. We use 4 different CNN models with 1 to 4 convolutional blocks. The results are depicted in Figures 8, 9, 10, and 11. CIFAR-100 is more difficult task with more classes and fewer samples per class in comparison with CIFAR-10. The effect of model depth and overfitting is more clear. First, as target models get deeper, the gap between the blind attack and the MI attack decreases and, consequently, MI attacks become less effective. Second, the overfitting of a shadow model, such as the CNN1, improves the MI attack on misclassified samples dramatically, and the MI attack on correctly classified samples non-negligibly.

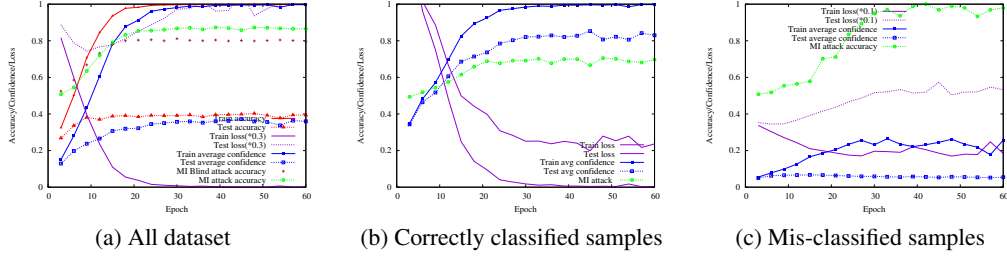


Figure 8: Training progress and MI attack on CIFAR-100 for CNN1 model with 1 convolutional blocks

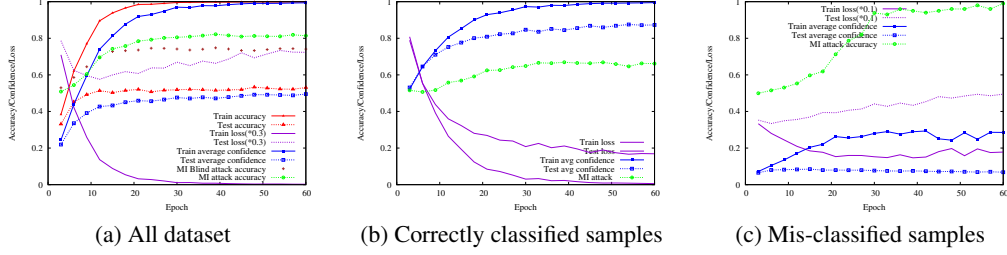


Figure 9: Training progress and MI attack on CIFAR-100 for CNN2 model with 2 convolutional blocks

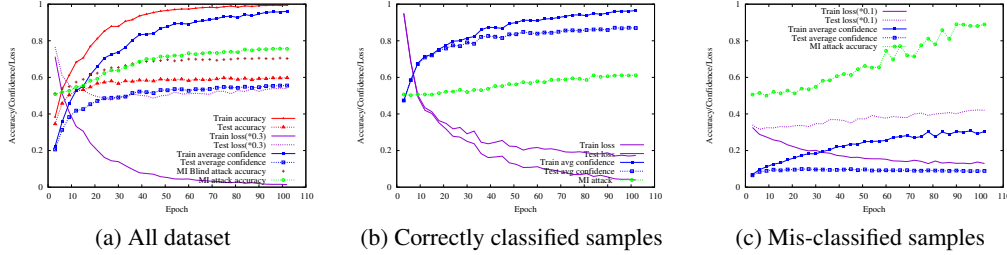


Figure 10: Training progress and MI attack on CIFAR-100 for CNN3 model with 3 convolutional blocks

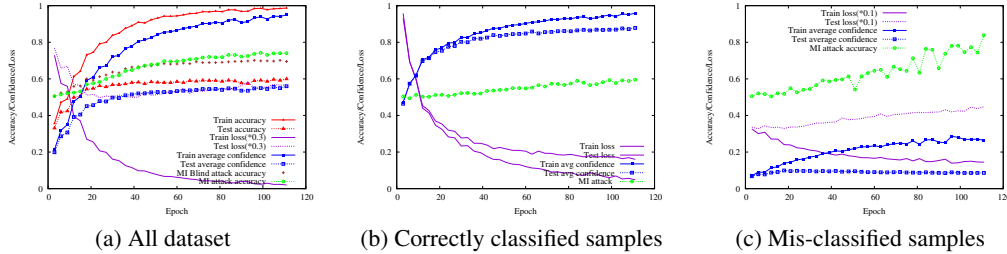


Figure 11: Training progress and MI attack on CIFAR-100 for CNN4 model with 4 convolutional blocks

Depending on how much accuracy improvement over a random guess is defined as a representation of a reliable MI attack classifier, overfitting of a shallow model may be considered to be detrimental in terms of protecting the privacy of training samples. However, as show in Figure 10, and 11, for

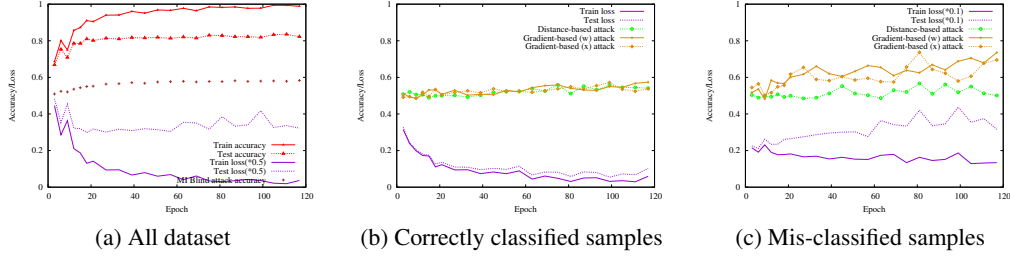


Figure 12: Training progress and MI attack based on gradient norms and distance to the decision boundary on CIFAR-10 for CNN2 model with 2 convolutional blocks

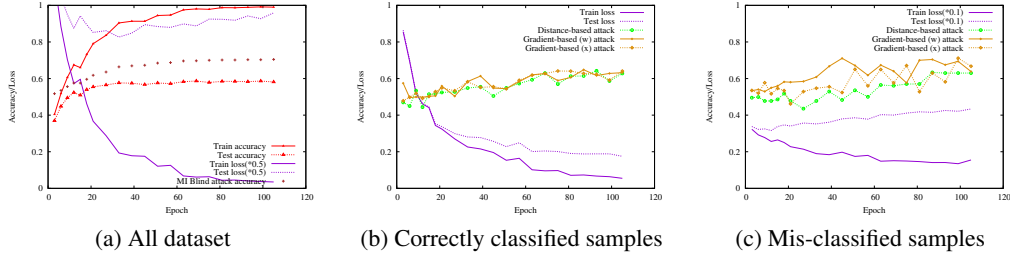


Figure 13: Training progress and MI attack based on gradient norms and distance to the decision boundary on CIFAR-100 for CNN3 model with 3 convolutional blocks

deeper models, the MI attack on correctly classified samples remain difficult and infeasible as the target models overfit.

A.5 Effect of overfitting on gradient and distance to the decision boundary

We conduct several experiments to investigate if overfitting helps MI attacks that use gradient norms or distance to the decision boundary. The experimental results are demonstrated in Figure 12 and 13 for CIFAR-10 and CIFAR-100, respectively. We only perform the experiments on the most suitable model, which is CNN2 for CIFAR-10 and CNN3 for CIFAR-100. The attack results are similar to the attack based on confidence values in previous sections. After overfitting happens, the MI attack accuracy barely improve for correctly classified samples. However, if the training procedure continues, the MI attack accuracy on misclassified samples slightly increases. Note that this large degree of overfitting rarely happens in practice since trainers often use early stop method to prevent extreme overfitting.