An Empirical Study on the Membership Inference Attack against Tabular Data Synthesis Models

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ABSTRACT
Tabular data typically contains private and important information; thus, precautions must be taken before they are shared with others. Although several methods (e.g., differential privacy and k-anonymity) have been proposed to prevent information leakage, in recent years, tabular data synthesis models have become popular because they can well trade-off between data utility and privacy. However, recent research has shown that generative models for image data are susceptible to the membership inference attack, which can determine whether a given record was used to train a victim synthesis model. In this paper, we investigate the membership inference attack in the context of tabular data synthesis. We conduct experiments on 4 state-of-the-art tabular data synthesis models under two attack scenarios (i.e., one black-box and one white-box attack), and find that the membership inference attack can seriously jeopardize these models. We next conduct experiments to evaluate how well two popular differentially-private deep learning training algorithms, DP-SGD and DP-GAN, can protect the models against the attack. Our key finding is that both algorithms can largely alleviate this threat by sacrificing the generation quality.

CCS CONCEPTS
• Security and privacy → Privacy protections: Usability in security and privacy.

KEYWORDS
tabular data synthesis; membership inference attack; differential privacy

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1 INTRODUCTION
Tabular data is one of the most popular data types in reality. It must be kept confidential when it includes valuable and sensitive information. To achieve this, many different approaches have been introduced to protect the privacy of tabular data [3, 18]. In recent years, tabular data synthesis using deep models has been actively investigated since it synthesizes fake records after learning from real records; synthesized tables show behavior similar to the original tables. Generative models guarantee enhanced privacy protection as they output fake records that do not directly correspond to any specific real record, unlike previous methods (e.g., k-anonymity [24] or differential privacy [7]). However, recent research has revealed that generative models are susceptible to the membership inference attack (MIA), where attackers can infer if a given record was used to train a victim model [11]. This can put its original training data at substantial risk of being leaked to the attackers.

Unfortunately, most of the research on MIA against generative models has focused on image data [6, 14, 15]. In this paper, we empirically study MIA in the context of tabular data synthesis. Using the state-of-the-art MIA methods, in other words, we attack the state-of-the-art tabular data synthesis models, which have not been done previously. To our knowledge, we are the first to report the results. More specifically, we conduct experiments in which the tabular synthesis models trained on 4 tabular datasets are attacked under the following two scenarios: i) the black-box attack, where attackers have access only to fake records generated by the victim model, and ii) the white-box attack, where attackers know the internals of the victim model.

We evaluate and compare attack success scores under the two attack scenarios. Moreover, we analyze under what condition tabular data synthesis models become vulnerable to the attack. As a countermeasure to MIA, we conduct additional experiments where the victim models are trained with the two differentially private (DP) deep learning training algorithms – DP-SGD [1] and DP-GAN [29] – and compare the results with the models trained without any DP algorithm. These analyses have not been studied yet under the context of tabular data synthesis. Our key findings are as follows:

(1) As the attacker collects more fake records, the attack is more successful, but there is a limit over which the success rate does not increase.

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We review various state-of-the-art tabular data synthesis models, which we adopt for our experiments as follows: well-known for its tabular data synthesis quality, takes a conditional membership inference attack victim model [11]. It can threaten privacy as not only does it dis-trusts tabular data using convolutional neural networks. OCT-GAN [30], well-known for handling various distributions and computational problems. For instance, TVAE [17] is a variational autoencoder that effectively handles mixed types of features in tabular data. There are also many variants of GANs for tabular data synthesis. Tab1eGAN [22] generates tabular data using convolutional neural networks. CTGAN [30], well-known for its tabular data synthesis quality, takes a conditional generator and incorporates its mode-specific normalization process. OCT-GAN [19] is a model based on neural ordinary differential equations both in generator and discriminator.

2.2 Membership Inference Attack

The membership inference attack (MIA) against generative models aims to determine whether a given record was used to train the victim model [11]. It can threaten privacy as not only does it disclose raw personal data used in training but also allows potential information leakage of the model. Shokri et al. [27] presented the first MIA against classification models in the black-box setting and quantified the membership information leakage. This led to increasing research on MIA in machine learning models, especially on generative models. Hayes et al. [14] proposed the first MIA against generative models for images both in the black and white-box settings. Hilprechet et al. [15] proposed two MIAs, one is for GANs in the black-box setting, and the other is for VAEs in the white-box one. Chen et al. [6] proposed a generic attack model which comprehends all scenarios from the black-box to the white-box setting, which we adopt for our experiments as follows:

As generative models are trained to estimate the training data distribution, attackers infer the membership \( m_i \) by using the probability of a given data \( x \) being generated by the victim model \( G_o \) as follows:

\[
P(m_i = 1|x, \theta_o) \propto P_{G_o}(x|\theta_o),
\]

However, as calculating the exact probability is intractable, they approximate it using the Parzen window density estimation [10]:

\[
P_{G_o}(x|\theta_o) = \frac{1}{k} \sum_{i=1}^{k} \exp(-\|x - G_o(z_i)\|_2).
\]

In the black-box scenario, attackers blindly collect \( k \) fake records generated by the victim model and get a reconstructed copy of a data \( x \) as \( \mathcal{R}(x|G_o) \) to approximate the probability in Eq. (2) as follows:

\[
\mathcal{R}(x|G_o) = \arg \min_{\hat{x} \in \{G_o(\cdot)\}_{i=1}^{k}} \|x - \hat{x}\|_2,
\]

where \( \{G_o(\cdot)\}_{i=1}^{k} \) is a set of \( k \) fake records collected by attackers.

In the white-box scenario, attackers get \( \mathcal{R}(x|G_o) \) to compute the probability in Eq. (2) through optimizing \( z \) as follows:

\[
\mathcal{R}(x|G_o) = G_o(z^*),
\]

However, all previous research has focused on generative models for image data, not for tabular data, albeit some used tabular data in their experiments by heuristically modifying the models for tabular data. However, as tabular data requires pre-processing of its complex data distribution, such heuristics can mislead the analysis. To this end, this paper aims to target tabular data synthesis models for an accurate analysis on MIA on tabular data.

2.3 Differential Privacy

Differential privacy (DP) is a stochastic defense mechanism for training machine learning models to preserve the membership privacy of individual samples against MIA [12]. As a model trained with DP does not remember any specific record, DP has known to protect well machine learning models against MIA [4, 6]. DP-SGD [1], which perturbs the gradients of the model during training by clipping and adding noise to them, is the most widely-accepted DP algorithm. Adjusting DP-SGD being specialized for GANs, DP-GAN [29] is another DP algorithm that achieves DP by replacing the gradient clipping with the weight clipping.

3 EMPIRICAL STUDY DESIGN

In this section, we describe our empirical study design. We conduct our experiments with 4 tabular data synthesis models and 4 real-world tabular datasets.

3.1 Datasets

We first introduce the following 4 real-world tabular datasets: i) Adult [20] consists of demographic information to predict whether each person’s income exceeds $50K per year based on census data, and the size of the dataset is 32K records. ii) Alphabank [21] contains 30K records. It is to predict the success of bank telemarketing
Table 1: Macro F1 scores ($R^2$ score for King) of victim models with 100 generation samples (1000 for King). All victim models show reasonable generation quality.

| Dataset     | Identity | CTGAN   | TVAE    | TableGAN | OCT-GAN |
|-------------|----------|---------|---------|----------|---------|
| Adult       | 0.778    | 0.562   | 0.665   | 0.536    | 0.546   |
| Alphabank   | 0.510    | 0.501   | 0.490   | 0.488    | 0.500   |
| Surgical    | 0.752    | 0.678   | 0.597   | 0.578    | 0.659   |
| King        | 0.421    | 0.250   | 0.444   | 0.357    | 0.293   |

based on personal financial information. iii) King [9] is a regression dataset to predict house sale prices, which consists of 25K records. iv) Surgical [26] is a binary classification dataset, which contains surgical patient information. The dataset contains 13K records.

3.2 Victim Generative Models
As attackers are more likely to target well-trained generative models in practice [6], we consider CTGAN, TVAE, TableGAN and OCT-GAN as our victim models, which all show high synthesis quality.

3.3 Evaluation Method and Metrics
To evaluate the generation quality, we i) train auxiliary machine learning algorithms, i.e., AdaBoost [25], DecisionTree [23], and Multi-layer Perceptron [5], with synthesized records, and ii) test them on a binary classification or a regression task using test records, which we repeat 10 times with different seeds. We use the following three metrics: i) Macro F1 (resp., $R^2$) score on a binary classification (resp., a regression) task, ii) the average of the minimum column-wise Euclidean distance between real and fake records, and iii) the average of column-wise Earth Mover’s Distance (EMD) for the dissimilarity between real and fake records distributions. We present the generation quality of victim models in Table 1. Identity is a baseline where we perform sampling with replacement from the training set, which means a model whose score is close to Identity has a good generation quality.

To evaluate attack success scores, we measure the area under the Receiver Operating Characteristic curve (AUROC), one of the most important metrics for binary classification. The most successful the membership inference attack, the close to 1 the AUROC score. If the inference is the same as a random classifier, AUROC is 0.5.

4 EMPIRICAL STUDY RESULTS
We summarize our empirical study analysis results for the black-box and the white-box attacks. Due to the page limit, we omit some of the results. For the full paper, please refer to [16]. Source codes and data are available at https://github.com/JayoungKim408/MIA.

4.1 Black-box Attack
We analyze experimental results on the black-box attack in twofold: i) how much the number of fake records collected by attackers influences the success of the attack and ii) how much the generation quality of victim models is correlated to the success of the attack. Fig. 1 (a) shows the AUROC scores of the black-box attack w.r.t. the number of fake records collected by attackers on CTGAN for King. There is a clear tendency for AUROC scores to increase with the larger number of collected fake records. As black-box attackers can only access fake records generated by victim models, a larger collection allows membership inference with more knowledge about the victims. Interestingly, the AUROC scores get flattened after more than 100 samples are collected, which means there exists a threshold that attackers may want to consider for practical attack efficiency. Table 2 shows Pearson correlation coefficient between the generation quality and the AUROC score of the black-box attack for Alphabank. For Macro F1, larger values are preferred in terms of the generation quality, while for Euclidean distance and EMD, smaller ones are. Thus, a positive (resp., negative) correlation for Macro F1 (resp., for Euclidean distance and EMD) to AUROC indicates victim models of better generation quality tend to be more vulnerable to the black-box attack and we can observe such patterns in our experiments. However, Euclidean distance has all positive correlations except CTGAN, which happens by the corner case of the metric where most fake records are close to few real records. Notably, in our cases, EMD explains the correlation better than Euclidean distance, which is widely used to evaluate the generation quality in research on attacks [6, 8, 14].

4.2 White-box Attack
As mentioned earlier, the AUROC scores of the black-box attack are satiated with more than 100 fake records collected. For fairness,
therefore, we conduct experiments on the white-box attack with 100 collected samples. Note that white-box attackers can generate fake records by themselves from victim models by feeding the noisy vector $z$. We let victim models generate 100 fake records for each attack and evaluate AUROC on them. Fig. 1 (c) and (d) shows a comparison between the AUROC scores of the black and white-box attack on all victim models for King and Alphabank. In all cases, the white-box attack has higher AUROC scores than the black-box attack, which is intuitive as white-box attackers have full control over victim models.

### 4.3 Defense with Differential Privacy

We conduct additional experiments on two DP algorithms, DP-SGD and DP-GAN. Due to the scarcity of study about training specific neural network designs with DP algorithms, e.g., moving of TableGAN is not studied, we target only on CTGAN, which consists of trainable network designs by DP algorithms that are currently available. However, as computing the gradient penalty of the WGAN-GP loss [13] of CTGAN is challenging with DP algorithms, we change it to the Wasserstein loss [2]. Accordingly, we retrain and evaluate the modified CTGAN without DP algorithms as well for an accurate comparison. We repeat each experiment more than 100 times to average out the effect of the randomness in the DP algorithms.

Fig. 2 summarizes the comparisons of Macro F1, Euclidean distance, and AUROC of the black and white-box attack on CTGAN for Adult with respect to $\sigma = \{1e^{-0.05}, 1e^{-0.04}, 0.5\}$. $\sigma$ controls how much noise to be added to the gradients; thus, there is a trade-off between privacy and model accuracy. In Fig. 2 (a) and (b), compared to training without DP algorithms, training with DP algorithms deteriorates the generation quality. However, DP-GAN shows the generation quality which is better than DP-SGD or even similar to models without DP at lower $\sigma$. Also, DP-GAN worsens the generation quality as $\sigma$ increases, while there is no such pattern for DP-SGD. This is because DP-GAN is specially designed for training GANs with theoretical correctness [28].

In Fig. 2 (c) and (d), models trained with DP algorithms show lower AUROC scores both on the black and white-box attack than models without DP algorithms, as expected. In Fig. 2 (c), DP-GAN shows better robustness to the black-box attack, albeit both show AUROC scores less than 0.5, which means incorrect inference towards membership. Interestingly, the white-box attackers can still infer membership correctly; in Fig. 2 (d), DP-SGD shows better robustness to the white-box attack than DP-GAN; as the white-box attackers can access victim models, DP-GAN, which less deteriorates victims, shows higher vulnerability to attacks.

### 5 CONCLUSIONS

In this paper, we investigated under which conditions tabular data synthesis models are vulnerable to two MIA paradigms, the black-box and the white-box attack, and how defense algorithms can protect them. We conducted experiments with 4 tabular data synthesis models and 4 real-world tabular datasets.

As expected, the experimental results show that i) as attackers are more knowledgeable about victim models, i.e., when they collect more fake records in the black-box attack or can access the models in the white-box attack, and ii) as models synthesize better representative samples, models are more vulnerable. iii) When models are trained with DP algorithms, models are more robust on the attacks. We also reported detailed findings in Sec. 1.

As shown in experimental results of the defense with two DP algorithms, both have pros and cons; DP-SGD largely ruins the generation quality of victim models while protecting them against the white-box attack; DP-GAN preserves the generation quality of victim models while exposing them more to the white-box attack. This implies that one may decide how to defend tabular data synthesis models based on his/her purpose. For instance, one may sacrifice high-quality generation for enhanced privacy guarantee by adopting DP-SGD. This also motivates future work of combining two different approaches from DP-SGD and DP-GAN.

Our paper delivered several empirical messages and findings that are hard to know without conducting all those experiments. We think our paper can enlighten and guide others worried about privacy concerns regarding their fake tabular data.

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