ABSTRACT
Generative Adversarial Networks (GAN)-synthesized table publishing lets people privately learn insights without access to the private table. However, existing studies on Membership Inference (MI) Attacks show promising results on disclosing membership of training datasets of GAN-synthesized tables. Different from those works focusing on discovering membership of a given data point, in this paper, we propose a novel Membership Collision Attack against GANs (TableGAN-MCA), which allows an adversary given only synthetic entries randomly sampled from a black-box generator to recover partial GAN training data. Namely, a GAN-synthesized table immune to state-of-the-art MI attacks is vulnerable to the TableGAN-MCA. The success of TableGAN-MCA is boosted by an observation that GAN-synthesized tables potentially collide with the training data of the generator.

Our experimental evaluations on TableGAN-MCA have five main findings. First, TableGAN-MCA has a satisfying training data recovery rate on three commonly used real-world datasets against four generative models. Second, factors, including the size of GAN training data, GAN training epochs and the number of synthetic samples available to the adversary, are positively correlated to the success of TableGAN-MCA. Third, highly frequent data points have high risks of being recovered by TableGAN-MCA. Fourth, some unique data are exposed to unexpected high recovery risks in TableGAN-MCA, which may attribute to GAN’s generalization. Fifth, as expected, differential privacy, without the consideration of the correlations between features, does not show commendable mitigation effect against the TableGAN-MCA. Finally, we propose two mitigation methods and show promising privacy and utility trade-offs when protecting against TableGAN-MCA.

1 INTRODUCTION
Big data have emerged as valuable resources that allow companies, researchers and governments to enhance decision making, insight discovery and process optimization. However, sharing sensitive datasets without violating individual’s privacy is a long-standing challenge. For example, in 2017, DeepMind was accused of an illegal acquisition of personal medical records of 1.6 million patients for developing a kidney injuries diagnosing application [34]. To analyze those sensitive data in a privacy-preserving manner, ideally, we need a trusted third party that collects and processes raw data, and then releases a sanitized version of data trading off privacy and utility through web queries (see the paradigm shown in Fig. 1).

However, state-of-the-art solutions for releasing the sanitized data achieving trade-offs between utility and privacy are vulnerable to privacy inference attacks. For example, de-identification (removing unique identifiers for all data entries) is susceptible to linkage attacks [32]. Anonymization [24, 29, 45] suffers from background information attacks. Other synthetic dataset publishing mechanisms, such as NetMechanism [4], Iterative Construction [16–19], are tailored for relatively small datasets [13]. More recently, Generative Networks, including Generative Adversarial Networks (GANs) [14] and Variational Autoencoders (VAEs) [23], produce synthetic data that achieve enhanced privacy and utility trade-offs. Such synthetic data conceal the detailed (privacy) of the raw data while keeping statistics similarity [35, 46]. Nevertheless, recent works [7, 20, 21, 35, 44] show the risk of membership disclosure (i.e., inferring whether a given data point belongs to the training dataset) against synthesized data by attacking generator APIs. They propose various Membership Inference Attacks (MIAs) against published generative models to disclose the membership information of training data.

To further explore the privacy disclosure risks of the GAN-synthesized tabular data, different from existing MIAs against generative models [7, 20, 21, 35, 44], we propose a novel attack model,
named Membership Collision Attack against GAN-synthesized Tables (TableGAN-MCA). Specifically, we reconstruct a proportion of actual training data from the published synthetic table with high confidence by inferring the membership collisions (substantiated in Section 3.1). Hence, TableGAN-MCA brings a novel privacy problem: training data exposure when analyzing published synthetic tabular data. In addition, TableGAN-MCA only queries a black-box generator (of the GAN) for synthetic data, which is similar to the most strict threat model introduced in the recent work - GAN-Leaks [7]. We conceptualize the differences among recent works in Table 1.

**Motivation.** Our work is motivated by two observations in GAN-synthesized table (low-dimensional data) releasing.

- **Observation 1.** Generated synthetic tables overlap with GAN’s training data (as the intersection illustrated in Fig. 2). For instance, in the Adult dataset, a synthetic dataset collides with the GAN’s training dataset by 16.9% (5350 entries). Clearly, such an overlap brings severe privacy breaches if adversaries could locate the intersection. In the remainder of this paper, we call the overlap/intersection membership collision.

- **Observation 2.** In the GAN-synthesized tabular data, membership collisions and data frequency are positively correlated (substantiated in Fig. 3). However, it is rare to trigger sample collisions in high-dimensional data, such as image synthesis, due to the curse of dimensionality. Thus, the distribution of tabular data with relatively small dimension brings additional privacy risks than that of image synthesis.

To perform the proposed TableGAN-MCA, we leverage shadow models [43] to learn the patterns behind the collision (Observation 1) while taking the density of each synthetic data by counting its sample frequency in synthetic distribution (Observation 2) as additional feature when training the attack model. TableGAN-MCA shows promising results on commonly used real-world datasets, including Adult, Lawschool and Compas. For instance, TableGAN-MCA recovers 36.1%, 12.7%, 36.5% of actual members released with the GAN-synthesized tabular data with approximately 80% confidence for Adult, Lawschool and Compas, respectively. Our results show that a well-trained GAN, robust to the MIAs proposed in [7, 20, 35], is still vulnerable to TableGAN-MCA.

In summary, our main contributions are as follows:

- We propose a novel membership collision attack against GAN-synthesized tabular data publishing, named TableGAN-MCA, which can reinstate partial training data with high confidence.

| Benchmark Datasets | Generator | Discriminator | Additional Information | Expose Trainset |
|--------------------|-----------|---------------|------------------------|-----------------|
| LOGAN [20]         | Image     | √             | √                      | False           |
| TableGAN-MCA [35]  | Table     | √             | √                      | False           |
| MC [21]            | Image     | ×             | √                      | False           |
| GAN-Leaks [7]      | Image/Table| ×             | √                      | False           |
| TableGAN-MCA       | Table     | √             | ×                      | True            |

TableGAN-MCA exploits the weaknesses of GAN synthesis observed on low-dimensional data, i.e., GAN-synthesized data collide with its training data, and members (in the colliding member set) occur more frequently than non-members.

- We extensively evaluate our proposed attacks on three commonly used real-world datasets, including Adult, Lawschool and Compas against four generative models, including TVAE [46], CTGAN [48], WGAN-GP [15] and WGAN-WC [2]. Furthermore, we explore the factors that may impact the attack effectiveness, such as the size of GAN training data, GAN training epochs, GAN training data frequencies and the number of synthetic samples available to the attacker.

- We discover that individuals in the training dataset have various risks of privacy leakage under TableGAN-MCA. Additionally, we show that GANs do not memorize those exposed data. Instead, when generalizing the distribution of the training data, GANs may increase or decrease the frequency of some individuals, and hence change their privacy risks.

- We examine the effect of differential privacy (DP) to mitigate TableGAN-MCA. Our empirical results show that differential private generative model training achieves sub-optimal trade-offs against TableGAN-MCA. It is mainly due to the fact that TableGAN-MCA relies more on the common pattern of a distribution (like attribute correlations) which is not the focus of DP. In addition to DP, we propose two mitigation methods, naive defense and improved defense, that mitigate the effect of TableGAN-MCA.

## 2 BACKGROUND OF GENERATIVE MODELS

Generative Adversarial Networks (GANs) [14] and its variants have made great achievements in generating high quality artificial data that mimic the real ones by modeling the underlying data distribution. It is composed of two neural networks: a discriminator $D$ and a generator $G$. It tries to minimize the distance between the real data distribution $P_r$ and the generated (artificial) data distribution $P_g$ by iteratively updating parameters of the networks.
We let $D_1$ that outputs a colliding member set dataset published synthetic datasets member set $I$ x set $D$ as: a published synthetic datasets sanitized version of $P$ G outputs a well learned generator distribution $P$ all the notations used throughout the paper in Table 2. sary's goals, capabilities and background knowledge. We introduce In this section, we formulate our membership collisions problem, 3 PROBLEM FORMULATION In this section, we formulate our membership collisions problem, followed by the description of the threat model according to adversary’s goals, capabilities and background knowledge. We introduce all the notations used throughout the paper in Table 2. 3.1 Membership Collision Problem We let $D_1 = \{x\}$ be a training set sampled from an implicit data distribution $P_x$. Each private entry takes the form as $x = (x, y) \in \mathcal{X} \times \mathcal{Y}$, where $x$ represents the features and $y$ represents the class label. A data release mechanism GAN trains on the training set $D_t$ and outputs a well learned generator $G$. Generator $G$ is a deterministic function that maps a prior distribution, i.e., Gaussian distribution $P_z$, to the generated distribution $P_g$ that mimic real distribution $P_x$. Then, a synthetic dataset $S \sim P_g$ is published and serves as a sanitized version of $D_t$. We formalize the membership collisions as : a published synthetic datasets $S \sim P_g$ collide with its training set $D_t \sim P_x$ and result in a colliding member set $I = S \cap D_t$. Notice that a data point $x \in I$ result in $x \in D_t$. Similarly, a synthetic data point $x \notin I$ result in $x \notin D_t$.

We aim to study how much an adversary increases its ability to assert whether a synthetic data point $x \sim S$ belongs to the colliding member set $I$ by estimating the generated distribution $P_g$ via the published synthetic dataset $S$. Formally,

Definition 3.1 (Membership Collision Attack). Given a synthetic dataset $S$ produced by a generative model $G(P_z, D_t)$ that contains a colliding member set $I = S \cap D_t$ and an attack algorithm $\mathcal{A}(x)$ that outputs 1 if it outputs the synthetic data $x \in I$, we say the

The Wasserstein GAN (WGAN) [2] applies Earth Mover (EM) distance under a K-Lipschitz constraint and achieves good performance in generating high fidelity samples. The loss function of the discriminator and the generator are as follows:

$$f^{(D)}(\theta^{(D)}, \theta^{(G)}) = -\frac{1}{2}EX_{x \sim P_{data}}D(x) + \frac{1}{2}EZD(G(z)), \quad(1)$$

$$f^{(G)} = \frac{1}{2}EZD(G(z)). \quad(2)$$

In this work, we use its weight clipping version (WGAN-WC) [2], Gradient Penalty version (WGAN-GP) [15] and CTA G (state-of-the-art) [46]. We also include TVAE from [46] for its comparable performance as CTA G. Following [46], all three GANs uses recurrent networks in the generator. For categorical features, we use the gumble-softmax activation in the output of the generator. For numerical features, we use the sigmoid or the tanh activation in the output of the generator. For performance as CTGAN. Following [46], all three GANs uses re-
4 MEMBERSHIP RECOVERY FRAMEWORK AGAINST GAN-SYNTHESIZED TABLES

In this section, we propose a membership indicator for inferring membership collisions from the statistics of the published table. Based on the membership indicator, we propose the TableGAN-MCA to recover the value of the training set of GAN-synthesized tables in the black-box setting.

4.1 Membership Indicator

The membership indicator is triggered by two observations. First, the released GAN-synthesized tables often overlap the training dataset of the GAN model. Second, such synthetic data points appearing frequently in the published GAN-synthesized data are more likely to be the colliding member of the training dataset. Therefore, \( \Pr[x \in D_t | P_g] \propto \Pr[x | P_g] \).

Fig. 3 depicts the observations from three datasets used in this paper, where we count the numbers of members and non-members, given numbers of appearance of the data points in the released synthetic tables. In Fig. 3 (left), approximately 96% of synthetic data with a sampled frequency of more than three are colliding members. Conversely, almost 91% unique synthetic data are non-colliding members in the Adult dataset. Thus, sample frequency is highly correlated with membership collisions and can be treated as an indicator to indicate membership. Formally, we estimated the membership indicator by the following equation.

\[
\Pr [x_i | P_g] \approx \frac{1}{|S|} \sum_{x_j \in S} \mathbb{I} (x_i = x_j) = \frac{1}{n} \sum_{j=1}^{n} \mathbb{I} (x_i = x_j), \tag{4}
\]

where an indicator function \( \mathbb{I} (\cdot) \) outputs 1 if its argument is true, \( S \) is the synthetic datasets available to the adversary following \( P_g \), of size \( |S| = n \).

To date, the adversary can launch a data reconstruction attack by setting a threshold for the value of a membership collisions indicator of Eq. (4), similar to [7]. The adversary then claims that the synthetic data, having collisions indicators greater than a given threshold, are the recovered data. However, choosing an optimal threshold is a non-trivial task for an adversary without background knowledge about training data except the published synthetic data. To deal with it, we additionally leverage shadow model techniques [43] to enhance the knowledge of adversaries to construct a robust TableGAN-MCA framework.

4.2 TableGAN-MCA

In a nutshell, TableGAN-MCA combines the membership collisions indicator and the shadow models [43] to train an attack model to learn the relation between membership collisions (labels) and indicator values (features) in released GAN-synthesized tables. Fig. 4 depicts the framework of TableGAN-MCA and Alg. 1 shows the detailed implementation. Each step in Alg. 1 corresponds to the step index in Fig. 4. In summary, steps 2, 3, 4 and 5 train an attack classifier by giving synthetic data. Steps 1 and 6 infer membership collisions to recover training data.

In Steps 1 and 4, \(#x\) represents estimated sample frequency following from Eq. 4. They are concatenated (“\(\ast\)”) to \( S_i \) (Step 1) and \( S_i \) (Step 4) as an extra feature.

Figure 4: The overview of the procedures of TableGAN-MCA against the black-box generator in data synthesis.

**Algorithm 1: TableGAN-MCA.**

**Input:** \( \{S_1, S_2, \ldots, S_{N_r}\} \): Released synthetic datasets; \( |D_t| \): Size of the training dataset;

**Output:** \( R \): Recovered data from \( D_t \)

while \( i : 1 \rightarrow N_r \) do

**Step 1:** Frequency \( \{sx_i\} \leftarrow \) Estimate frequency for each \( x_i \in S_i \) by Eq. (4);

**Step 2:** Shadow GAN generator \( \tilde{G}_t \leftarrow \) Train on \( S_i \);

**Step 3:** Shadow set \( \tilde{S}_i \leftarrow \) Sample from \( \tilde{G}_t, |\tilde{S}_i| = N_s \times |D_t| \);

**Step 4:** Frequency \( \{sx'_i\} \leftarrow \) Count the frequency for each \( x'_i \in \tilde{S}_i \) by Eq. (4);

|\( \tilde{S}_i \leftarrow \tilde{S}_i \leftarrow (sx'_i) \);

Ground truth label \( y'_i \leftarrow 1 \{x'_i \in \tilde{S}_i \} \);

end

**Step 5:** TableGAN-MCA attack model \( f(\cdot) \leftarrow \) Train on \( \{\tilde{S}_1, \ldots, \tilde{S}_{N_r}\} \) with member/non-member labels \( \{y'_i\} \), where \( \|\tilde{S}_1\| = \|\tilde{S}_2\| = \ldots = \|\tilde{S}_{N_r}\| ; \)

\( \{y'_1\} \| \ldots \| \{y'_{N_r}\} \);

**Step 6:** \( R_A \leftarrow f(\{S_i\}) \);

return \( R_A \)

In Step 4, a label function is required to claim membership collisions in shadow datasets. For a shadow dataset \( \tilde{S}_i \) such that \( S_i \cap \tilde{S}_i = \tilde{I}_i \), a membership collisions label for each data \( x'_i \) will be \( y'_i = \mathbb{I} (x'_i \in \tilde{I}_i) \).

In Step 6, attack model \( f(\cdot) \) outputs the predicted probability about whether a synthetic data is colliding member. Adversaries then expose a data set \( R_A \) that with high prediction scores.

For attack model (2) (unlimited synthetic data) such that \( N_R > 1 \), the adversary repeat the Step 1 to Step 4 \( N_R \) times and gets \( N_R \) labeled shadow datasets \( \{\tilde{S}_1, \tilde{S}_2, \ldots, \tilde{S}_{N_R}\} \) such that each of them with size \( N_s \times |D_t| \). Then the adversary concat (“\(\ast\)”) all shadow datasets together to train the attack model.

Note that in the worst-case (to the adversary), where the intersection between the training set and the synthetic dataset could be empty, the adversary of TableGAN-MCA cannot recover anything.
from the private training data. To avoid such a case, we would discretize the synthetic dataset to generalize the range of each feature such that there is a non-empty intersection. In this way, we could (at least) recover coarse-grained information regarding the members within the training data. We show the details of the discretization operation in Section 5.1.

5 EVALUATION

In this section, we first introduce the methods of tabular data synthesis, then introduce the evaluation metrics. Next we show the attack performance of TableGAN-MCA as well as the comparisons with recent works.

5.1 Dataset Synthesis

We perform experimental evaluations on three commonly used [3, 8, 35, 40, 46] real-world tables, Adult [39], Lawschool [38] and Compas [22].

Adult: The US Adult Census dataset is a repository of 48842 entries extracted from 1994 US Census dataset, where 45222 entries have complete information. After pre-processing, it remains 1 numerical feature, 12 categorical features and 1 binary label.

Lawschool: This dataset comes from the Law School Admission Council’s National Longitudinal Bar Passage Study. It contains application records for 25 different law schools with 86022 entries. It has 2 numerical features, 5 categorical features and 1 binary label.

Compas: COMPAS recidivism risk score and criminal history data is collected by ProPublica in 2016. After pre-processing, it remains 5278 entries with 4 numerical features, 6 categorical features and 1 binary labels.

Note that unlike MIAs attacking classifiers that produce predicted labels with probability, generative models only output synthetic samples. The labels in generated datasets serve as an ordinary feature like other features when training attack models. Therefore, for simplicity, we use the three binary-labeled datasets in our experiments.

Tabular data synthesis. For training generative models, we apply Tabular Variational Autoencoder (TVAE) [46], CTGAN [46], WGAN-GP [15] and WGAN-WC [2] for their superior modeling quality in tabular synthesis. To facilitate data synthesis, we have the following additional data pre-processing. (1) We discretize imbalanced and sparse numerical values in given columns to categorical values. (2) We normalize numerical columns into (0, 1) or (−1, 1). (3) We one-hot encode all categorical features (4) We split the dataset into the training set ($D_t$, 70% records) and test set ($D_s$, 30% records) (see row 1 and row 2 in Table 3). The training set is used for dataset synthesis and the test set is used for examining the utility of the synthetic data.

Discretization in pre-processing. Features in tabular dataset are either categorical or numerical variables. Unlike pictures, some numerical columns are non-Gaussian distribution, that is, it either has long tails, sparse distribution or multiple modes. Generative models cannot model them well without appropriate pre-processing. To address this issue, we discretize the imbalanced and sparse numerical values to categorical values. In the experiments, such simple discretization in pre-processing exhibits decent performance in generating complex features while keeping original statistics. Note that discretization definitely makes some records of the original dataset share the same values (similar to k-anonymity [45]). We show the uniqueness of the records after pre-processing in Table 3 (row three and four), where a large proportion of sensitive data points can still be uniquely identified before feeding into generative models.

5.2 Metrics

5.2.1 Data Utility Metrics. For data utility evaluation, we consider two measurements: machine learning efficacy (models trained on a synthetic dataset and the original dataset provide similar predictions) and distribution fitness (a synthetic dataset is statistically similar to its original dataset in all attributes).

For distribution fitness, we present 1-way marginals that are approximated by the Empirical Cumulative Distribution Function (ECDF) for each attribute. Having ECDFs of real and synthetic data, we compute attribute-wise Wasserstein distance, i.e., $W_1(x_i, y_i) = \int_{-\infty}^{\infty} |U_i - V_i|$, where $U_i$ and $V_i$ are respective CDFs of real attribute $x_i$ and synthetic attribute $y_i$ [37]. We compare the expected value of ECDFs by $E_i(l_i) = \frac{1}{n} \sum_{i=1}^{n} l_i(x_i, y_i)$.

5.2.2 Attack Performance Metrics. To evaluate the privacy of the released synthetic table, we consider membership collisions privacy, i.e., the TableGAN-MCA effect. We use precision and recall to evaluate the attack performance (following Shokri et al. [43]), since the synthetic dataset that is used to inference has a skewed label distribution. Specifically, precision measures the probability of an entry inferred as a member is indeed the member of the training data set, denoted as $P(y = 1|\hat{y} = 1)$. Intuitively, it implies the confidence of the attacker in guessing positive membership. Recall measures the probability of a member is correctly inferred as a member by the attacker, denoted as $P(y = 1|\hat{y} = 1)$. It reflects the percentage of positives exposed in the attack. In evaluation, we report precision and recall by Precision-Recall (PR) curve since it is more informative than ROC-curve under the case of skewed label distribution [10]. A higher Area under the PR-curve (AUPRC) implies both higher precision and recall, and thus they are used to compare the attack efficacy.

In addition to the attack precision and recall, we also consider a recovery rate because it reflects what the proportion of training data $D_t$ are being exposed to TableGAN-MCA. Let $R_{\mathcal{A}}$ be recovered training data sets of the attack algorithm $\mathcal{A}$. The recovery rate $r_{\mathcal{A}}$ of $\mathcal{A}$ is defined as below:

$$r_{\mathcal{A}} = \frac{|R_{\mathcal{A}}|}{|D_t|}.$$  

Note that the recovery rate shares the same numerator as the recall of the attack model $f(\cdot)$ but the different denominator ($|D_t|$ vs $|l|$).
Table 4: Model prediction accuracy (%) trained on real training $D_s$ (“Base”) and GAN-synthesized datasets $S$. $E_i(l_1)$ denotes the average of all attribute-wise Wasserstein distance.

| Methods       | Adult | Lawschool | Compas |
|---------------|-------|-----------|--------|
| Base          | 85.39 | 79.24     | 81.90  |
| VTAE          | 84.11 | 77.53     | 89.54  |
| CTGAN         | 86.28 | 78.72     | 87.23  |
| WGANWC        | 84.74 | 82.3      | 81.02  |
| WGAN-GP       | 83.96 | 84.16     | 81.37  |

5.3 Synthetic Data Utility

We evaluate machine learning efficacy of synthetic data generated by four generative models, CTGAN [46], TVAE [46], WGAN-GP and WGAN-WC vary four binary classifiers: DecisionTreeClassifier, MLPClassifier, AdaBoostClassifier, and LogisticRegression (Standard scikit-learn machine learning library; see middle columns in Table 4). We also compare ECDFs using the average of all attribute-wise Wasserstein distance $E_i(l_1)$ (see the last column in Table 4). All numerical features are min-max scaled to $(0, 1)$ and categorical features are one-hot encoded before feeding into the classifier. For “base”, we trained on the sensitive dataset $D_s$ that is used for data synthesis and test on the real test set $D_t$ (see Table 3). For synthetic data, we trained on a synthetic dataset $S$ of the same size as the sensitive dataset and test on the synthetic test set $D_t$. To implement CTGAN and TVAE, we directly feed our pre-processed data into the module CTGANSynthesizer and TVAESynthesizer of the SDGym [5] (published code for [46]).

According to Table 4, the synthetic dataset generated by WGAN-GP, WGAN-WC, CTGAN and TVAE can greatly restore the prediction ability of the model trained on original dataset. TVAE is least ideal than the others in the Adult dataset. CTGAN is least ideal than the others in the Compas dataset. We will use these learned generative models to perform TableGAN-MCA experiments later.

For marginal fitness, we depict an additional ECDF comparison between real and synthetic Adult, Lawscholl and Compas datasets generated by WGAN-GP in Fig. 5. In our experiments, we depict ECDFs of continuous variables (i.e., age, isat) and more complex categorical variables (i.e., hours per week, priors count) since they are more difficult to fit. As can be seen in Fig. 5, the marginals of the synthetic dataset are almost indistinguishable from the original one, thus supporting any statistical queries.

5.4 Attack Performance

5.4.1 Performance Evaluation on TableGAN-MCA. In this section, we evaluate TableGAN-MCA of Alg. 1 on the Adult, Lawscholl and Compas datasets. The training and inference data statistics of TableGAN-MCA are presented in Table 5, where positive percentage implies the membership collisions proportion. Both target models and shadow models are WGAN-GP. The attack model is trained on the shadow dataset $S$ and tested on the synthetic dataset $S$.

Figure 5: The Empirical Cumulative Distribution of each attribute in the Adult, Compas and Lawscholl datasets (Orange line for real and blue line for synthetic).

Table 5: Training and inference statistics for the Adult, Compas and Lawscholl datasets in TableGAN-MCA.

| Method      | Adult | Lawscholl | Compas |
|-------------|-------|-----------|--------|
| $|S|$ (Train) | 31655 | 43011 | 3694 |
| $|S|$ (Inference) | 31655 | 43011 | 3694 |
| $Pr_S[y_t = 1]$ | 15.99% | 22.68% | 40.49% |
| $Pr_S[y_t = 1]$ | 16.90% | 23.89% | 34.00% |

TableGAN-MCA provides a promising attack against the GAN-synthesized tables. We report the PR-curve of the attack model in Fig. 6 when $N_s = 1$, i.e., $|S| = |D_t|$. In Fig. 6, PR-curve reflects the trade-off between precision and recall for different probability thresholds $T$. Particularly, after providing the inference data (the released GAN-synthesized tables) to the TableGAN-MCA attack model, we receive a set of probabilities for each record of the test data that predicts whether a record is a member.

As illustrated in Fig. 6, we find that by setting a suitable threshold $T$, the adversary can expose approximate sensitive attributes with confidence over 83.91%, 69.40% and 81.24% for the Adult, Lawscholl and Compas datasets, respectively. This means that the adversary significantly increases its ability to assert that these entities are members. Furthermore, when setting confidence to 80%, we have 36.1%, 12.7%, 36.5% positive percentages being exposed, which correspond to 1931, 1304 and 458 individual’s sensitive entries in the Adult, Lawscholl and Compas datasets, respectively. According to Fig. 6, we list TableGAN-MCA’s recovery rates (Eq.5) with different precision configurations in Table 6.

Adversary’s knowledge enhances the attack performance of TableGAN-MCA. Fig. 7 reports the PR-curve and AUPRC of TableGAN-MCA when $N_s = 10$. That is, the adversary has multiple copies of the released synthetic data. In particular, when $N_s = 10$, the adversary trains 10 independent shadow GAN for each one of
Table 6: TableGAN-MCA’s recovery rate $\rho_A$, (|R_A|: # of recovered data points under attack algorithm $A$)

| Datasets | $\rho_A$ (%) | |R_A| |D_A| Precision | Recall |
|----------|---------------|---------|--------|-------------|---------|
| Adult    | 3.04          | 962     | 31655  | 0.9         | 0.16    |
|          | 6.10          | 1931    | 31655  | 0.8         | 0.36    |
| Lawsch   | 3.03          | 1305    | 43011  | 0.8         | 0.13    |
|          | 4.66          | 2003    | 43011  | 0.75        | 0.18    |
| Compas   | 12.41         | 458     | 3694   | 0.8         | 0.37    |
|          | 17.17         | 634     | 3694   | 0.75        | 0.43    |

The success of TableGAN-MCA is mainly due to the observed collision, the membership collisions indicator and the shadow model in use. In particular, the collision between synthetic data and training set provides the opportunity for recovering training data. The membership collisions indicator, which captures the statistical patterns behind colliding members, guarantees more accurate and informative features for training the attack model. The shadow model in use provides enough labeled data to train the attack model so as to learn from the statistical patterns of the colliding members.

**Attack scalability.** The key to the success of the TableGAN-MCA is the possibility of collisions between raw training datasets and synthetic datasets. For real-world tabular data, attributes usually have a finite domain range. Hence, the dataset dimension indicates its overall domain range. Namely, low-dimensional tables are more likely to incur sample collisions when the generator creates those synthetic tables. Therefore, TableGAN-MCA discovers additional privacy risks – membership disclosure via collision attacks – for low-dimensional data. TableGAN-MCA potentially fits high-dimensional data if adversaries reduce the data granularity by generalizing attributes. The TableGAN-MCA works since the synthetic data would have a higher chance to collide with the training datasets. In our experiments, TableGAN-MCA achieves 0.871 AUPRC by bucketizing the “age” attribute in synthetic Adult datasets into 10 bins (no-bucketization baseline: 0.668).

### 5.4.2 Comparisons between TableGAN-MCA and existing MIAs

Firstly, TableGAN-MCA recovers member data points from the GAN-synthesized tables previously assumed to be resilient to table-GAN [35]. We evaluate the performance of table-GAN against the same WGAN-GP that used in TableGAN-MCA evaluation. Notice that we test their MIAs directly on the target discriminative model instead of the shadow discriminator instead of the shadow discriminator due to the fact that if the target discriminator fails, the shadow model will perform even worse. We report the accuracy of membership prediction (member/non-member) of table-GAN, which are 50.17%, 50.80% and 50.67% for Adult, Lawschool and Compas datasets, respectively (50% is the baseline of random guess). Taken altogether the experiment results in Fig. 6, we conclude that GAN APIs with a black-box access assumed to be resilient to table-GAN (targeting on a discriminative model) [35] may still disclose partial sensitive training information under TableGAN-MCA.

Secondly, the MIAs proposed in GAN-Leaks and LOGAN cannot disclose membership collisions. Note that the existing MIAs against GANs may work in the MCA scenario. Thus, we perform additional experiments to infer membership collisions of each
synthetic data point using their methods. In particular, we evaluate LOGAN (black-box attack with no auxiliary knowledge) and GAN-Leaks (full black-box generator attacks) under threat model (1) (given one copy synthetic data, see details in Section 3.2) and report the result in Table 7. MC and table-GAN are not included in this experiment. The reason is two-fold. First, the distance function of MC is not directly applicable to non-image datasets. Second, table-GAN requires predicted probability vectors of the target discriminator, which is not permitted in our threat model. Note that the synthetic dataset S has imbalanced membership collisions labels (Row 1 in Table 7) that are different from Shokri’s shadow model MIA [43] (random observation with 50% real members) since the number of colliding data points (members) is usually unequal to non-colliding ones (non-members).

We observed that the results in GAN-Leaks are close to the random guess baseline. This is due to the reconstruction loss \(L(x, x^*) = 0\) for all synthetic data regardless of membership collisions (the optimal reconstruction of a synthetic data x is itself). Furthermore, LOGAN did not show convincing inference results since it never learns the intersection between the synthetic data and the private training data. In comparison, TableGAN-MCA learns such an intersection (by which we recover partial training data) through the intersections of the published synthetic data (by mimicking the private training data) and shadow (synthetic) data (by mimicking the original synthetic data).

In summary, the MIA classifiers that identify membership fail to identify those membership collisions since the decision boundaries of our attack classifier is different from those of MIAs against GANs.

### 6 TABLEGAN-MCA ANALYSIS

In this section, we discuss the factors that may impact the attack performance of TableGAN-MCA from the following aspects, such as GAN training set size, GAN training epochs and GAN training data frequencies. We choose WGAN-GP as targets as well as shadow model for its superior modeling quality and stability in TableGAN-MCA experiments.

#### 6.1 GAN Training Set Size

The size of the training dataset for a GAN model positively impacts the attack performance. Fig. 9 depicts the positive impact of training dataset size on prediction accuracy and AUPRC of TableGAN-MCA, where 1.0 in x-axis indicates the full size of a given dataset, \(N_s = 1\). Especially, when the size of the training dataset is less than 0.5 of the full dataset, increasing the size has a significant impact on the attack performance. The intuition behind the experimental results is two-fold. First, less training data decrease the number of colliding members (positives) in fixed amount of synthetic datasets thus decreases the attack effect. Second, GAN learns a less accurate data distribution if trained on a smaller dataset. Synthetic data generated by such a distribution contain less information than the original training data hence hard for the adversary to learn the statistical patterns of the members/non-members. Note that our results do not conflict with [7, 20, 27] since we use different measurements (PR space vs ROC space) that focus on different domains [10]. Additionally, our attack target (test data) is also different. We aim to recover the colliding member data from the released synthetic dataset whereas they aim to infer the membership of...
Figure 9: The impact of GAN training data size on synthetic data utility (left) and TableGAN-MCA effect (right). The x-axis indicates the amount of GAN training data.

Figure 10: The impact of GAN training epochs on synthetic data utility (left) and TableGAN-MCA effect (right).

6.2 GAN Training Epochs

Epochs impact the attack performance of TableGAN-MCA by impacting the knowledge learned by GAN models. We study the attack performance on different training stages by setting different epochs in Fig. 10, where we report the attack prediction accuracy and attack AUPRC.

As seen from Fig. 10, we find that the membership leakage starts at the very beginning of the training epoch, even before the GAN reaches the Nash equilibrium. Interestingly, in Adult and Compas, the attack effect seems to slightly decrease when we set a larger epochs for training GAN models. Since TableGAN-MCA tends to recover the data with high appearance frequency (recall Fig. 3), we conclude that with increasing epochs, GAN models learn more about the training data distribution; hence, the released synthetic data contain more information, which enhances the attack performance. However, once the GAN models learn the details of the data distribution, such details about the distribution would dilute the frequency of those data supposed to have high frequency. The attack performance of TableGAN-MCA is then potentially dropped.

6.3 Training Data Frequencies

Training data frequencies are positively correlated with training data recovery probabilities by TableGAN-MCA. We first compute the recovery possibility and appearance frequency for each data point. We then plot the recovery possibility over the values of data points frequency in Fig. 11. For each dataset, we set two precision-scores of TableGAN-MCA and plot the training data frequency-recovery rate curves. Overall, highly frequent training data are more susceptible to TableGAN-MCA. For instance, when attacking Adult datasets with 80% precision, 41.5%(784/1892) training data with appearance more than three times are recovered by TableGAN-MCA whereas only 0.6%(510/25130) of unique training data (#x = 1) are recovered by TableGAN-MCA.

For highly frequent training data, GANs inevitably learn and output these common representations frequently; thus it is easy to recover such highly frequent data by TableGAN-MCA. The re-identification threats of these data caused by TableGAN-MCA are limited since each of them correspond to several individuals and lack of uniqueness.

Unique training data, on the other hand, have more risks for being linked to specific people once recovered by TableGAN-MCA. Therefore, it deserves further exploration for the reason of being exposed.

Generalization of GAN models may accidentally increase the appearance of some unique data points in the synthetic data, therefore increasing their probability to be recovered by TableGAN-MCA. Since the TableGAN-MCA is based on data density in modeled distribution $P_g$, for a recovered unique training data point $x_i$, we study how TableGAN-MCA is impacted by the difference between data density of $x_i$ in the training distribution $P_r$ and that of the modeled distribution $P_g$.

According to our experiments, we discover that some unique training data ($\forall x \in P_r, \#x = 1$) have unexpected high exposure in modeled distribution $P_g$. For example, in Fig. 12, we illustrate...
the average counts (from 100 synthetic datasets following modeled distribution $P_g$) of five data points that appear in the training dataset only once. As we can see, these five data points have higher counts than what they have in the training dataset ($=1$). Such an observation indicates that the generator of GAN models unfairly increases the probability of exposure of some data points under TableGAN-MCA. We also find that such an observation is not rare. For instance, according to the statistics in Fig. 12 (Adult), roughly 470 (1.5% of the training dataset) unique entries at least double their exposure; roughly 150 (0.47% of the training dataset) unique entries at least triple their exposure.

Next, we explore the factors that potentially trigger our observations by a set of experiments inspired by unintended memorization [6]. Specifically, unintended memorization identifies the impact of the presence of one training input on the modeled distribution $P_g$ learned by GAN. Note that this experiment resembles the definition of differential privacy (DP) [12]. DP is more generic and rigorous as it measures that the probability difference varies all possible functions and all data points, which is computationally infeasible in our measurements. In this case, we narrow down the design by observing the difference between a sample density in two generated distributions $P_g$ trained on neighboring training sets.

Let $D_t$ be the sensitive training set, $x_i \in D_t$ be a target data point and $D'_t = D_t \setminus \{x_i\}$ be the neighboring dataset such that the Hamming distance $h(D_t, D'_t) = 1$. Let $G$ be a learned generator trained on $D_t$ and $G'$ be a generator trained on $D'_t$. We measure the difference between the probability of producing a synthetic data point $x_i$ with (prior) and without (posterior) the input data point $x_i$,

$$\frac{\Pr(G(z) = x_i \mid D_t)}{\Pr(G'(z) = x_i \mid D'_t)}$$

Following a recent work [6], GAN models do not memorize a data point if it does not exist in the training dataset $D_t$. Thus, if Eq. (6) approaches 1, we say that the target data $x_i$ is unlikely to be memorized by the GAN. The pseudo-code of the experiment is presented in Alg. 2. In the experiment, we use 20 different GANs ($N_g = 20$) and some of target data to estimate Eq. (6). We report the experimental results of five target data ($N_c = 5$) in Fig. 13.

From Fig. 13, we choose the same samples (data points) as in Fig. 12 to compare how prior (with a target $x_i$) and posterior densities (without target $x_i$) differ in modeled distribution. We find that the presence of the target entry $x_i$ has limited influence on its frequency in modeled distribution $P_g$. Even if some data point $x_i$ is absent in the training set, its probability density in synthetic distribution $P_g$ is still high, e.g., $x_4, x_5$ in the Adult dataset. This is perhaps because GAN’s generalization smooths the sudden change that happened in the probability space of the training set. For instance, the density of the a target point $x_i$ in $P_r$ may be lower than the surrounding points, whereas the GAN smooths such sudden changes in the probability space, and thus it is unintended to increase its probability of exposure. In another aspect, such a rough probability space in real distribution may be attributed to insufficient sampling or unbalanced sampling. As such, cautious data collection may have positive impact in mitigating such influence. Understanding this complicated phenomenon with more explicit proof is our future work. Currently, we summarize that the unique training data recovered by TableGAN-MCA is mainly due to the GAN’s generalization.

**Algorithm 2: Memorization Experiment.**

**Input:** $\{x_1, \ldots, x_{N_c}\}$: sample data points; $D_t$: private training dataset.

**Output:** $\{\Pr(x_k \mid G_t(z))\}$: prior frequency; $\{\Pr(x_k \mid G'_t(z))\}$: posterior frequency.

while $k : 1 \rightarrow N_c$ do
  Generative model $G_t \leftarrow$ Train on $D_t$;
  $\Pr(x_k \mid G_t(z)) \leftarrow$ Estimate by Eq. (4);
  $D'_t \leftarrow D_t \setminus \{x_k\}$;
  Generative model $G'_t \leftarrow$ Train on $D'_t$;
  $\Pr(x_k \mid G'_t(z)) \leftarrow$ Estimate by Eq. (4);
end
return $\{\Pr(x_k \mid G_t(z))\}$, $\{\Pr(x_k \mid G'_t(z))\}$
rather than the unintended memorization. This result implies that mitigating the attack effect of TableGAN-MCA may inevitably compromise the availability of released synthetic datasets, since GAN generalization is closely related to its generation ability, which potentially impacts the quality of generated data.

7 MITIGATION

In this section, we evaluate the mitigation effects of differential privacy and two customized defense methods against TableGAN-MCA.

7.1 Differentially Private WGAN-WC

Differentially Private WGAN (DP-GAN) only has acceptable trade-offs for larger privacy budgets, and may hardly eliminates TableGAN-MCA without compromise synthetic data utility. Differential privacy [12] provides a quantified solution to inates trade-offs for larger privacy budgets, and may hardly eliminate synthetic data in Fig. 14. The shadow GANs in use are non-utility. Differential privacy provides a quantified solution to utility.

TableGAN-MCA achieves sub-optimal trade-offs when protecting against TableGAN-MCA. The generation quality and TableGAN-MCA effect of non-private baseline are shown in Fig. 14 followed by Table 4 and Fig. 8.

To implement DP-WGAN, we train a differentially private discriminator. The generator is differentially private because of the post-processing [13]. We add calibrated noise into each gradient of the discriminator during training. The accumulation of multiple Gaussian noise addition [11] relies on privacy accountant techniques [1] and Renyi differential privacy [31]. We provide DP-related hyper-parameters in Table 8, Appendix C.1.

We provide the experimental results of the machine learning utility and TableGAN-MCA effect when sharing differentially private synthetic data in Fig. 14. The shadow GANs in use are non-private WGAN-WC. The privacy budget $\epsilon$ measures the amount of privacy leakage and a smaller value means more privacy-preserved. $\delta$ denotes the probability of violating $\epsilon$-DP, which is set to $\frac{1}{|\text{Domain}|}$. As can be seen from Fig. 14, the DP method has some positive effect in defending against the TableGAN-MCA. For Adult datasets, when privacy budget $\epsilon \approx 2.0$, the attack AUPRC decreases by 16.01% and model’s predicted accuracy decreases by 1.18% in comparison to the no-DP baseline (see dash dots in Fig. 14). For the Compas dataset, when privacy budget $\epsilon \approx 8.0$, the attack AUPRC decreases by 48.33% and model’s predicted accuracy decreases by 5.13% in comparison to the no-DP baseline. We also depict the ECDF comparison between the original training data and differentially private synthetic data for each marginal to show marginal fitness compromise in Fig. 18 (Appendix C.1). It is not surprising that DP-WGAN achieves sub-optimal trade-offs when protecting against TableGAN-MCA, since the memorization experiment shows that the presence of individuals does not significantly affect the generated distribution. The membership collisions information that we intend to infer is perhaps highly correlated to population statistics (attributes correlation), which will be preserved even under DP training.

7.2 Customized Defense

7.2.1 Remove Colliding Members. Removing colliding members protects against TableGAN-MCA but it reduces the distribution fitness. The straightforward solution against TableGAN-MCA is to manually remove colliding members from the sampled synthetic dataset and share a cleaned version to the analysts (customers). The whole process is denoted as the “naive defense” (last steps in Alg. 3). We acknowledge the cleaned version can decrease the utility of original synthetic data, especially for distribution fitness. For example, we present the ECDF comparison of synthetic datasets generated by the naive defense (Fig. 15(b)) and no-defense (Fig. 15(a)). We show that the naive defense exhibits decreased marginal fitness compared with no-defense baseline. More ECDFs can be found in Figs. 19(a), 20(a), and 21(a) (Appendix C.2).

7.2.2 GAN-constrained Training. We propose a GAN-constrained training technique, to further improve synthetic data utility while protecting against TableGAN-MCA. This strategy is denoted as an “improved defense”. Simply put, we motivate GANs to generate a synthetic dataset $S \sim P_T$ that is disjoint with the training set $D_t$ while minimizing the distance between training data and generated data $\mathcal{L}(D_t, S)$, which is

$$ S = \arg\min_{S_t} \mathcal{L}(S_t, D_t)|_{S_t \cap D_t = \emptyset}, \quad (7) $$

where $\mathcal{L}$ denotes a distance metric. Since the discriminator of the WGAN minimizes the Wasserstein distance, we additionally add a constraint during training to force each sampled batch of the generator to be disjoint with $D_t$. To do so, we remove the intersection between the sampled batch and the training set every iteration before computing the loss function (see Alg. 3). Thus, WGAN automatically searches for the best substitution for such colliding samples at training.

---

**Algorithm 3: GAN-constrained Training (Improved defense)**

**Input:** $D_t$: private training data; $N_g$: number of discriminator iterations per generator iteration; $m$: batch size

**Output:** A Synthetic dataset $S$ for each iteration do

```
while i = 1 → $N_g$ do
  Sample $\{x^{(1)}_i\}_{i=1}^m \sim P_T$;
  Sample $\{x^{(1)}_i\}_{i=1}^m \sim P_T, n > m$; Choose $m$ of $n$ priors
  \{ $x^{(1)}_i$ \}_{i=1}^m, s.t., G(z) \notin D_t
  Compute loss, backward, update gradients;
end
Sample $\{x^{(1)}_i\}_{i=1}^m \sim P_T$; Choose $m$ of $n$ priors \{ $x^{(1)}_i$ \}_{i=1}^m, s.t.,
G(z) \notin D_t;
Compute loss, backward, update gradients;
end
S ← $G(z), s.t., G(z) \notin D_t$; $\quad \rightarrow$ Naive defense
return S
```

---
Figure 14: Differential private GAN-synthesized data utility (left) and TableGAN-MCA effect (right) for Adult, Lawschool and Compas benchmarks. Dash dot line denotes non-private WGAN with weight clipping baseline.

Figure 15: ECDF comparisons for synthetic datasets generated by three methods. We choose "priors count" attribute in the Compas dataset.

7.2 Improved Defenses Evaluation. The improved defense in large part achieves superior trade-offs than the naive defense, and is almost comparable to the no-defense baseline. We evaluate synthetic data utility of the naive defense, the improved defense and the no-defense (baseline) on WGAN-GP. Note that the baseline is vulnerable to TableGAN-MCA while naive and improved defenses protect against it. We evaluate machine learning efficacy in Fig. 16(a) and marginal fitness in Fig. 16(b).

In Fig. 16(a), we train machine learning models (Logistic Regression Classifier) on synthetic data sampled from the naive defense, the improved defense and the no-defense generator and predict on the real test data. Fig. 16(a) shows that synthetic data generated by naive and improved defenses achieve satisfying prediction accuracy on the Adult and Lawschool datasets. In the Compas dataset, mitigation methods decrease the prediction accuracy compared to the no-defense baseline.

In Fig. 16(b), we compare ECDFs using $E_l(l_1)$ (recall Section 5.2.1). The lower score implies better marginal fitness. The experimental result shows that the improved defense outperforms the naive defense, and is on par with the no-defense baseline. The improved defense succeeds in compensating the statistical deviation caused by the naive defense (see Fig. 15(c)). More ECDFs of the naive defense and the improved defense are shown in Figs. 19, 20, and 21.

In summary, both naive and improved defenses protect against TableGAN-MCA and in part preserve learning ability of released synthetic data. Moreover, the improved defense achieves better marginal fitness than the naive defense. Despite the potentially effective mitigation, TableGAN-MCA still remains a threat since the proposed defenses achieve sub-optimal privacy-utility trade-offs, eg, reduced synthetic data diversity, under-performance for tiny-domain datasets (see Compas datasets for details).

8 RELATED WORK

Membership privacy is the existence of individuals [25, 36]. Existing studies show membership disclosure on discriminative machine learning models, e.g., classifiers [28, 33, 41–43, 47] and generative machine learning models, e.g., Generative Adversarial Networks [7, 20, 21, 35]. In the discriminative settings, an adversary infers whether a specific data point is used to train a target model by querying classifier APIs and using predicted probability vectors, labels, logits, etc., to train attack models. For instance, Shokri’s shadow model [43] infers membership against overfitted multi-class classifiers by training an attack model with labeled synthetic data, which mimic the private training data. Subsequent works further relax the adversary’s background knowledge [42] by extending attacks to the white-box [33] and the label-only settings [9, 26].

In the track of inferring membership against the generative models, there are several successful approaches, such as, tableGAN [35], LOGAN [20], MC [21] and GAN-leaks [7]. Note that some of these approaches is originally proposed against image data; however, they are possibly extendable to attack tabular data. That is, they are all related to this study. Hence, we briefly summarize these methods in this section. The conceptual comparisons are shown in Table 1. LOGAN [20] and table-GAN [35] leverage the output of the overfitting discriminator to train an attack model, which is a variant of Shokri et al. [43] in the context of GAN synthesis. However, their attacks require the predicted probability vector of the target discriminator at the inference phase (see column 3 in Table 1). In our experiment, we have already shown that a GAN resilient to their attacks may still expose training data to TableGAN-MCA. MC [21] and GAN-leaks [7] extract a customized membership indicator of the overfitting generator to train an attack model. We share a similar theoretical bases with theirs, that is, the modeled distribution of the generator behaves differently on training input versus the non-training one. However, our attack further recovers partial training
data by inferring membership of published synthetic data, which is out of their scope (see Columns 4 and 5 in Table 7). In this work, we empirically show that the membership inference classifier cannot be directly used to identify membership collisions in our attack model (see Table 7). Compared to those works, we propose a novel attack model, TableGAN-MCA, that exposes partial training data by exploiting the weakness of tabular data synthesis. Even though we share similar ideas with MIAs in generative setting, the attack model of TableGAN-MCA learns different decision boundaries. According to the experimental results, the success of the proposed attack relies more on population knowledge than individual presence, which is different from MIAs.

9 CONCLUSION
GAN-synthesized table releasing provides unprecedented opportunities for private data sharing that aims to study the regular pattern of population. In this work, we propose a novel membership collision attack, TableGAN-MCA, against the GAN-synthesized table. Our comprehensive experiments over the real-world datasets conclude some important findings. TableGAN-MCA achieves high recovering rate against the private training data from the published GAN-synthesized tables. Our in-depth studies suggest that the target model, training data size, training epochs and training data frequencies impact the attack performance of TableGAN-MCA. We further conclude that the training data leakage is mainly related to the published population statistics (attributes correlations), rather than the model memorization. To mitigate the effect of TableGAN-MCA, we find that differential privacy (applying DP-WGAN) does not show a satisfying result mainly due to the correlations between training data features. Based on our understanding on TableGAN-MCA, we propose two mitigation approaches, which substitute the published colliding members with similar non-private data entries. We hope that the concept of membership collisions defined and the attack methodology developed in this paper could inform the privacy community of such new potential leakage of data synthesis.

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APPENDIX

A  NETWORK STRUCTURE AND PARAMETERS

WGAN-GP, WGAN-WC shares the same network architecture. We set the Generator as Recurrent Neural Networks (RNNs). According to our experiments, the RNN has a positive effect on stabilizing the generator’s outputs. Eq. (8) represents the Generator networks and Eq. (9) represents the Discriminator networks.

\[
\begin{align*}
    h_1 &= \text{ReLU}(\text{BN}(\mathcal{F}c(z) - 256(z))) \\
    h_2 &= \text{ReLU}(\text{BN}(\mathcal{F}c(z) - 256(z) \oplus h_1))) \\
    G(\cdot)_{\text{con}} &= \text{gumbel}_0.5(\mathcal{F}(c(z) | 512 \rightarrow | h_1))) \\
    G(\cdot)_{\text{cat}} &= \text{tanh}(\mathcal{F}(c(z) | 512 \rightarrow | h_2))) \\
    h_1 &= \text{dropout}_{0.5}(\text{leakyReLU}_{0.2}(\mathcal{F}(c(z) - 256(r)))) \\
    h_2 &= \text{dropout}_{0.5}(\text{leakyReLU}_{0.2}(\mathcal{F}(256 - 256(h_1)))) \\
    D(\cdot) &= \mathcal{F}(256 - 1(h_2))
\end{align*}
\]

For TVAE and CTGAN, we apply the module CTGANSynthesizer and TVAESynthesizer of the SDGym [5]. Thus, the structures and hyper-parameters are exactly same as the originals’ [46].

Hyper-parameters. For Adult and Lawscholar datasets, we train 300 epochs and set batch size to 500. For Compas dataset, we train 600 epochs and set batch size to 100. Since the Compas dataset is much smaller than others, we find that less iterations could incur under-fitting. Additionally, balancing the number of D and G training sessions also helps to converge faster.

B  NUMBER OF SYNTHETIC QUERIES

We thoroughly discuss how the number of synthetic queries influences the attack performance and corresponding attack tricks.

B.1 Limited Synthetic Queries

Many target model prediction APIs (MLaaS) implement a pay-per-query business model. Hence, reducing the number of synthetic queries saves the cost of performing TableGAN-MCA. However, a smaller synthetic dataset, having less membership collisions with the training dataset, decays the attack performance. To tackle this problem, we propose an approach that uses shadow data to fill up the synthetic data to match the size of the training set. That is, the adversaries obtain a synthetic dataset \( S \) of size \( 0.25 \times N \) by querying the target Generator. The adversaries then generate the shadow dataset of size \( |S| = 0.75 \times N \). After that, the TableGAN-MCA adversaries attack \( S \) instead of the original \( S \).

We show the impact of a small \( N_s \) on TableGAN-MCA in Fig. 17. We find that few synthetic queries also yield decent attack performance. This resonates with the memorization experiment that the success of TableGAN-MCA is contingent on basic data patterns.

B.2 Unlimited Synthetic Queries

The TableGAN-MCA adversary continues to expose more training data when increasing the number of synthetic queries. In Fig. 7, we evaluate the TableGAN-MCA up to \( N_s = 10 \), which is not the ceiling of TableGAN-MCA capabilities. Due to computational constraints, we are limited to performing the attack up to \( N_s = 20 \) and observe that the number of exposed training data of TableGAN-MCA is still increasing. This leaves open an interesting problem of whether the adversary could reconstruct the whole training dataset with unlimited queries.

Figure 17: TableGAN-MCA performance when \( N_s \leq 1 \).
Figure 18: ECDF comparison between training data and differentially private GAN-synthesized data.

Table 8: Hyper-parameters in DP-WGAN. \((\epsilon, \delta)\): privacy budget; \(S\): clip threshold; \(\sigma\): standard deviation of the noise added in each step.

| Datasets | \((\epsilon, \delta)\) | \((S, \sigma)\) | Sampling rate |
|----------|-----------------|----------------|---------------|
| Adult    | \((0.5, 10^{-5})\) | \((0.1, 0.5)\) | 500/31655     |
|          | \((1.0, 10^{-5})\) | \((0.1, 0.45)\) | 500/31655     |
|          | \((2.0, 10^{-5})\) | \((0.1, 0.4)\)  | 500/31655     |
|          | \((4.0, 10^{-5})\) | \((0.1, 0.3)\)  | 500/31655     |
|          | \((8.0, 10^{-5})\) | \((0.1, 0.17)\) | 500/31655     |
|          | \((16.0, 10^{-5})\)| \((0.1, 0.11)\) | 500/31655     |
|          | \((0.5, 10^{-5})\) | \((0.1, 0.4)\)  | 500/43011     |
|          | \((1.0, 10^{-5})\) | \((0.1, 0.45)\) | 500/43011     |
|          | \((2.0, 10^{-5})\) | \((0.1, 0.48)\) | 500/43011     |
|          | \((4.0, 10^{-5})\) | \((0.1, 0.25)\) | 500/43011     |
|          | \((8.0, 10^{-5})\) | \((0.1, 0.15)\) | 500/43011     |
|          | \((16.0, 10^{-5})\)| \((0.1, 0.11)\) | 500/43011     |
|          | \((2.0, 10^{-4})\) | \((0.1, 0.9)\)  | 100/3694      |
|          | \((4.0, 10^{-4})\) | \((0.1, 0.48)\) | 100/3694      |
|          | \((8.0, 10^{-4})\) | \((0.1, 0.27)\) | 100/3694      |
|          | \((16.0, 10^{-4})\)| \((0.1, 0.16)\) | 100/3694      |
|          | \((32.0, 10^{-4})\)| \((0.1, 0.11)\) | 100/3694      |

C.2 Naive and Improved Defenses

We show additional ECDFs of marginals for “Remove Colliding Members” mitigation and “GAN-constrained Training” mitigation in Figs. 19, 20, and 21.

C MITIGATION

C.1 DP-WGAN

We show the ECDFs of marginals for \((\epsilon, \delta)\)-DP synthesized data in Fig. 18. Smaller training data usually gains less satisfactory generation quality under DP training with a similar privacy budget.
Figure 19: ECDF comparisons for “Remove Overlapping” mitigation and “GAN-constrained Training” mitigation.

Figure 20: ECDF comparisons for “Remove Overlapping” mitigation and “GAN-constrained Training” mitigation.

Figure 21: ECDF comparisons for "Remove Overlapping" mitigation and "GAN-constrained Training" mitigation.