

CTAB-GAN: Effective Table Data Synthesizing

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ABSTRACT

While data sharing is crucial for knowledge development, privacy concerns and strict regulation (e.g., European General Data Protection Regulation (GDPR)) unfortunately limit its full effectiveness. Synthetic tabular data emerges as an alternative to enable data sharing while fulfilling regulatory and privacy constraints. The state-of-the-art tabular data synthesizers draw methodologies from Generative Adversarial Networks (GAN) and address two main data types in industry, i.e., continuous and categorical. In this paper, we develop CTAB-GAN, a novel conditional table GAN architecture that can effectively model diverse data types, including a mix of continuous and categorical variables. Moreover, we address data imbalance and long tail issues, i.e., certain variables have drastic frequency differences across large values. To achieve those aims, we first introduce the information loss and classification loss to the conditional GAN. Secondly, we design a novel conditional vector, which efficiently encodes the mixed data type and skewed distribution of data variable. We extensively evaluate CTAB-GAN with the state of the art GANs that generate synthetic tables, in terms of data similarity and analysis utility. The results on five datasets show that the synthetic data of CTAB-GAN remarkably resembles the real data for all three types of variables and results into higher accuracy for five machine learning algorithms, by up to 17%.

KEYWORDS

GAN, data synthesis, tabular data, imbalanced distribution

1 INTRODUCTION

“Data is the new oil” is a quote that goes back to 2006, which is credited to mathematician Clive Humby. It has recently picked up more steam after The Economist published a 2017 report [21] titled “The world’s most valuable resource is no longer oil, but data”. Many companies nowadays discover valuable business insights from various internal and external data sources. However, the big knowledge behind big data often impedes personal privacy and leads to unjustified analysis [17]. To prevent the abuse of data and the risks of privacy breaching, the European Commission introduced the European General Data Protection Regulation (GDPR) and enforced strict data protection measures. This however instills

a new challenge in the data-driven industries to look for new scientific solutions that can empower big discovery while respecting the constraints of data privacy and governmental regulation.

An emerging solution is to leverage synthetic data [16], which statistically resembles real data and can comply with GDPR due to its synthetic nature. The industrial datasets (at stakeholders like banks, insurance companies, and health care) present multi-fold challenges. First of all, such datasets are organized in tables and populated with both continuous and categorical variables, or a mix of the two, e.g., the value of mortgage for a loan holder. This value can be either 0 (no mortgage) or some continuous positive number. Here, we term such a type of variables, **mixed variable**. Secondly data variables often have a wide range of values as well as skewed frequency distribution, e.g., the statistic of transaction amount for credit card. Most transactions should be within 0 and 500 bucks (i.e. daily shopping for food and clothes), but exceptions of a high transaction amount surely exist.

Generative Adversarial Network (GAN) [7] is one of the emerging data synthesizing methodologies. The GAN is first trained on a real dataset. Then used to generate data. Beyond its success on generating images, GAN has recently been applied to generate tabular data [16, 19, 24, 25]. The state of the art of tabular generators [24] treats categorical variables via conditional GAN, where each categorical value is considered as a condition. However, their focus is only on two types of variables, namely continuous and categorical, overlooking an important class of mixed data type. In addition, it is unclear if existing solutions can efficiently handle highly imbalanced categorical variables and skewed continuous variables.

In this paper, we aim to design a tabular data synthesizer that addresses the limitations of the prior state-of-the-art: (i) encoding mixed data type of continuous and categorical variables, (ii) efficient modeling of long tail continuous variables and (iii) increased robustness to imbalanced categorical variables along with skewed continuous variables. Hence, we propose a novel conditional table generative adversarial network, CTAB-GAN. Two key features of CTAB-GAN are the introduction of classification loss in conditional GAN, and novel encoding for the conditional vector that efficiently encodes mixed variables and helps to deal with highly skewed distributions for continuous variables.

*Both authors contributed equally to this research.

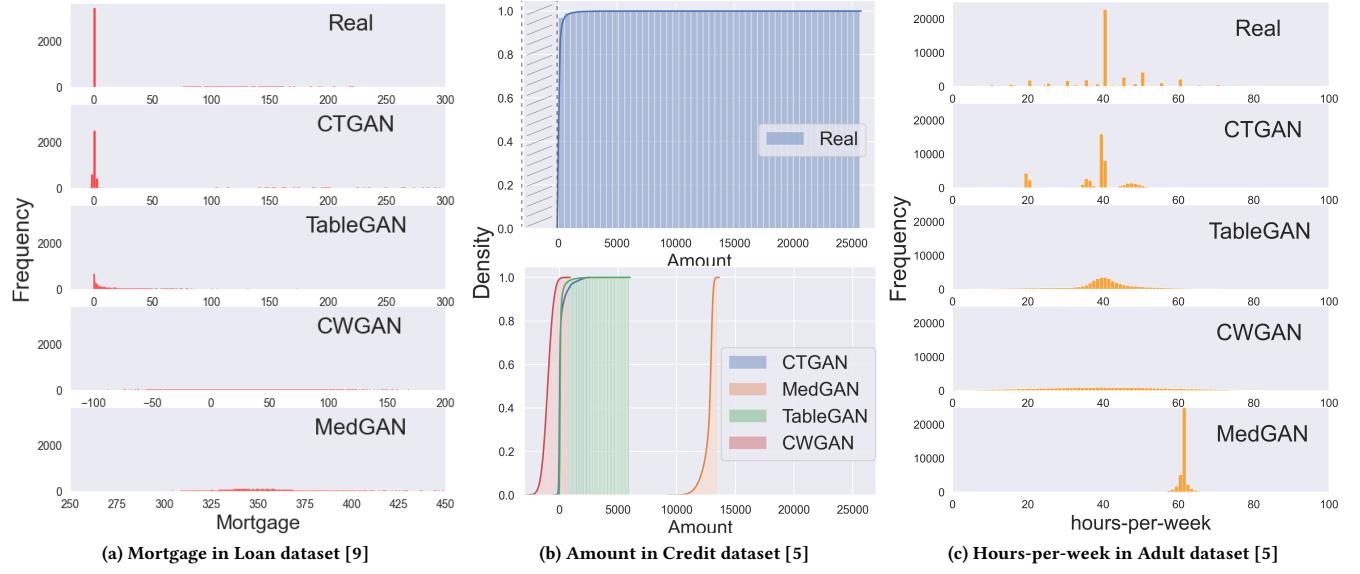


Figure 1: Challenges of modeling industrial dataset using existing GAN-based table generator: (a) mixed type, (b) long tail distribution, and (c) skewed data

We rigorously evaluate CTAB-GAN in three dimensions: (i) utility of machine learning based analysis on the synthetic data, (ii) statistical similarity to the real data, and (iii) privacy preservability. Specifically, the proposed CTAB-GAN is tested on 5 widely used machine learning datasets: Adult, Covertype, Credit, Intrusion and Loan, against 4 state-of-the-art GAN-based tabular data generation algorithms: CTGAN, TableGAN, CWGAN and MedGAN. Our results show that CTAB-GAN not only outperforms all the comparisons in machine learning utility and statistical similarity but also provides better distance-based privacy guarantees than TableGAN, the second best performing algorithm in the machine learning utility and statistical similarly evaluation.

The main contributions of this study can be summarized as follows:

- Novel conditional adversarial network which introduces a classifier providing additional supervision to improve its utility for ML applications.
- Efficient modelling of continuous, categorical, and **mixed** variables via novel data encoding and conditional vector.
- Light-weight data pre-processing to mitigate the impact of long tail distribution of continuous variables.
- Providing an effective data synthesizer for the relevant stakeholders.

1.1 Motivation

In this subsection, we empirically demonstrate how the prior state-of-the-art methods fall short in solving challenges in industrial data sets. The detailed experimental setup can be found in Sec. 4.1.

Mixed data type variables. To the best of our knowledge, existing GAN-based tabular generators only consider table columns as either categorical or continuous. However, in reality, a variable can be a mix of these two types, and often variables have missing values.

The *Mortgage* variable from the *Loan* dataset is a good example of mixed variable. Fig. 1a shows the distribution of the original and synthetic data generated by 4 state-of-the-art algorithms for this variable. According to the data description, a loan holder can either have no mortgage (0 value) or a mortgage (any positive value). In appearance this variable is not a categorical type due to the numeric nature of the data. So all 4 state-of-the-art algorithms treat this variables as continuous type without capturing the special meaning of the value zero. Hence, all 4 algorithms generate a value around 0 instead of exact 0. And the negative values for Mortgage have no/wrong meaning in the real world.

Long tail distributions. Many real world data can have long tail distributions where most of the occurrences happen near the initial value of the distribution, and rare cases towards the end. Fig. 1c plots the cumulative frequency for the original (top) and synthetic (bottom) data generated by 4 state-of-the-art algorithms for the *Amount* in the *Credit* dataset. This variable represents the transaction amount when using credit cards. One can imagine that most transactions have small amounts, ranging from few bucks to thousands of dollars. However, there definitely exists a very small number of transactions with large amounts. Note that for ease of comparison both plots use the same x-axis, but Real has no negative values. Real data clearly has 99% of occurrences happening at the start of the range, but the distribution extends until around 25000. In comparison none of the synthetic data generators is able to learn and imitate this behavior.

Skewed multi-mode continuous variables. The term *multi-mode* is extended from Variational Gaussian Mixtures (VGM). More details are given in Sec. 3.3. The intuition behind using multiple modes can be easily captured from Fig. 1c. The figure plots in each row the distribution of the working *Hours-per-week* variable from the *Adult* dataset. This is not a typical Gaussian distribution. There

is an obvious peak at 40 hours but with several other lower peaks, e.g. at 50, 20 and 45. Also the number of people working 20 hours per week is higher than those working 10 or 30 hours per week. This behavior is difficult to capture for the state-of-the-art data generators (see subsequent rows in Fig.1c). The closest results are obtained by CTGAN which uses Gaussian mixture estimation for continuous variables. However, CTGAN loses some modes compared to the original distribution.

The above examples show the shortcomings of current state-of-the-art GAN-based tabular data generation algorithms and motivate the design of our proposed CTAB-GAN.

2 RELATED STUDIES

We divide the related studies using GAN to generate tabular data into two categories: (i) based on GAN, and (ii) based on conditional GAN.

GAN-based generator Several studies extend GAN to accommodate categorical variables by augmenting GAN architecture. MedGAN [4] combines an auto-encoder with a GAN. It can generate continuous or discrete variables, and has been applied to generate synthetic electronic health record (EHR) data. CrGAN-Cnet [16] uses GAN to conduct Airline Passenger Name Record Generation. It integrates the Cramér Distance [2] and Cross-Net architecture [23] into the algorithm. In addition to generating with continuous and categorical data types, CrGAN-Cnet can also handle missing value in the table by adding new variables. TableGAN [19] introduces information loss and a classifier into GAN framework. It specifically adopts Convolutional Neural Network (CNN) for generator, discriminator and classifier. Although aforementioned algorithms can generate tabular data, they cannot specify how to generate from a specific class for particular variable. For example, it is not possible to generate health record for users whose sex is female. In addition to data generation, privacy is another important factor for synthetic tabular data. PATE-GAN [27] is not specifically designed for tabular data generation, but it proposes a framework which generates synthetic data with differential privacy guarantees.

Conditional GAN-based generator Due to the limitation of controlling generated data via GAN, Conditional GAN is increasingly used, and its conditional vector can be used to specify to generate a particular class of data. CW-GAN [6] applies the Wasserstein distance [1] into the conditional GAN framework. It leverages the usage of conditional vector to oversample the minority class to address imbalanced tabular data generation. CTGAN [24] integrates PacGAN [14] structure in its discriminator and uses WGAN loss plus gradient penalty [8] to train a conditional GAN framework. It also adopts a strategy called training-by-sampling, which takes advantage of conditional vector, to deal with the imbalanced categorical variable problem.

In our paper, we not only focus on modelling continuous or categorical variables, but also cover the mixed data type (i.e., variables that contain both categorical and continuous values, or even missing values). We effectively combine the strengths of prior art, such as classifier, information loss, effective encoding, and conditional vector. Furthermore, we proactively address the pain point of long tail variable distributions and propose a new conditional vector structure to better deal with imbalanced datasets.

3 CTAB-GAN

CTAB-GAN is a tabular data generator designed to overcome the challenges outlined in Sec. 1.1. In CTAB-GAN we invent a *Mixed-type Encoder* which can better represent mixed categorical-continuous variables as well as missing values. CTAB-GAN is based on a conditional GAN (CGAN) to efficiently treat minority classes [6, 24], with the addition of classification and information loss [18, 19] to improve semantic integrity and training stability, respectively. Finally, we leverage a log-frequency sampler to overcome the mode collapse problem for imbalanced variables.

3.1 Technical background

GANs are a popular method to generate synthetic data first applied with great success to images [10, 11] and later adapted to tabular data [26]. GANs leverage an adversarial game between a generator trying to synthesize realistic data and a discriminator trying to discern synthetic from real samples.

To address the problem of dataset imbalance, we leverage *conditional generator* and *training-by-sampling* methods [24]. The idea behind this is to use an additional vector, termed as the conditional vector, to represent the classes of categorical variables. This vector is both fed to the generator and used to bound the sampling of the real training data to subsets satisfying the condition. We can leverage the condition to resample all classes giving higher chances to minority classes to train the model.

To enhance the generation quality, we incorporate two extra terms in the loss function of the generator [18, 19]: information and classification loss. The information loss penalizes the discrepancy between statistics of the generated data and the real data. This helps to generate data which is statistically closer to the real one. The classification loss requires to add to the GAN architecture an auxiliary classifier in parallel to the discriminator. For each synthesized label the classifier outputs a predicted label. The classification loss quantifies the discrepancy between the synthesized and predicted class. This helps to increase the semantic integrity of synthetic records. For instance, (sex=female, disease=prostate cancer) is not a semantically correct record as women do not have a prostate, and no such record should appear in the original data and is hence not learnt by the classifier.

To counter complex distributions in continuous variables we embrace the *mode-specific normalization* idea [24] which encodes each value as a value-mode pair stemming from Gaussian mixture model.

3.2 Design of CTAB-GAN

The structure of CTAB-GAN comprises three blocks: Generator \mathcal{G} , Discriminator \mathcal{D} and an auxiliary Classifier \mathcal{C} (see Fig. 2). Since our algorithm is based on conditional GAN, the generator requires a noise vector plus a conditional vector. Details on the conditional vector are given in Sec. 3.4. To simplify the figure, we omit the encoding and decoding of the synthetic and real data detailed in Sec. 3.3.

GANs are trained via a zero-sum minimax game where the discriminator tries to maximize the objective, while the generator tries to minimize it. The game can be seen as a mentor (\mathcal{D}) providing feedback to a student (\mathcal{G}) on the quality of his work. Here, we

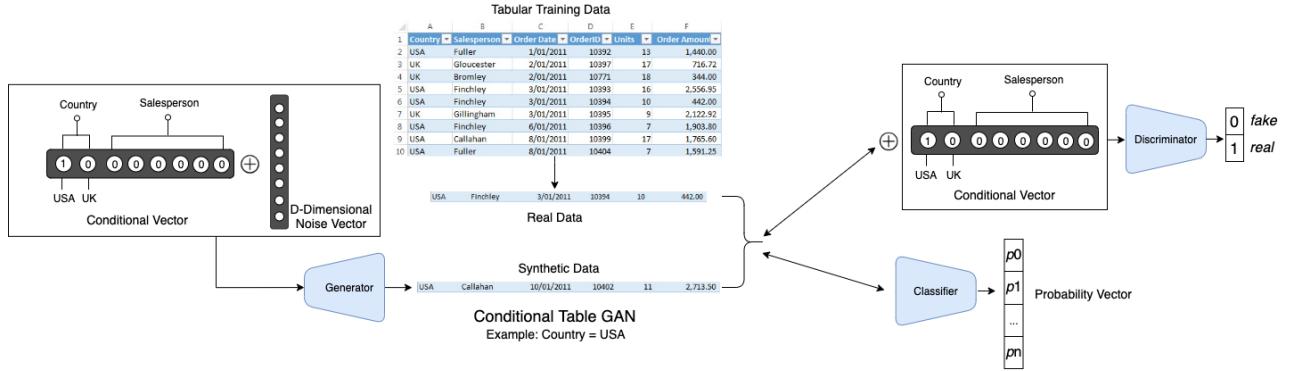


Figure 2: Synthetic Tabular Data Generation via CTAB-GAN

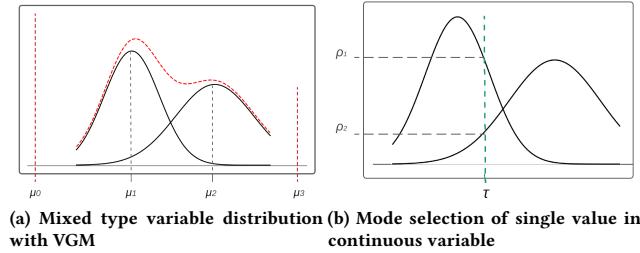


Figure 3: Encoding for mix data type variable

introduce additional feedback for \mathcal{G} based on the information loss and classification loss. The information loss matches the first-order (i.e., mean) and second-order (i.e., standard deviation) statistics of synthesized and real records. This leads the synthesized records to have the same statistical characteristics as the real records. In addition, the classifier is trained to learn the correlation between classes and the other variable values using the real training data. The classification loss helps to check the semantic integrity, and penalizes synthesized records where the combination of values are semantically incorrect. These two losses are added to the original loss term of \mathcal{G} during training.

\mathcal{G} and \mathcal{D} are implemented by a four and a two layers CNN, respectively. CNNs are good at capturing the relation between pixels within an image [12], which in our case, can help to increase the semantic integrity of synthetic data. \mathcal{C} uses a 7 layers MLP. The classifier is trained on the original data to better interpret the semantic integrity. Hence synthetic data are reverse transformed from their encoding (details in Sec. 3.3) before being used as input for \mathcal{C} to create the class label predictions.

3.3 Mixed-type Encoder

The tabular data is encoded variable by variable. We distinguish three types of variables: categorical, continuous and mixed. We define variables as mixed if they contain both categorical and continuous values or continuous values with missing values. We propose the new Mixed-type Encoder to deal with such variables. With this encoder, values of mixed variables are seen as concatenated value-mode pairs. We illustrate the encoding via the exemplary

distribution of a mixed variable shown in red in Fig. 3a. One can see that values can either be exactly μ_0 or μ_3 (the categorical part) or distributed around two peaks in μ_1 and μ_2 (the continuous part). We treat the continuous part using a variational Gaussian mixture model (VGM) [3] to estimate the number of modes k , e.g. $k = 2$ in our example, and fit a Gaussian mixture. The learned Gaussian mixture is:

$$\mathbb{P} = \sum_{k=1}^2 \omega_k \mathcal{N}(\mu_k, \sigma_k) \quad (1)$$

where \mathcal{N} is the normal distribution and ω_k , μ_k and σ_k are the weight, mean and standard deviation of each mode, respectively.

To encode values in the continuous region of the variable distribution, we associate and normalize each value with the mode having the highest probability (see Fig. 3b). Given ρ_1 and ρ_2 being the probability density from the two modes in correspondence of the variable value τ to encode, we select the mode with the highest probability. In our example ρ_1 is higher and we use mode 1 to normalize τ . The normalized value α is:

$$\alpha = \frac{\tau - \mu_1}{4\sigma_1} \quad (2)$$

Moreover we keep track of the mode β used to encode τ via one hot encoding, e.g. $\beta = [0, 1, 0, 0]$ in our example. The final encoding is giving by the concatenation of α and β : $\alpha \oplus \beta$ where \oplus is the vector concatenation operator.

The categorical values are treated similarly, except α directly represents the value of the mode, e.g. corresponding to μ_0 or μ_3 in our example. Hence, for a value in μ_3 , the final encoding is given by $\mu_3 \oplus [0, 0, 0, 1]$. Note that categorical values are not limited to numbers. They can be of any type such as a string or even missing. We can map these symbols to a numeric value outside of the range of the continuous region.

Categorical variables use the same encoding as the continuous intervals of mixed variables. Categorical variables are encoded via a one-hot vector γ . Missing values are treated as a separate unique class and we add an extra bit to the one-hot vector for it. A row with $[1, \dots, N]$ variables is encoded by concatenation of the encoding of all variable values, i.e. either $(\alpha \oplus \beta)$ for continuous and mixed variables or γ for categorical variables. Having n continuous/mixed variables and m categorical variables ($n + m = N$) the final encoding

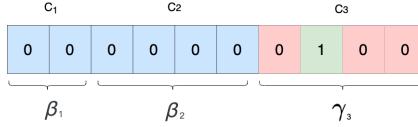


Figure 4: Conditional vector: example selects class 2 from third variable out of three

is:

$$\bigoplus_{i=1}^n \alpha_i \oplus \beta_i \bigoplus_{j=n+1}^N \gamma_j \quad (3)$$

3.4 Counter imbalanced training datasets

In CTAB-GAN, we use conditional GAN to counter imbalanced training datasets. When we sample real data, we use the conditional vector to filter and rebalance the training data.

The conditional vector \mathcal{V} is a bit vector given by the concatenation of all mode one-hot encodings β (for continuous and mixed variables) and all class one-hot encodings γ (for categorical variables) for all variables present in Eq. (3). Each conditional vector specifies a single mode or a class. More in detail, \mathcal{V} is a zero vector with a single one in correspondence to the selected variable with selected mode/class. Fig. 4 shows an example with three variables, one continuous (C_1), one mixed (C_2) and one categorical (C_3), with class 2 selected on C_3 .

To rebalance the dataset, each time we need a conditional vector during training, we first randomly choose a variable with uniform probability. Then we calculate the probability distribution of each mode (or class for categorical variables) in that variable using frequency as proxy and sample a mode based on the logarithm of its probability. Using the log probability instead of the original frequency gives minority modes/classes higher chances to appear during training. This helps to alleviate the collapse issue for rare modes/classes.

3.5 Treat long tail

We encode continuous values using variational Gaussian mixtures to treat multi-mode data distributions (details in Sec. 3.3). However, Gaussian mixtures can not deal with all types of data distribution, notably distributions with long tail where few rare points are far from the bulk of the data. VGM has difficulty to encode the values towards the tail. To counter this issue we pre-process variables with long tail distributions with a logarithm transformation. For such a variable having values with lower bound l , we replace each value τ with compressed τ^c :

$$\tau^c = \begin{cases} \log(\tau) & \text{if } l > 0 \\ \log(\tau - l + \epsilon) & \text{if } l \leq 0, \text{ where } \epsilon > 0 \end{cases} \quad (4)$$

The log-transform allows to compress and reduce the distance between the tail and bulk data making it easier for VGM to encode all values, including tail ones. We show the effectiveness of this simple yet performant method in Sec. 4.5.

4 EXPERIMENTAL ANALYSIS

To show the efficacy of the proposed CTAB-GAN, we select five commonly used machine learning datasets, and compare with four

Table 1: Description of datasets. The notations C , B , M & M_i represent number of continuous, binary, multi-class categorical, mixed variables and imbalance ratios (i.e no. of minority samples/no. of majority samples) respectively.

Dataset	Train/Test Split	Target variable	#C	#B	#M	#Mi
Adult	39k/9k	"income"	3	2	7	2
Covertype	45k/5k	"Cover_Type"	9	44	1	1
Credit	40k/10k	"Class"	30	1	0	0
Intrusion	45k/5k	"Class"	4	6	14	18
Loan	4k/1k	"Personal-Loan"	5	5	2	1

state-of-the-art GAN based tabular data generators. We evaluate the effectiveness of CTAB-GAN in terms of the resulting ML utility, statistical similarity to the real data, and privacy distance. Moreover, we provide an ablation analysis to highlight the efficacy of the unique components of CTAB-GAN.

4.1 Experimental setup

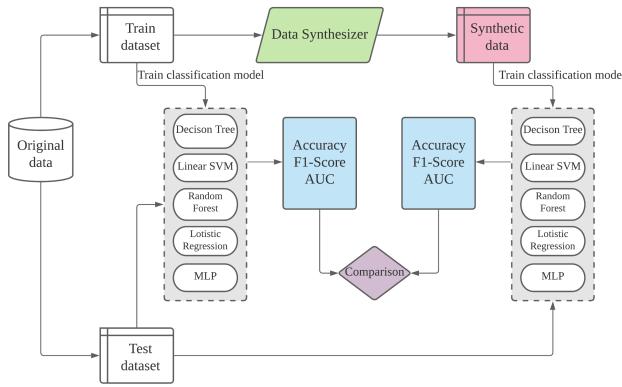
Datasets. Our algorithm is tested on five commonly used machine learning datasets. Three of them – **Adult**, **Covertype** and **Intrusion** – are from the UCI machine learning repository [5]. The other two – **Credit**[22] and **Loan**[9] – are from Kaggle. All five tabular datasets have a target variable, for which we use the rest of the variables to perform classification. Due to computing resource limitations, 50K rows of data are sampled randomly in a stratified manner with respect to the target variable for Covertype, Credit and Intrusion datasets. However, the Adult and Loan datasets are not sampled. The details of each dataset are shown in Tab. 1.

Baselines. Our CTAB-GAN is compared with 4 state-of-the-art GAN-based tabular data generators: CTGAN, TableGAN, CWGAN and MedGAN. To have a fair comparison, all algorithms are coded using Pytorch, with the generator and discriminator structures matching the descriptions provided in their respective papers. For Gaussian mixture estimation of continuous variables, we use the same settings as the evaluation of CTGAN, i.e. 10 modes. All algorithms are trained for 150 epochs for Adult, Covertype, Credit and Intrusion datasets, whereas the algorithms are trained for 300 epochs on Loan dataset. This is because, the Loan dataset is significantly smaller than the others containing only 5000 rows and requires a long training time to converge. Lastly, each experiment is repeated 3 times.

Environment. Experiments are run under Ubuntu 20.04 on a machine equipped with 32 GB memory, a GeForce RTX 2080 Ti GPU and a 10-core Intel i9 CPU.

4.2 Evaluation metrics

The evaluation is conducted on three dimensions: (1) machine learning (ML) utility, (2) statistical similarity and (3) privacy preservability. The first two are used to evaluate if the synthetic data can be used as a good proxy of the original data. The third criterion sheds light on the nearest neighbour distances within and between the original and synthetic datasets, respectively.

**Figure 5: Evaluation flows for ML utility**

4.2.1 Machine learning (ML) utility. As shown in Fig. 5, to evaluate the ML utility of synthetic data, the original and synthetic data are evaluated by 5 widely used machine learning algorithms: decision tree classifier, linear support-vector-machine (SVM), random forest classifier, multinomial logistic regression and multi-layer-perceptron (MLP).

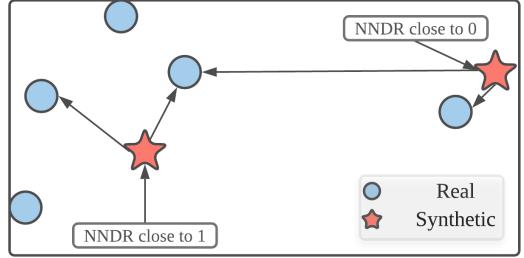
We first split the original dataset into training and test datasets. The training set is used as input to the GAN models as the real dataset. Once the training is finished, we use the GAN models to generate synthetic data with the same size as the training set. The synthetic and real training datasets are then separately used to train the above-mentioned machine learning models and evaluated on the real test datasets. The machine learning performance is measured via the accuracy, F1-score and area under the ROC. The aim of this design is to test how close the ML utility is when we train a machine learning model using the synthetic data vs the real data. This responds to the question, “Can synthetic data be used as a proxy of the original data for training ML models?”.

4.2.2 Statistical Similarity. Three metrics are used to quantitatively measure the statistical similarity between the real and synthetic data.

Jensen-Shannon divergence (JSD) [13]. The JSD provides a measure to quantify the difference between the probability mass distributions of individual categorical variables belonging to the real and synthetic datasets, respectively. Moreover, this metric is bounded between 0 and 1 and is symmetric allowing for an easy interpretation of results.

Wasserstein distance (WD) [20]. In similar vein, the Wasserstein distance is used to capture how well the distributions of individual continuous/mixed variables are emulated by synthetically produced datasets in correspondence to real datasets. We use WD because we found that the JSD metric was numerically unstable for evaluating the quality of continuous variables, especially when there is no overlap between the synthetic and original dataset. Hence, we resorted to utilize the more stable Wasserstein distance.

Difference in pair-wise correlation (Diff. Corr.). To evaluate how well feature interactions are preserved in the synthetic datasets, we first compute the pair-wise correlation matrix for the columns within real and synthetic datasets individually. To measure

**Figure 6: Illustration of NNDR metric with its privacy risk implications**

the correlation between any two continuous features, the Pearson correlation coefficient is used. It ranges between $[-1, +1]$. Similarly, the Theil uncertainty coefficient is used to measure the correlation between any two categorical features. It ranges between $[0, 1]$. Lastly, the correlation ratio between categorical and continuous variables is used. It also ranges between $[0, 1]$. Note that the dython¹ library is used to compute these metrics. Finally, the differences between the pair-wise correlation matrices for the real and synthetic datasets is computed.

4.2.3 Privacy preservability. To quantify the privacy preservability, we resort to distance metrics (instead of differential privacy [27]) as they are intuitive and easy to understand by data science practitioners. Specifically, the following two metrics are used to evaluate the privacy risk associated with synthetic datasets.

Distance to Closest Record (DCR). The DCR is used to measure the Euclidean distance between any synthetic record and its closest corresponding real neighbour. Ideally, the higher the DCR the lesser the risk of privacy breach. Furthermore, the 5th percentile of this metric is computed to provide a robust estimate of the privacy risk.

Nearest Neighbour Distance Ratio (NNDR) [15]. Instead of only measuring the closest neighbour, the NNDR measures the ratio between the Euclidean distance for the closest and second closest real neighbour to any corresponding synthetic record. This ratio is within $[0, 1]$. Higher values indicate better privacy. Low NNDR values between synthetic and real data may reveal sensitive information from the closest real data record. Fig. 6 illustrates the case. Hence, this ratio helps to evaluate the privacy risk with greater depth and better certainty. Note that the 5th percentile is computed here as well.

4.3 Results analysis

ML Utility. Tab. 2 shows the averaged ML utility differences between real and synthetic data in terms of accuracy, F1 score, and AUC. A better synthetic data is expected to have low differences. It can be seen that CTAB-GAN outperforms all other state-of-the-art methods in terms of Accuracy, F1-score and AUC. Accuracy is the most commonly used classification metric, but since we have imbalanced target variable, F1-score and AUC are more stable metrics for such cases. AUC ranges value from 0 to 1. CTAB-GAN largely

¹http://shakedzy.xyz/dython/modules/nominal/#compute_associations

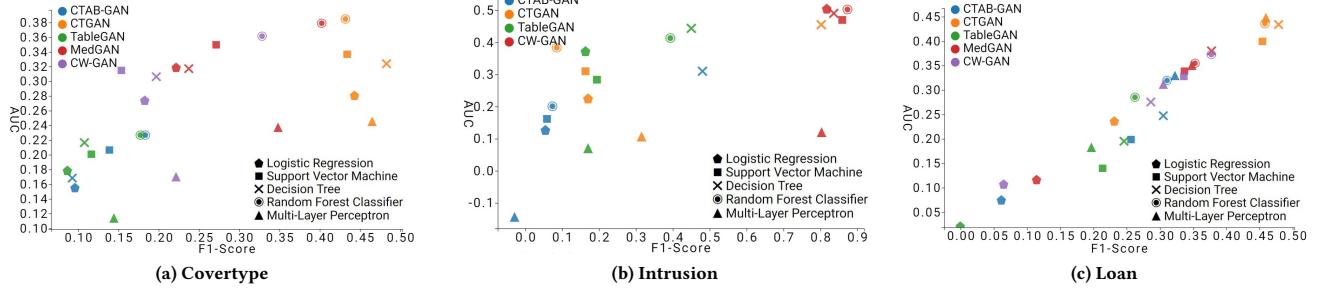


Figure 7: ML utilities difference (i.e., AUC and F1-score) for five algorithms based on five synthetically generated data

Table 2: Difference of ML accuracy (%), F1-score, and AUC between original and synthetic data: average over 5 different datasets and 3 replications.

Method	Accuracy	F1-score	AUC
CTAB-GAN	9.83%	0.127	0.117
CTGAN	21.51%	0.274	0.253
TableGAN	11.40%	0.130	0.169
MedGAN	14.11%	0.282	0.285
CW-GAN	20.06%	0.354	0.299

shortens the AUC difference from 0.169 (best in state-of-the-art) to 0.117.

To obtain a better understanding, Fig. 7 plots the (F1-score, AUC) for all 5 ML models for the Covertype, Intrusion and Loan datasets. Due to the page limit restrictions, results for Adult and Credit datasets are not shown. Their results are similar as the ones of the Covertype dataset. Furthermore, Fig. 7b shows that for the Intrusion dataset CTAB-GAN largely outperforms all others across all ML models used for evaluation. For datasets such as Covertype, the results of CTAB-GAN and TableGAN are similar and clearly better than the rest. This is because apart from CTGAN, the other models fail to deal with the imbalanced categorical variables. Furthermore, as CTGAN uses a VGM model with 10 modes, it fails to converge to a suitable optimum for Covertype that mostly comprises single mode Gaussian distributions.

For the Loan dataset, TableGAN is better than CTAB-GAN and others, but the difference between the two is smaller than for the Intrusion dataset. We believe that the reason CTAB-GAN outperforms the others by such a wide margin (17% higher than second best for averaged accuracy across the 5 machine learning algorithms) for the Intrusion dataset is that it contains many highly imbalanced categorical variables. In addition, Intrusion also includes 3 long tail continuous variables. Our results indicate that none of the state-of-the-art techniques can perform well under these conditions. The Loan dataset is significantly smaller than the other 4 datasets and has the least number of variables. Moreover, all continuous variables are either simple one mode Gaussian distributions or just uniform distributions. Therefore, we find that the encoding method in CTAB-GAN which works well for complex cases, fails to converge to a better optimum for simple and small datasets.

Table 3: Statistical similarity: three measures averaged over 5 datasets and three repetitions.

Method	Avg JSD	Avg WD	Diff. Corr.
CTAB-GAN	0.0697	1050	2.10
CTGAN	0.0704	1769	2.73
TableGAN	0.0796	2117	2.30
MedGAN	0.2135	46257	5.48
CW-GAN	0.1318	238155	5.82

Statistical similarity. Statistical similarity results are reported in Tab. 3. CTAB-GAN stands out again across all comparisons. For categorical variables (i.e. average JSD), CTAB-GAN and CTGAN perform similarly (1% difference), and better than the other methods by at least 12.4%, i.e. against the next best TableGAN. This is due to the use of a conditional vector and the log-frequency sampling of the training data, which works well for both balanced and imbalanced distributions. For continuous variables (i.e. average WD), we still benefit from the design of the conditional vector. The average WD column shows some extreme numbers such as 46257 and 238155 comparing to 1050 of CTAB-GAN. The reason is that these algorithms generate extremely large values for long tail variables. Besides divergence and distance, our synthetic data also maintains better correlation. We can see that TableGAN also performs well here. However, as the extended conditional vector enhances the training procedure, this helps to maintain even more so the correlation between variables. This is because the extended conditional vector allows the generator to produce samples conditioned even on a given VGM mode for continuous variables. This increases the capacity to learn the conditional distribution for continuous variables and hence leads to an improvement in the overall feature interactions captured by the model.

Privacy preservability. As only PATE-GAN can generate synthetic data within tight differential privacy guarantees, we only use distance-based algorithms to give an overview on privacy in our evaluation. On the one hand, if the distance between real and synthetic data is too large, it simply means that the quality of generated data is poor. On the other hand, if the distance between real and synthetic data is too small, it simply means that there is a risk to reveal sensitive information from the training data. Therefore, the evaluation of privacy is relative. The privacy results are shown in Tab. 4. It can be seen that the DCR and NNDR between real and

Table 4: Privacy impact: between real and synthetic data (R&S) and within real data (R) and synthetic data (S).

Model	DCR			NNDR		
	R&S	R	S	R&S	R	S
CTAB-GAN	1.101	0.428	0.877	0.714	0.414	0.558
CTGAN	1.517	0.428	1.026	0.763	0.414	0.624
TableGAN	0.988	0.428	0.920	0.681	0.414	0.632
MedGAN	1.918	0.428	0.254	0.871	0.414	0.393
CW-GAN	2.197	0.428	1.124	0.847	0.414	0.675

synthetic data all indicate that generation from TableGAN has the shortest distance to real data (highest privacy risk). The algorithm which allows for greater distances between real and synthetic data under equivalent ML utility and statistical similarity data should be considered. In that case, CTAB-GAN not only outperforms TableGAN in ML utility and statistic similarity, but also in all privacy preservability metrics by 10.3% and 4.6% for DCR and NNDR, respectively. Another insight from this table is that for MedGAN, DCR within synthetic data is 41% smaller than within real data. This suggests that it suffers from the mode collapse problem.

4.4 Ablation analysis

To illustrate the efficiency of each strategy we implement an ablation study which cuts off the different components of CTAB-GAN one by one:

w/o classifier. In this experiment, Classifier and the corresponding classification loss for Generator is taken away from CTAB-GAN.

w/o information loss. In this experiment, we remove information loss from CTAB-GAN.

w/o VGM and mode vector. In this case, we substitute VGM for continuous variables with min-max normalization and use simple one-hot encoding for categorical variables. Here the conditional vector is the same as for CTGAN.

The results are compared with the baseline implementing all strategies. All experiments are repeated 3 times, and results are evaluated on the same 5 machine learning algorithms introduced in Sec. 4.2.1. The test datasets and evaluation flow are the same as shown in Sec. 4.1 and Sec. 4.2. Tab. 5 shows the results. Each part of CTAB-GAN has different impacts on different datasets. For instance, **w/o classifier** has a negative impact for all datasets except Credit. Since Credit has only 30 continuous variables and one target variable, the semantic check can not be very effective. **w/o information loss** has a positive impact for Loan, but results degenerate for all other datasets. It can even make the model unusable, e.g. for Intrusion. **w/o VGM and mode vector** performs bad for Covertype, but has little impact for Intrusion. Credit w/o VGM and mode vector performs better than original CTAB-GAN. This is because out of 30 continuous variables, 28 are nearly single mode Gaussian distributed. The initialized high number of modes, i.e. 10, for each continuous variable (same setting as in CTGAN) degrades the estimation quality. In general, if we average the column values, all the ablation tests have a negative impact for the performance which justifies our design choices for CTAB-GAN.

Table 5: F1-score difference to CTAB-GAN. CTAB-GAN column reports the absolute averaged F1-score as baseline.

Dataset	w/o Classifier	w/o Info. Loss	w/o VGM and Mode vector	CTAB-GAN
Adult	-0.01	-0.037	-0.05	0.704
Covertype	-0.018	-0.184	-0.118	0.532
Credit	+0.011	-0.177	+0.06	0.71
Intrusion	-0.031	-0.437	+0.003	0.842
Loan	-0.044	+0.028	+0.013	0.803

4.5 Further discussion

After reviewing all the metrics, let us recall the three motivation cases from Sec. 1.1.

Mixed data type variables. Fig. 8a compares the real and CTAB-GAN generated data for variable *Mortgage* in the Loan dataset. CTAB-GAN encodes this variable as mixed type. We can see that CTAB-GAN generates clear 0 values. One drawback which can be observed is that CTAB-GAN amplifies the dominance of the 0 in this variable. Even with our log-frequency-based sampling of Gaussian mixture modes and categorical classes, CTAB-GAN generates more 0 values than in the original distribution. That means there is still room for improvement for extremely imbalanced cases.

Long tail distributions. Fig. 8b compares the cumulative frequency graph for the *Amount* variable in Credit. This variable is a typical long tail distribution. One can see that CTAB-GAN perfectly recovers the real distribution. Due to log-transform data pre-processing, CTAB-GAN learns this structure significantly better than the state-of-the-art methods shown in Fig. 1b.

Skewed multi-mode continuous variables. Fig. 8c compares the frequency distribution for the continuous variable *Hours-per-week* from Adult. Except the dominant peak at 40, there are many side peaks. Fig. 1c, shows that TableGAN, CWGAN and MedGAN struggle since they can learn only a simple Gaussian distribution due to the lack of any special treatment for continuous variables. CTGAN, which also use VGM, can detect other modes. Still, CTGAN is not as good as CTAB-GAN. The reason is that CTGAN lacks the mode of continuous variables in the conditional vector. By incorporating the mode of continuous variables into conditional vector, we can apply the training-by-sample and logarithm frequency also to modes. This gives the mode with less weight more chance to appear in the training and avoids the mode collapse.

5 CONCLUSION

Motivated by the importance of data sharing and fulfillment of governmental regulations, we propose CTAB-GAN – a conditional GAN based tabular data generator. CTAB-GAN advances beyond the prior state-of-the-art methods by modeling mixed variables and provides strong generation capability for imbalanced categorical variables, and continuous variables with complex distributions. To such ends, the core features of CTAB-GAN include (i) introduction of the classifier into conditional GAN, (ii) effective data encoding for mixed variable, and (iii) a novel construction of conditional vectors. We exhaustively evaluate CTAB-GAN against four tabular data generators on a wide range of metrics, namely resulting ML utilities,

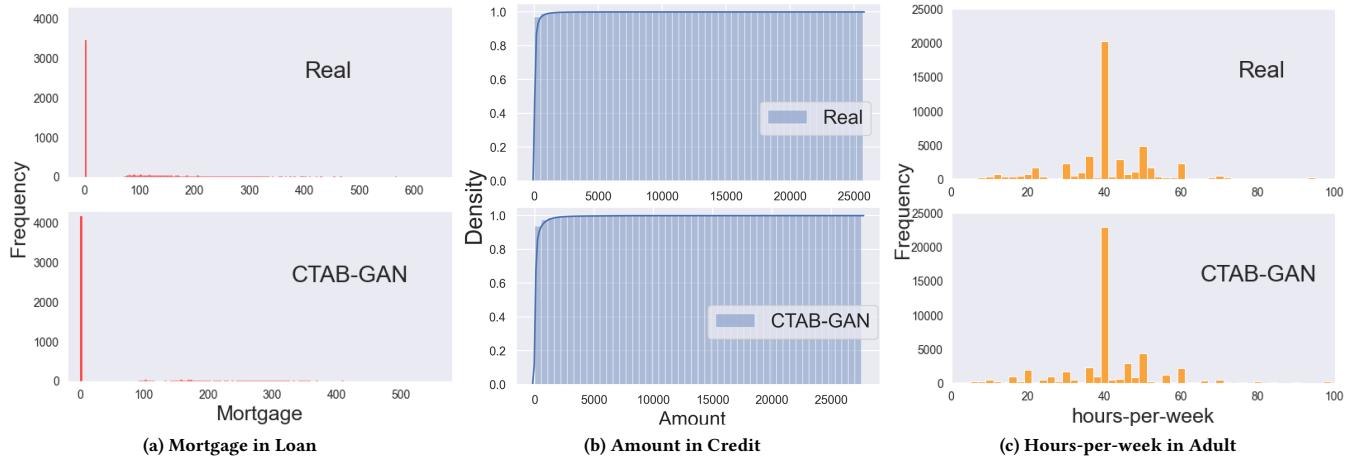


Figure 8: Challenges of modeling industrial dataset using existing GAN-based table generator: (a) mixed type, (b) long tail distribution, and (c) skewed data

statistical similarity and privacy preservation. The results show that the synthetic data of CTAB-GAN results into high utilities, high similarity and reasonable privacy guarantee, compared to existing state-of-the-art techniques. The improvement on complex datasets is up to 17% in accuracy comparing to all state-of-the-art algorithms. The remarkable results of CTAB-GAN demonstrate its potential for a wide range of applications that greatly benefit from data sharing, such as banking, insurance, manufacturing, and telecommunications.

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A USER MANUAL

A.1 Introduction

The software demo developed by us comprises of a synthetic tabular data generation pipeline. It was implemented using python 3.7.* along with the flask library to work as a web application on a local server. The application functionality and usage can be found listed under the Functionality & Usage sections respectively. In addition, a video of the demo can be seen [here](#).

A.2 Functionality

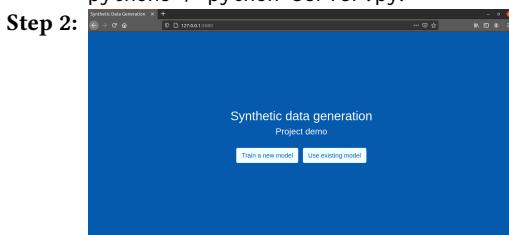
Our demo comprises of the following salient features:

- (1) **Synthetic Data Generator:** Our software is a cross-platform application that sits on top of a python interpreter. Moreover, it is relatively lightweight and can be set-up easily using pip. Our application is also robust against missing values and supports date-type formats. We believe these factors increases its usability in real-world scenarios.
- (2) **Synthetic Data Evaluator:** In addition to our generator, we also provide a detailed evaluation of the synthetic data. The report provides end users with visual plots comparing the real and synthetic distributions of individual columns as shown in sub-figures A.1a & A.1b of Fig. A.1. In addition, the synthetic data's utility for ML applications along with its privacy preservability metrics are reported as can be seen in sub-figures A.2a & A.2b of Fig. A.2. Note that the table-evaluator² library aided us in generating this evaluating report.

A.3 Usage

The following step-by-step instructions are provided to allow end-users to use our product in a hassle-free manner.

Step 1: Open the terminal and navigate to the root directory of the software package to run the following command
`python3 / python server.py`

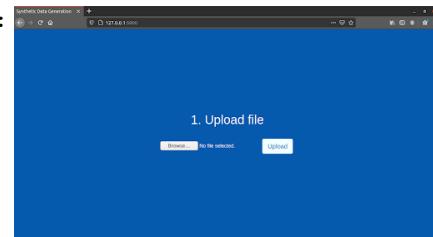


Open the browser, the application should now be available at the following address:

<http://127.0.0.1:5000/>.

Step 3: If this is the first time running the web application, it is advised to click on the “Train a new model” button to begin training the model with a dataset. Otherwise, click on the “Use existing mode” button to use an existing trained model. If you clicked on the “Use existing mode” button, please go to **step 8**. If not, please continue with the next step.

Step 4:



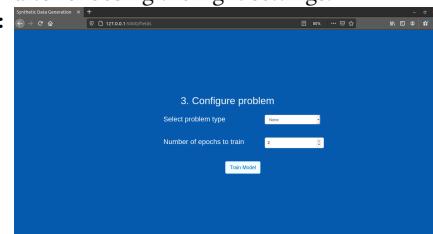
Click on the “Browse” button to select the dataset for which the model needs to train. Afterwards click on the “Upload” button.

Step 5:



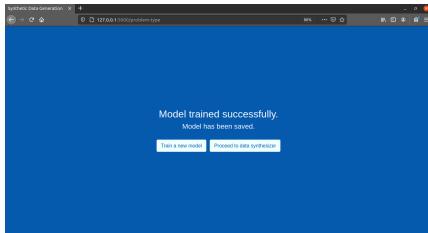
The software will auto-detect the column types, and will give the option to adjust a column’s data type and inclusion in the training. Note that the red highlighted column shows the current columns in the uploaded csv file. The yellow highlighted column gives the option to include or exclude a particular column in the training process by clicking on the switch button. The highlighted green column is the auto detected data type. It also has the option to be adjusted as needed. Simply click on it and select the desired data type from the drop down menu. Click on the “Submit” button after choosing the right settings.

Step 6:

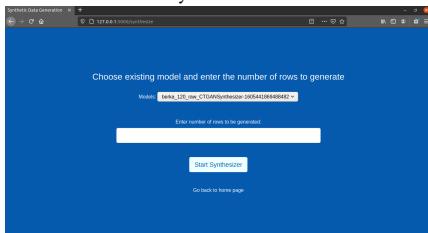


In the following page, specify the problem type for the given dataset. The software currently provides the following problem types: None, Binary Classification and Multi-class Classification. If unsure, leave it as None. Then enter the number of epochs needed to train the model. Click on “Train Model” to start the training.

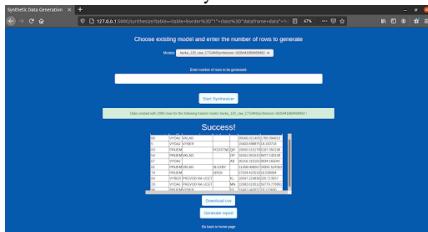
²<https://github.com/Baukebrenninkmeijer/Table-Evaluator>

Step 7:

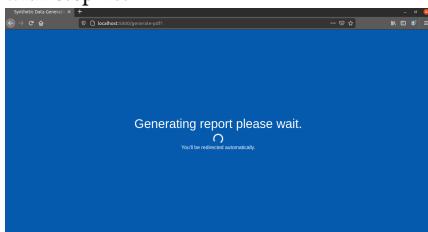
Once the model has finished training, the option to train a new model or proceed to the synthesizer is presented. To generate synthetic data, click on “Proceed to data synthesizer”.

Step 8:

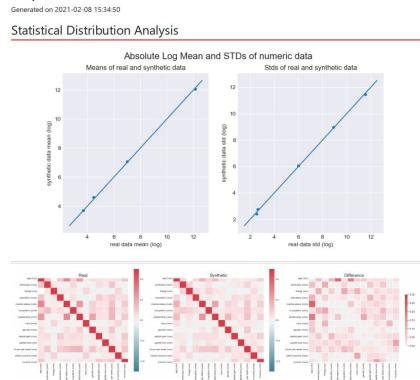
The trained models can be found in the dropdown menu of the Models field, as seen in the figure above. Click on it, and select the trained model. After this, type the amount of rows to be generated in the second field, and click on “Start Synthesizer” to start the process.

Step 9:

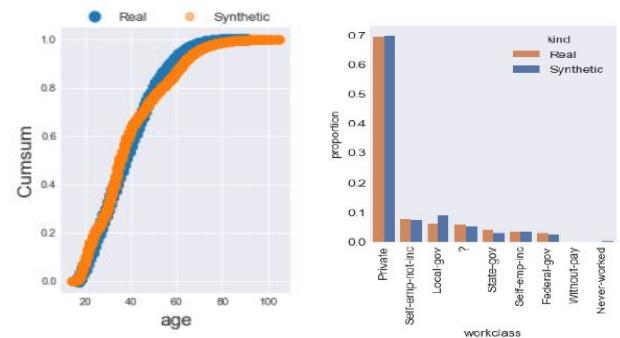
Once the data is generated, the following page shows a snippet of the synthetic data. The generated data can be saved locally by clicking on “Download csv”. This page also gives you the option to generate a report for the given data. In order to generate the report in PDF format, simply click on “Generate report” and continue with step 10.

Step 10:

The following page is presented while the report is being generated. It will automatically redirect to the PDF once it is completed.

Step 11: Report for Adult-CTABGAN

Finally, once the PDF has been generated, it can be saved locally by clicking on “Save as” or “Print” in the browser.



(a) Cumulative distribution comparison of Age in Adult
(b) Frequency comparison of categories within Workclass in Adult

Figure A.1: Visual plots comparing the generated vs real data distribution.

Utility

Index	Classifier F1-scores and their Jaccard similarities:	f_1_{real}	$f_1_{synthetic}$	jaccard_similarity
LogisticRegression_real	0.7955	0.7783	0.8574	
LogisticRegression_synthetic	0.7924	0.8001	0.8168	
RandomForestClassifier_real	0.8243	0.8226	0.8594	
RandomForestClassifier_synthetic	0.8288	0.8327	0.7763	
DecisionTreeClassifier_real	0.8186	0.7675	0.6244	
DecisionTreeClassifier_synthetic	0.7777	0.7926	0.6189	
MPLClassifier_real	0.8286	0.7957	0.7688	
MPLClassifier_synthetic	0.8134	0.8276	0.7971	

(a) ML Utility

Privacy

Result	
Column Correlation Distance RMSE	0.0541
Column Correlation distance MAE	0.0338
Duplicate rows between sets (real/synthetic)	0.0000
5th percentile of DCR between real and synthetic datasets	0.4712
5th percentile of DCR for records within real dataset	0.3730
5th percentile of DCR for records within synthetic dataset	0.4160
5th percentile of NNDR between real and synthetic datasets	0.5052
5th percentile of NNDR of records within real dataset	0.4322
5th percentile of NNDR of records within synthetic dataset	0.4437

(b) Privacy Preservability

Figure A.2: ML utility and privacy preservability of the generated data.