KNOWLEDGE-ENHANCED TABULAR DATA GENERATION

Anonymous authors
Paper under double-blind review

ABSTRACT

Tabular data generation methods aim to synthesize artificial samples by learning the distribution of training data. However, most existing tabular data generation methods are purely data-driven. They perform poorly when the training samples are insufficient or when there exists a distribution shift between training and true data. In many real-world scenarios, data owners are often able to provide additional knowledge beyond the raw data, such as domain-specific description or dependencies among features. Motivated by this, we categorize the types of knowledge that can effectively support tabular data generation, and incorporate selected knowledge as auxiliary information to guide the generation process. To this end, we propose KTGen, a **K**nowledge-enhanced **T**abular data **Gen**eration framework. KTGen leverages auxiliary information by training a correction network in the latent space produced by a VAE, aligning the generated data with the auxiliary information. Our experiments demonstrate that, when training on limited, biased data, incorporating auxiliary information makes the distribution of synthetic samples closer to the true data distribution, and also improves the performance of downstream models trained on the synthetic samples.

1 INTRODUCTION

Tabular data is one of the most widely used data modalities and frequently appears in domains such as healthcare (Yang et al., 2021; Gong et al., 2020), finance (Zheng et al., 2020), industry (Du et al., 2021), and recommendation systems (Zhang et al., 2023; Wu et al., 2021). However, real-world tabular data often contains sensitive information and is costly to acquire (Mehrabi et al., 2021; Dastin, 2022), which limits its quality, and availability in machine learning task. Data generation emerges as a standard remedy to address this data scarcity. Researchers propose various embedding strategies (Xu et al., 2019; Kotelnikov et al., 2023) to handle the highly structured nature of tabular data and its column-exchangeability property. By leveraging these approaches alongside well-established advances in image generation (Shorten & Khoshgoftaar, 2019; Goodfellow et al., 2014; Kingma & Welling, 2013; Sohl-Dickstein et al., 2015), significant progress is made in tabular data generation. Synthetic tabular data has already been applied to a wide range of downstream tasks, including disease prediction (Cui & Mitra, 2024; Alcazer et al., 2024), credit risk assessment (Clements et al., 2020; Chang et al., 2024), or personalized recommendation (Huang et al., 2023).

Most existing tabular data generation methods are purely data-driven and rely on sufficient data to train generative models. Unlike image generation, where large-scale datasets are relatively easy to obtain, tabular data is often limited in quantity (Cao et al., 2024; Du & Li, 2024). In cross-domain collaborations, due to privacy protection policies, data owners may be unable to provide researchers with large-scale datasets and can only share a small number of samples as examples. Current data-driven generation methods struggle under such circumstances. Prior studies (Margeloiu et al., 2024) shows that the quality of the synthetic data degrades significantly as the number of training samples decreases. On the one hand, a smaller sample size increases uncertainty, making it more difficult to infer the underlying data distribution. On the other hand, distribution shifts often occur between the limited training data and the abundant test data, so even if a generative method can accurately learn the distribution of the training data, it may still fail to generalize to the test data. On the other hand, distribution shifts (Rubachev et al., 2025) often exist between the limited training data and the abundant test data. In such cases, even if the generative model successfully learns the distribution of the training set, this knowledge may not transfer to unseen data drawn from a shifted distribution.

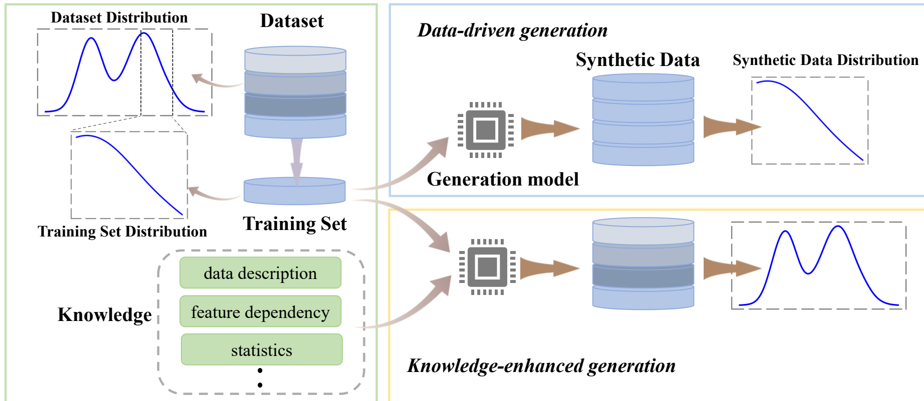


Figure 1: Illustration of how incorporating external knowledge can improve data generation quality. When the training data distribution differs from the real data, knowledge enables the generative model to capture patterns beyond the training set.

In many practical scenarios, beyond the limited training samples, data owners or domain experts can often provide a wealth of additional knowledge. Such knowledge can take various forms: at the data level, it may include domain-specific background information about the dataset (Lin et al., 2025); at the feature level, it may involve the semantic meaning of features, dependencies among features, and the distribution of feature values; and at the sample level, it may reflect the identification and annotation of anomalous samples. These forms of knowledge capture information that may not be revealed by the available training samples. It is necessary to explore how such knowledge can be incorporated into the tabular data generation process as guidance.

These types of knowledge can generally be categorized into two forms. The first type is unstructured textual information, which can be any description related to the data, often provided by humans. The second type is statistical knowledge with explicit semantic meaning, usually derived from large-scale data analysis. Such information summarizes key characteristics of the data distribution and can provide crucial guidance without directly disclosing raw data. In this work, we primarily focus on the second type, which allows us to encode statistical properties into the generative model.

This paper proposes KTGen, a **K**nowledge-enhanced **T**abular data **Gen**eration method. KTGen consists of a variational autoencoders (VAE) that maps samples between the data space and the latent space, and a score-based diffusion model (Song et al., 2021) that performs denoising sampling from the noise space to the latent space. During training, KTGen additionally trains a correction network in the latent space to align the synthetic data with the auxiliary information. In our experiments, we construct biased training sets from eight datasets and compare KTGen with eleven existing tabular data generation methods. When trained on biased training sets, KTGen generates higher-quality samples than other methods. It also achieves strong performance on randomly sampled training sets. Furthermore, we conduct additional visualization studies to illustrate how KTGen improves the quality of synthetic data. Our contributions are as follows:

- We investigate previously overlooked knowledge in tabular data generation and incorporate it into the generation process to improve the quality of synthetic data.
- We propose KTGen, which employs a VAE and a diffusion model for generation. KTGen additionally trains a correction network in latent space to align the synthetic data with knowledge.
- We conduct extensive experiments on eight datasets, comparing KTGen with various tabular data generation methods, and demonstrate the effectiveness of our approach.

2 RELATED WORKS

2.1 CLASSICAL TABULAR DATA AUGMENTATION

Classical data augmentation methods for tabular data aim to improve model performance when data is limited. SMOTE (Chawla et al., 2002) generates synthetic minority-class samples by interpolating between existing instances, effectively alleviating class imbalance. ADASYN (He et al.,

2008) extends SMOTE by adaptively generating more samples for harder-to-learn minority examples. Mixup (Zhang et al., 2018) produces new samples by taking convex combinations of feature vectors and their labels, smoothing decision boundaries and improving robustness. Other traditional approaches include random oversampling, undersampling, feature perturbation, and bootstrapping (Ling & Li, 1998; Blagus & Lusa, 2015), which create additional data by resampling or slightly modifying existing observations. These classical techniques are simple yet effective for enhancing sample diversity and mitigating overfitting in downstream models.

2.2 Generative Methods for Tabular Data

Image-Inspired Tabular Generative Models. Many modern tabular data generation models are derived from classical generative models originally developed for images. For instance, Generative Adversarial Networks (GAN) based approaches such as ADSGAN (Yoon et al., 2020) and CT-GAN (Xu et al., 2019) leverage adversarial training to learn the joint distribution of tabular features. Similarly, VAE based methods like TVAE (Xu et al., 2019) employs a latent-variable framework to model feature dependencies and generate realistic samples. More recently, diffusion-based models such as TabDDPM (Kotelnikov et al., 2023), TabDiff (Shi et al., 2024), and TabSyn (Zhang et al., 2024) have been applied to tabular data, demonstrating strong performance by learning the denoising process in a latent or data space.

Table-Specific Generative Methods. In addition to these approaches, other methodologies have also been explored for tabular data generation. Bayesian methods (Ankan & Textor, 2024) represent variables and their conditional dependencies through a directed acyclic graph and sample new data points accordingly. Normalizing Flows (Durkan et al., 2019) are generative models that construct tractable distributions, enabling both efficient sampling and exact density evaluation. Random Forest-based methods, such as Adversarial Random Forests (Watson et al., 2023) for density estimation and generative modeling, provide a non-parametric alternative that can capture complex feature interactions. With the rapid development of LLM, several recent (Kim et al., 2024; Borisov et al., 2023) works explore transforming tabular data into textual representations and leveraging LLM for data generation. In addition, with the introduction of the tabular foundation model TabPFN (Hollmann et al., 2025), which demonstrates strong performance on tabular prediction, subsequent works such as TabPFGen (Ma et al., 2023) and TabEBM (Margeloiu et al., 2024) combined TabPFN with energy-based models (Grathwohl et al., 2020). These approaches leverage the in-context learning capabilities of TabPFN while incorporating the flexibility of energy-based modeling, resulting in significantly improved synthetic data quality and downstream task performance.

3 Preliminaries

Before presenting our proposed framework, we first introduce several preparatory steps. Section 3.1 defines the mathematical notations commonly used in tabular data task. Section 3.2 presents our categorization of knowledge. It further specifies which parts of this knowledge are intended to be incorporated into the generation process. These steps lay the foundation for the design of our model.

3.1 Notation

Regard a tabular dataset with m rows and n columns as an matrix $\boldsymbol{X}\in\mathbb{R}^{m\times n}$. Dataset contains a total of m samples. The i-th sample $\boldsymbol{x}_i\in\mathbb{R}^n$ can be represented as an n-dimensional vector:

$$\boldsymbol{x}_i = (x_1, x_2, \dots x_n), \quad i = 1, 2, 3, \dots, m. \tag{1}$$

Similarly, the j-th column $\boldsymbol{c}_j\in\mathbb{R}^m$ records the j-th feature of the dataset. Among these n features, some are categorical while others are numerical. In this paper, when it is necessary to distinguish between categorical and numerical features, we denote them as x_j^{cat} or x_j^{num}, respectively; if no distinction is needed, the superscript is omitted.

A common task for tabular data is prediction, where one feature is treated as the target, and all other features are used to predict it. If the target feature is categorical, the task is a classification problem; otherwise, it is a regression problem. We focus on the task of tabular data generation, with the objective of training a generative model $\mathcal{G}_m$ or employing a generative algorithm $\mathcal{G}_a$. When given a dataset $\boldsymbol{X}$, $\mathcal{G}_m$ or $\mathcal{G}_a$ can generate a new dataset based on the dataset:

$$\hat{\boldsymbol{X}} = \mathcal{G}\left(\boldsymbol{X}\right). \tag{2}$$

The synthetic data $\hat{\boldsymbol{X}}$ are expected to approximate the distribution of the original dataset $\boldsymbol{X}$, thereby serving as a augmentation or replacement for $\boldsymbol{X}$ in downstream tasks. Our objective is to enhance the data generation process by leveraging not only the training data $\boldsymbol{X}$ but also related knowledge $\mathcal{K}$, thereby guiding the generative model beyond purely data-driven learning.

3.2 Knowledge Categorization

For a tabular data generation task, any information related to the dataset but not explicitly presented in the form of training data can be regarded as knowledge. Properly leveraging such knowledge can improve the quality of the generated data. From the perspective of representation, this knowledge can generally be categorized into two forms.

Semantic-Level Knowledge. The first type of knowledge lies at the semantic level, which typically takes the form of descriptive text. Examples include descriptions about the domain of the dataset, the intended meaning of individual features, or instructions on how certain variables are measured. When introducing this type of knowledge into a tabular data task, such textual descriptions can be embedded or tokenized and appended to the feature representation, enabling models to capture semantic cues that are not explicitly present in numerical values (Jiang et al., 2024; Berkovitch et al., 2025; Huynh et al., 2023). This approach allows language models to provide guidance to the generator.

Data-Level Knowledge. The second category is data-level knowledge. In many real-world scenarios, although a sufficient amount of real data exists, privacy concerns or regulatory restrictions make direct data sharing infeasible. In this case, data owners may provide partial statistical characteristics of the original data instead. These pieces of knowledge can come from multiple aspects: they may include sample-level knowledge, insights obtained from clustering analysis; information about inter-feature dependencies; or intra-feature statistics such as the empirical distribution of a feature. By integrating such diverse knowledge, generative models can be better guided to produce data that faithfully reflects both the structure and characteristics of the underlying dataset.

Some studies (Lin et al., 2025) incorporate feature names and meta descriptions of datasets into the generation process, leading to improved data quality. We primarily focus on the second type of knowledge. In our envisioned scenario, the data owner provides a small set of samples. In addition, certain statistical information derived from a large dataset can be shared without violating privacy-preserving principles. For these statistical pieces of information, we focus primarily on inter-feature dependencies and the estimated distributions of individual features. By integrating such diverse knowledge, generative models can be better guided to produce data that faithfully reflects both the structure and characteristics of the underlying dataset.

4 KTGen

In this section, we present our proposed framework KTGen in detail, with its overall workflow illustrated in Figure 2. The essence of KTGen lies in training a correction network in the latent space of a VAE, such that the generated data, after passing through the correction network, are aligned with the incorporated knowledge. We provide a detailed description of the different components of KTGen, along with their respective training procedures. Each part of the framework is introduced in turn, illustrating how they work together to enable effective generative modeling of tabular data.

4.1 Tabular Data Generator

We follow the generation framework of TABSYN (Zhang et al., 2024), which consists of a VAE that maps tabular data into a latent space, and a score-based diffusion model that samples from the noise space and denoises into the latent space. The detailed generation framework and training objective are provided in Appendix B.

VAE for Tabular Data. Each feature of the input sample is embedded into a d-dimensional feature embedding, resulting in a sequence of embeddings $\boldsymbol{E} \in \mathbb{R}^{n\times d}$ of length m for the entire sample.

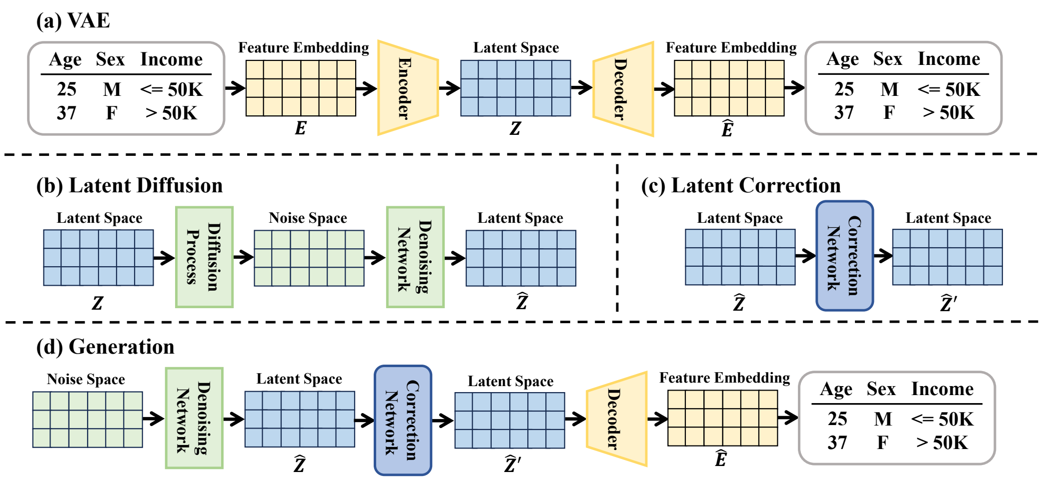


Figure 2: Overview of KTGen: (a) the VAE component of KTGen, which maps a sample into a latent space; (b) the diffusion component, which learns the denoising process from noise space to latent space; (c) the correction network, which refines the sampled latent representations using auxiliary information; (d) the complete data generation process of KTGen.

A Transformer (Vaswani et al., 2017) is used as the encoder of the VAE to process the embedding sequence and output the mean and log-variance of the latent distribution. The reparameterization trick is then applied to sample a latent embedding $\boldsymbol{Z}$ from this distribution. The decoder maps $\boldsymbol{Z}$ back to a feature embedding sequence, which is subsequently converted to actual feature values using a trained reconstructor.

Diffusion in Latent Space. On top of the latent space, we employ a score-based diffusion model (Song et al., 2021; Karras et al., 2022) to enable sampling from noise into the latent space. After training the VAE, we obtain latent embeddings $\boldsymbol{Z}$ from the encoder and model their distribution using diffusion. The forward process gradually perturbs $\boldsymbol{Z}$ by adding Gaussian noise with a time-dependent variance $\sigma(t)$. The diffusion model is trained to predict the injected noise given the noisy latent variable and the time step, which allows us to approximate the score function. With the estimated score, the reverse denoising process can be applied to iteratively transform noise samples back into latent embeddings. Once trained, this procedure enables efficient generation of synthetic latent representations $\hat{\boldsymbol{Z}}$ that can be decoded into tabular data.

4.2 Knowledge Correction

During training, we incorporate two types of statistics as auxiliary information: (i) inter-feature dependencies, captured by a correlation matrix $\boldsymbol{P}$, and (ii) feature-wise statistics, represented by empirical category frequencies for categorical features and Gaussian Mixture Model (Dempster et al., 1977) parameters for numerical features.

KTGen aim to perform a knowledge correction on the latent embeddings obtained from the diffusion model and make the reconstructed data better align with the provided auxiliary knowledge. We train a correction network g_ϕ in the latent space. Its input is the synthetic latent embedding $\hat{\boldsymbol{Z}}$ produced by the diffusion model. After passing through g_ϕ, we obtain the corrected latent embedding $\hat{\boldsymbol{Z}}'$, which is then decoded by the VAE decoder to generate a synthetic sample $\hat{\boldsymbol{x}}$:

$$\hat{\boldsymbol{x}} = \text{Reconstruction}\left(\text{Decoder}\left(g_\phi\left(\hat{\boldsymbol{Z}}\right)\right)\right) \tag{3}$$

Inter-Feature Dependencies. Since the number of generated samples is virtually unlimited, we can use a large set of synthetic samples $\hat{\boldsymbol{X}} \in \mathbb{R}^{\hat{m} \times n}$ to match the auxiliary information of the real data. For inter-feature dependencies, we compute the correlation matrix $\hat{\boldsymbol{P}}$ from the synthetic samples and enforce it to match the true correlation matrix $\boldsymbol{P}$:

$$\mathcal{L}_{\text{rela}} = \text{MSE}\left(\text{Triu}(\boldsymbol{P}), \text{Triu}(\hat{\boldsymbol{P}})\right), \tag{4}$$

Table 1: The downstream models trained with synthetic data are evaluated on the test set, and the rankings are averaged across all datasets. For classification tasks, AUROC is used as the metric, while for regression tasks, RMSE is employed. The best-performing generation method in each case is highlighted in **bold**. Here, "Basic" refers to training only on the sample set without using any synthetic samples. "KTGen_b" denotes the base version, which does not include the correction network or any auxiliary information, whereas "KTGen_c" represents the complete method.

	high-bias				medium-bias				unbias			
	XGB	RF	PFN	LR	XGB	RF	PFN	LR	XGB	RF	PFN	LR
Basic	6.6562	6.8281	5.1719	7.1406	7.5938	7.4375	5.2500	7.0000	8.8438	8.0312	6.3750	7.3125
SMOTE	7.9531	7.6406	8.2656	8.0156	6.4844	5.8750	6.9062	7.9688	6.6406	7.2500	5.1875	7.5625
Mixup	8.1094	8.0000	9.0312	9.1562	5.5781	6.3125	7.3906	8.1875	7.0000	7.0000	6.5000	8.3125
TVAE	8.8750	8.8438	8.2812	8.8125	8.3906	8.2188	8.3750	8.0938	7.9062	7.6562	8.1250	7.4375
CTGAN	9.1094	8.9688	8.9062	8.8750	9.5156	9.8750	9.8906	9.5938	10.5625	11.3438	11.1875	10.3750
TabDDPM	9.8125	9.9375	9.8125	9.0938	9.1406	9.1250	9.7812	8.7812	10.4375	10.1875	10.9062	9.9688
TABSYN	7.5938	7.2812	7.6250	8.0312	8.4844	8.5938	7.4688	8.1875	7.6250	8.0000	9.2188	8.6562
ARF	9.3281	8.9062	9.3438	7.9688	10.0000	10.3125	8.9062	9.3125	9.1562	9.0312	9.6250	8.2188
BN	7.7969	8.4375	9.8438	8.8750	7.4844	8.3125	8.6094	8.1250	9.6875	9.8125	9.7812	9.6250
TabPFGen	7.1562	6.8750	5.2188	6.1250	8.4062	8.2188	8.0938	7.3438	5.9844	4.9375	5.4375	5.3750
TabEBM	6.6250	7.3125	6.7188	6.3125	5.3906	5.1250	6.6562	6.1875	6.1250	6.9688	6.8438	6.1250
TabPFN	5.6094	6.0625	6.4688	5.7500	6.1875	5.9375	6.0938	5.3750	4.3750	4.0938	4.5312	4.8438
KTGen_b	7.2344	7.3125	6.5625	7.9375	9.0469	8.5625	7.8594	7.7812	7.1875	7.6875	7.4375	8.6562
KTGen_c	**3.1406**	**2.5938**	**3.7500**	**2.9062**	**3.2969**	**3.0938**	**3.7188**	**3.0625**	**3.4688**	**3.0000**	**3.8438**	**2.5312**

Triu represents the vector obtained by straightening the upper triangular matrix.

Feature-Wise Statistics. To ensure that the generated data matches the feature-wise statistics of the real dataset, we define a distribution alignment loss over all features. We denote the j-th feature of the i-th sample in $\hat{\boldsymbol{X}}$ as $\hat{x}_{i,j}$. For a categorical feature with k possible values (categorical features are represented using label encoding with values ranging from 0 to $k-1$), the probabilities of each value are defined as $p_0, p_1, \ldots, p_{k-1}$. The log-likelihood is computed via a lookup table:

$$\log p\left(\hat{x}_{i,j}^{\text{cat}}\right) = \log p_{\hat{x}_{i,j}^{\text{cat}}}. \tag{5}$$

A small smoothing term is applied for unseen categories to avoid numerical issues. For a numerical feature, let the Gaussian mixture have k components with weights α, means μ, and variances σ^2. The log-likelihood of a sample value $\hat{x}_{i,j}$ under the mixture is:

$$\log p\left(\hat{x}_{i,j}^{\text{num}}\right) = \log\left(\sum_{l=1}^{k} \alpha_l \mathcal{N}\left(\hat{x}_{i,j}^{\text{num}} | \mu_l, \sigma_l^2\right)\right). \tag{6}$$

Finally, the distribution alignment loss over all features and samples is defined as the negative average log-likelihood:

$$\mathcal{L}_{\text{dist}} = -\frac{1}{\hat{m}} \sum_{i=1}^{\hat{m}} \frac{1}{n} \sum_{j=1}^{n} \log p\left(\hat{x}_{i,j}\right). \tag{7}$$

Training Loss. We train the correction network jointly using the loss functions defined above:

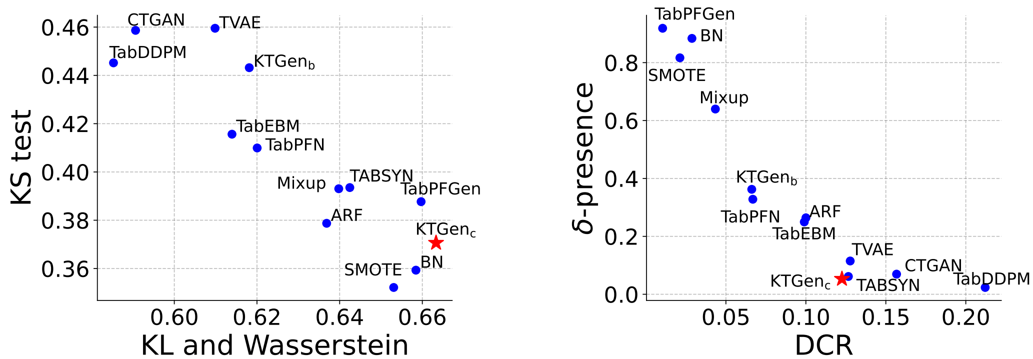
$$\mathcal{L}_{\text{corr}} = \lambda_1 \mathcal{L}_{\text{rela}} + \lambda_2 \mathcal{L}_{\text{dist}} + \lambda_3 \text{MSE}\left(\hat{\boldsymbol{Z}}, \hat{\boldsymbol{Z}}'\right). \tag{8}$$

The third term encourages the correction network not to make excessive deviations to the latent representations, thereby preventing the correction process from disrupting the primary structure generated by the diffusion model.

5 Experiments

5.1 Experimental Setups

Datasets. We obtained eight datasets from UCI (Asuncion et al., 2007) and scikit-learn (Pedregosa et al., 2011), including six binary classification tasks and two regression tasks. The dataset sizes



(a) Statistical Fidelity Metric.

(b) Privacy Preservation Metric.

Figure 3: Figure (a) shows the column-wise distribution matching and KS test statistic of data generated by various generative models, while Figure (b) shows the DCR and δ-presence result. The lower-right corner indicates the best result.

range from 768 to 48,842 samples, with the number of features varying from 9 to 24. For a more comprehensive description of the datasets, please refer to the Appendix C.

Preprocessing. For all categorical features, ordinal encoding is applied, preserving the order if it exists. All numerical features are standardized using z-score normalization. The data are first split into a candidate set and a test set in an 8:2 ratio. The candidate set is used to extract auxiliary information. To capture inter-feature dependencies, we compute a correlation matrix $\boldsymbol{P}$ based on the candidate set. For feature-wise statistics, we treat categorical and numerical features separately. For a categorical feature, we record the empirical frequency of all its possible categories. For a numerical feature, we fit a Gaussian Mixture Model to approximate its distribution and store the parameters of each mixture component, including its mean, variance, and weight.

A biased training set is then obtained through sampling from the candidate set. We perform multiple sampling runs and compute the distribution differences between each sampled subset and the original dataset. The 4 subsets with the largest distribution differences are designated as the high-bias group, 4 subsets with moderate distribution differences as the medium-bias group, and 4 randomly sampled subsets as the unbias group. The number of training samples is set to 20, 50, and 100, while the experimental results reported in the main text are based on 20 training samples. The detailed sampling strategy is provided in the Appendix D.

Baselines Generators. We compare KTGen with 11 existing tabular data generation methods: two classical augmentation methods (i) SMOTE (Chawla et al., 2002) and (ii) Mixup (Zhang et al., 2018); (iii) a VAE based method TVAE (Xu et al., 2019); (iv) a GAN based method CTGAN (Xu et al., 2019); two diffusion based methods (v) TabDDPM (Kotelnikov et al., 2023) and (vi) TabSYN (Zhang et al., 2024); (vii) a tree-based method ARF (Watson et al., 2023); (viii) Bayesian network based method (Ankan & Textor, 2024); two energy-based methods (ix) TabPFGen (Ma et al., 2023); and (x) TabEBM (Margeloiu et al., 2024); and (xi) PFN-based (Hollmann et al., 2025) density estimation methods. For some of the methods that require hyperparameter tuning, we performed 20 optimization trials. Implementation details can be found in the Appendix E.

Downstream Predictors. We select four representative downstream predictors: XGBoost (Chen & Guestrin, 2016), Random Forest (Breiman, 2001), TabPFN (Hollmann et al., 2025), and Linear Regression or Logistic Regression (Cox, 1958). For XGBoost and Random Forest, we perform hyperparameter tuning using the training data, while synthetic data is used to train the models. Implementation details can be found in the Appendix F.

5.2 Evaluation

Downstream Predictors Utility. For each sample set, we split it into tiny training and validation sets with a 7:3 ratio to tune the downstream model and determine its hyperparameters. First, the downstream model is trained on all samples of the sample sets using the optimized hyperparameters

Table 2: Performance of downstream models trained on synthetic data generated by models trained with different amounts of training set.

		high-bias				medium-bias				unbias			
		KTGen$_b$	KTGen$_r$	KTGen$_d$	KTGen$_c$	KTGen$_b$	KTGen$_r$	KTGen$_d$	KTGen$_c$	KTGen$_b$	KTGen$_r$	KTGen$_d$	KTGen$_c$
abalone (RMSE)	XGB	1.2624	1.0973	1.1565	**1.0677**	1.1000	1.3090	1.1273	**0.9667**	0.9096	**0.8622**	0.9265	0.8635
	RF	1.1845	**0.9929**	1.1284	1.0049	1.1763	**0.9669**	1.1926	0.9697	0.9162	**0.8405**	0.8647	0.8460
	PFN	1.2373	1.1166	1.2804	**1.0624**	1.2189	**1.0166**	1.1896	1.1711	0.9634	0.8518	0.8995	**0.8390**
	LR	3.2123	**0.9965**	1.0182	1.0855	**1.2826**	1.5049	1.5034	1.4591	0.9347	**0.7920**	0.8464	0.7972
adult (AUROC)	PFN	0.6641	**0.6717**	0.6380	0.6327	0.6140	0.6705	**0.7115**	0.6588	0.7789	0.7067	**0.7937**	0.7458
	RF	0.6747	**0.7025**	0.6783	0.6877	0.6183	0.6367	**0.7042**	0.6543	0.7812	0.7775	**0.7954**	0.7713
	XGB	0.7225	0.6881	0.7339	**0.7479**	0.6776	0.6691	0.7006	**0.7146**	0.8135	0.7830	0.8135	**0.8175**
	LR	0.6872	0.7044	0.6213	**0.7166**	0.6938	0.6469	**0.7128**	0.6727	0.7807	0.7662	**0.8208**	0.7586

and evaluated on the test set. Then, for each data generation method, 1,000 synthetic samples are generated, and the downstream model is trained on both the synthetic and real samples, followed by evaluation on the test set. The quality of the downstream models trained with different generated data is then ranked, with the ranking results reported in Table 1.

The experimental results reported in the main text are based on using 20 samples as the training data. In the most extreme scenarios (the distribution deviates significantly from the real data), it can be observed that KTGen2, which incorporates auxiliary knowledge, achieves a substantial improvement over KTGen1, which does not include knowledge in the correction network. Models trained with the synthetic samples from KTGen2 outperform those trained with synthetic samples from other generation methods. More detailed experimental results can be found in the Appendix G.

Statistical Fidelity and Privacy Preservation. Statistical fidelity and privacy preservation are two important metrics for evaluating synthetic data. For statistical fidelity, we estimate the similarity between the candidate set (i.e., not the sampled training set) and the generated samples using: (i) Column-wise distribution matching: Kullback–Leibler divergence (Csiszár, 1975) is computed for categories features, Wasserstein distance (Monge, 1781) for numerical features, and the results are inversely mapped to $[0, 1]$ range and then averaged; (ii) Kolmogorov–Smirnov test (Karson, 1968) statistic. For privacy protection, we assess the risk of data leakage using the following two metrics (computed with respect to the sampled training set): (i) Average Distance to Closest Record (Zhao et al., 2021): larger values indicate greater differences between generated and training samples; (2) δ-presence (Van Tilborg & Jajodia, 2011): smaller values indicate a lower probability of identifying training samples from the generated data.

Figure 3 illustrates the performance of KTGen under various metrics. Figures 3a shows the column distribution matching and the KS test results, respectively, where KTGen achieves the best performance as expected. Other methods are trained only on a small, biased subset of the data and thus struggle to capture the true distribution of the candidate dataset. In contrast, KTGen incorporates additional statistical information from the candidate dataset during training. Figures 3b reports the average DCR and δ-presence. Achieving a good trade-off between data fidelity and privacy protection remains challenging. While KTGen attains high quality in the generated data, it does not achieve the optimal privacy guarantees.

5.3 Ablation Studies

	λ_1	λ_2	λ_3
KTGen$_{\text{rela}}$	1	0	0.1
KTGen$_{\text{dist}}$	0	1	0.1
KTGen$_{\text{corr}}$	1	1	0.1

Table 3: Eq 8 hyperparameters.

As described in Section 3, we construct the loss to incorporate two types of auxiliary information: inter-feature correlations and column-wise distributions. To evaluate their effects, we conduct experiments by introducing these types of information separately into the generation process. Specifically, KTGen$_b$ uses no correction network, i.e., no auxiliary information is incorporated into the data generation process; KTGen$_r$ uses only the correlation-based loss $\mathcal{L}_{\text{rela}}$; auxiliary information is incorporated into the data generation process; KTGen$_d$ uses only the column-distribution-based loss $\mathcal{L}_{\text{dist}}$; and KTGen$_c$ uses both $\mathcal{L}_{\text{rela}}$ and $\mathcal{L}_{\text{dist}}$. Table 3 lists the detailed parameter settings, and Table 2 reports the experimental results on two datasets. It can be observed that in the vast majority of experiments, incorporating auxiliary knowledge improves the quality of the generated data. Notably, there are many cases where introducing a single type of knowledge yields better results than using both types simultaneously.

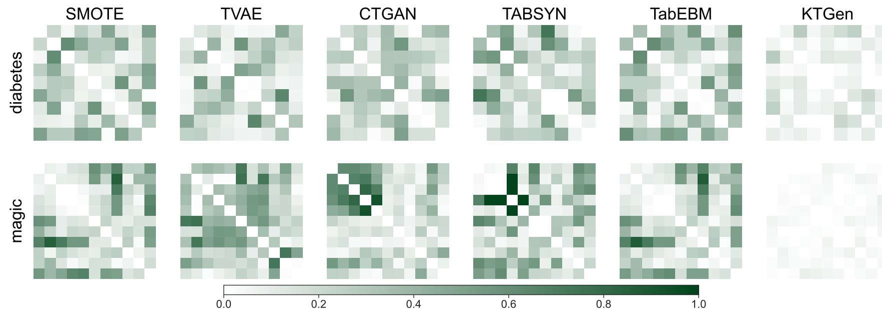


Figure 4: Visualizes the absolute differences between the correlation matrix computed from the synthetic samples and that obtained from the training set. Lighter colors indicate smaller differences, reflecting better learning of the dependencies between features.

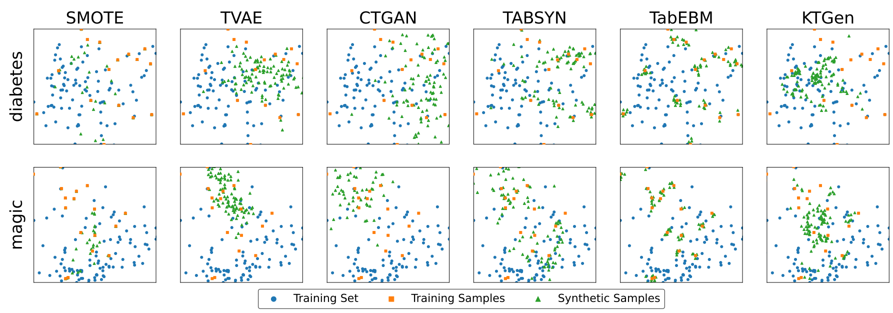


Figure 5: Demonstrates the PCA-based dimensionality reduction trained on the training set (blue), applied to both the actual training samples (orange) and the generated data (green).

5.4 Visualization

Figure 4 presents the absolute differences between the correlation matrices computed from the synthetic samples and those from the candidate set. It can be observed that KTGen achieves the most accurate estimation of the underlying correlations. Figure 5 illustrates the two-dimensional scatter plots obtained via PCA for the training set, the training samples (high-bias 20 samples), and the synthetic samples. It can be observed that, for typical generation methods, the scatter distribution of the training samples and synthetic samples are largely similar. In contrast, when using KTGen, the synthetic samples distribution shifts from the biased training samples toward the overall training set distribution. Figure 6 shows the performance improvement of generative models as the number of training samples increases. KTGen outperforms other methods in low-sample scenarios, though this advantage diminishes as the sample size increases.

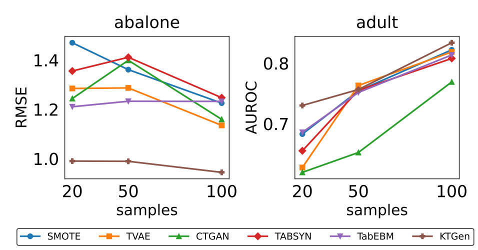


Figure 6: The downstream model performance trained on generated data.

6 Conclusion

In this work, we presents KTGen, a knowledge-enhanced tabular data generation method. Unlike conventional data-driven methods that rely solely on limited training samples, KTGen leverages auxiliary information to guide the generation process. We conducted extensive experiments on both biased and unbiased small-sample training sets, and our analysis shows that incorporating knowledge can significantly alleviate issues arising from insufficient training data or distribution shifts between training and real data. In the current work, the introduced knowledge is derived from large-scale statistical information, and a corresponding loss is designed to incorporate it into the training of the generative model. However, this represents only one form of knowledge. In future work, we aim to explore other types of knowledge that can guide the generation process and develop more elegant methods to leverage such information effectively.

Ethics Statement

This work adheres to the ICLR Code of Ethics. Our study is purely methodological and does not involve human subjects, personally identifiable information, or sensitive data. All datasets used are publicly available benchmark datasets, and their usage strictly follows the respective licenses. The proposed method does not raise foreseeable risks of harm, privacy infringement, or discrimination, and all experiments are conducted in compliance with accepted standards of research integrity. We believe our contributions align with the principles of responsible stewardship, fairness, and transparency, and we commit to releasing the source code and results upon acceptance to further support reproducibility and openness.

Reproducibility Statement

Our work is fully reproducible. In Appendix C, we provide detailed descriptions of each dataset and their sources. Appendix E presents the baselines used for comparison along with their implementations. The architecture of our model is also described in detail in Appendix B.

References

Vincent Alcazer, Grégoire Le Meur, Marie Roccon, Sabrina Barriere, Baptiste Le Calvez, Bouchra Badaoui, Agathe Spaeth, Olivier Kosmider, Nicolas Freynet, Marion Eveillard, et al. Evaluation of a machine-learning model based on laboratory parameters for the prediction of acute leukaemia subtypes: a multicentre model development and validation study in france. *The Lancet Digital Health*, 6(5):e323–e333, 2024.

Ankur Ankan and Johannes Textor. pgmpy: A python toolkit for bayesian networks. *Journal of Machine Learning Research*, 25(265):1–8, 2024. URL `http://jmlr.org/papers/v25/23-0487.html`.

Arthur Asuncion, David Newman, et al. Uci machine learning repository, 2007.

Yevgeni Berkovitch, Oren Glickman, Amit Somech, and Tomer Wolfson. Generating tables from the parametric knowledge of language models. In *Proceedings of the 4th International Workshop on Knowledge-Augmented Methods for Natural Language Processing*, pp. 50–65, 2025.

Rok Blagus and Lara Lusa. Joint use of over-and under-sampling techniques and cross-validation for the development and assessment of prediction models. *BMC bioinformatics*, 16(1):363, 2015.

Vadim Borisov, Kathrin Sessler, Tobias Leemann, Martin Pawelczyk, and Gjergji Kasneci. Language models are realistic tabular data generators. In *The Eleventh International Conference on Learning Representations*, 2023.

Leo Breiman. Random forests. *Machine learning*, 45(1):5–32, 2001.

Chengtai Cao, Fan Zhou, Yurou Dai, Jianping Wang, and Kunpeng Zhang. A survey of mix-based data augmentation: Taxonomy, methods, applications, and explainability. *ACM Computing Surveys*, 57(2):1–38, 2024.

Victor Chang, Sharuga Sivakulasingam, Hai Wang, Siu Tung Wong, Meghana Ashok Ganatra, and Jiabin Luo. Credit risk prediction using machine learning and deep learning: A study on credit card customers. *Risks*, 12(11):174, 2024.

Nitesh V Chawla, Kevin W Bowyer, Lawrence O Hall, and W Philip Kegelmeyer. Smote: synthetic minority over-sampling technique. *Journal of artificial intelligence research*, 16:321–357, 2002.

Tianqi Chen and Carlos Guestrin. Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*, pp. 785–794, 2016.

Jillian M Clements, Di Xu, Nooshin Yousefi, and Dmitry Efimov. Sequential deep learning for credit risk monitoring with tabular financial data. *arXiv preprint arXiv:2012.15330*, 2020.

David R Cox. The regression analysis of binary sequences. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 20(2):215–232, 1958.

Imre Csiszár. I-divergence geometry of probability distributions and minimization problems. *The annals of probability*, pp. 146–158, 1975.

Suhan Cui and Prasenjit Mitra. Automated multi-task learning for joint disease prediction on electronic health records. In A. Globerson, L. Mackey, D. Belgrave, A. Fan, U. Paquet, J. Tomczak, and C. Zhang (eds.), *Advances in Neural Information Processing Systems*, volume 37, pp. 129187–129208. Curran Associates, Inc., 2024.

Jeffrey Dastin. Amazon scraps secret ai recruiting tool that showed bias against women. In *Ethics of data and analytics*, pp. 296–299. Auerbach Publications, 2022.

Arthur P Dempster, Nan M Laird, and Donald B Rubin. Maximum likelihood from incomplete data via the em algorithm. *Journal of the royal statistical society: series B (methodological)*, 39(1): 1–22, 1977.

Lun Du, Fei Gao, Xu Chen, Ran Jia, Junshan Wang, Jiang Zhang, Shi Han, and Dongmei Zhang. Tabularnet: A neural network architecture for understanding semantic structures of tabular data. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, pp. 322–331, 2021.

Yuntao Du and Ninghui Li. Towards principled assessment of tabular data synthesis algorithms. *CoRR*, 2024.

Conor Durkan, Artur Bekasov, Iain Murray, and George Papamakarios. Neural spline flows. *Advances in Neural Information Processing Systems*, 32, 2019.

Mengchun Gong, Shuang Wang, Lezi Wang, Chao Liu, Jianyang Wang, Qiang Guo, Hao Zheng, Kang Xie, Chenghong Wang, and Zhouguang Hui. Evaluation of privacy risks of patients' data in china: case study. *JMIR Medical Informatics*, 8(2):e13046, 2020.

Ian J Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. *Advances in Neural Information Processing Systems*, 27, 2014.

Yury Gorishniy, Ivan Rubachev, Valentin Khrulkov, and Artem Babenko. Revisiting deep learning models for tabular data. *Advances in neural information processing systems*, 34:18932–18943, 2021.

Will Grathwohl, Kuan-Chieh Wang, Joern-Henrik Jacobsen, David Duvenaud, Mohammad Norouzi, and Kevin Swersky. Your classifier is secretly an energy based model and you should treat it like one. In *International Conference on Learning Representations*, 2020.

Haibo He, Yang Bai, Edwardo A Garcia, and Shutao Li. Adasyn: Adaptive synthetic sampling approach for imbalanced learning. In *2008 IEEE international joint conference on neural networks (IEEE world congress on computational intelligence)*, pp. 1322–1328. Ieee, 2008.

Irina Higgins, Loic Matthey, Arka Pal, Christopher Burgess, Xavier Glorot, Matthew Botvinick, Shakir Mohamed, and Alexander Lerchner. beta-vae: Learning basic visual concepts with a constrained variational framework. In *International Conference on Learning Representations*, 2017.

Noah Hollmann, Samuel Müller, Lennart Purucker, Arjun Krishnakumar, Max Körfer, Shi Bin Hoo, Robin Tibor Schirrmeister, and Frank Hutter. Accurate predictions on small data with a tabular foundation model. *Nature*, 637(8045):319–326, 2025.

Feiran Huang, Zefan Wang, Xiao Huang, Yufeng Qian, Zhetao Li, and Hao Chen. Aligning distillation for cold-start item recommendation. In *Proceedings of the 46th international ACM SIGIR conference on research and development in information retrieval*, pp. 1147–1157, 2023.

Viet-Phi Huynh, Yoan Chabot, and Raphaël Troncy. Towards generative semantic table interpretation. In *VLDB Workshops*, 2023.

Jun-Peng Jiang, Han-Jia Ye, Leye Wang, Yang Yang, Yuan Jiang, and De-Chuan Zhan. Tabular insights, visual impacts: transferring expertise from tables to images. In *Forty-first International Conference on Machine Learning*, 2024.

Tero Karras, Miika Aittala, Timo Aila, and Samuli Laine. Elucidating the design space of diffusion-based generative models. *Advances in neural information processing systems*, 35:26565–26577, 2022.

Marvin Karson. Handbook of methods of applied statistics. volume i: Techniques of computation descriptive methods, and statistical inference. volume ii: Planning of surveys and experiments. im chakravarti, rg laha, and j. roy, new york, john wiley; 1967, 9.00., 1968.

Jinhee Kim, Taesung Kim, and Jaegul Choo. Epic: Effective prompting for imbalanced-class data synthesis in tabular data classification via large language models. *Advances in Neural Information Processing Systems*, 37:31504–31542, 2024.

Diederik P Kingma and Max Welling. Auto-encoding variational bayes. *arXiv preprint arXiv:1312.6114*, 2013.

Akim Kotelnikov, Dmitry Baranchuk, Ivan Rubachev, and Artem Babenko. Tabddpm: Modelling tabular data with diffusion models. In *International Conference on Machine Learning*, pp. 17564–17579. PMLR, 2023.

Guillaume LemaÃŽtre, Fernando Nogueira, and Christos K Aridas. Imbalanced-learn: A python toolbox to tackle the curse of imbalanced datasets in machine learning. *Journal of Machine Learning Research*, 18(17):1–5, 2017.

Xiaofeng Lin, Chenheng Xu, Matthew Yang, and Guang Cheng. Ctsyn: A foundational model for cross tabular data generation. In *International Conference on Learning Representations*, 2025.

Charles X Ling and Chenghui Li. Data mining for direct marketing: Problems and solutions. 1998.

Junwei Ma, Apoorv Dankar, George Stein, Guangwei Yu, and Anthony Caterini. Tabpfgen–tabular data generation with tabpfn. In *NeurIPS 2023 Second Table Representation Learning Workshop*, 2023.

Andrei Margeloiu, Xiangjian Jiang, Nikola Simidjievski, and Mateja Jamnik. Tabebm: A tabular data augmentation method with distinct class-specific energy-based models. *Advances in Neural Information Processing Systems*, 37:72094–72144, 2024.

Ninareh Mehrabi, Fred Morstatter, Nripsuta Saxena, Kristina Lerman, and Aram Galstyan. A survey on bias and fairness in machine learning. *ACM computing surveys (CSUR)*, 54(6):1–35, 2021.

Gaspard Monge. Mémoire sur la théorie des déblais et des remblais. *Mem. Math. Phys. Acad. Royale Sci.*, pp. 666–704, 1781.

Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, et al. Scikit-learn: Machine learning in python. *the Journal of Machine Learning Research*, 12:2825–2830, 2011.

Zhaozhi Qian, Rob Davis, and Mihaela Van Der Schaar. Synthcity: a benchmark framework for diverse use cases of tabular synthetic data. *Advances in Neural Information Processing Systems*, 36: 3173–3188, 2023.

Ivan Rubachev, Nikolay Kartashev, Yury Gorishniy, and Artem Babenko. Tabred: Analyzing pitfalls and filling the gaps in tabular deep learning benchmarks. In *The Thirteenth International Conference on Learning Representations*, 2025.

Juntong Shi, Minkai Xu, Harper Hua, Hengrui Zhang, Stefano Ermon, and Jure Leskovec. Tabdiff: a multi-modal diffusion model for tabular data generation. *arXiv e-prints*, pp. arXiv–2410, 2024.

Connor Shorten and Taghi M Khoshgoftaar. A survey on image data augmentation for deep learning. *Journal of big data*, 6(1):1–48, 2019.

Jascha Sohl-Dickstein, Eric Weiss, Niru Maheswaranathan, and Surya Ganguli. Deep unsupervised learning using nonequilibrium thermodynamics. In *International Conference on Machine Learning*, pp. 2256–2265. pmlr, 2015.

Yang Song, Jascha Sohl-Dickstein, Diederik P Kingma, Abhishek Kumar, Stefano Ermon, and Ben Poole. Score-based generative modeling through stochastic differential equations. In *International Conference on Learning Representations*, 2021.

Henk CA Van Tilborg and Sushil Jajodia. *Encyclopedia of cryptography and security*, volume 1. Springer Science & Business Media, 2011.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.

David S Watson, Kristin Blesch, Jan Kapar, and Marvin N Wright. Adversarial random forests for density estimation and generative modeling. In *International Conference on Artificial Intelligence and Statistics*, pp. 5357–5375. PMLR, 2023.

Chuhan Wu, Fangzhao Wu, Yang Cao, Yongfeng Huang, and Xing Xie. Fedgnn: Federated graph neural network for privacy-preserving recommendation. *arXiv preprint arXiv:2102.04925*, 2021.

Lei Xu, Maria Skoularidou, Alfredo Cuesta-Infante, and Kalyan Veeramachaneni. Modeling tabular data using conditional gan. *Advances in Neural Information Processing Systems*, 32, 2019.

Qian Yang, Jianyi Zhang, Weituo Hao, Gregory P Spell, and Lawrence Carin. Flop: Federated learning on medical datasets using partial networks. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, pp. 3845–3853, 2021.

Jinsung Yoon, Lydia N Drumright, and Mihaela Van Der Schaar. Anonymization through data synthesis using generative adversarial networks (ads-gan). *IEEE Journal of Biomedical and Health Informatics*, 24(8):2378–2388, 2020.

Hengrui Zhang, Jiani Zhang, Balasubramaniam Srinivasan, Zhengyuan Shen, Xiao Qin, Christos Faloutso, Huzefa Rangwala, and George Karypis. Mixed-type tabular data synthesis with score-based diffusion in latent space. In *12th International Conference on Learning Representations, ICLR 2024*, 2024.

Honglei Zhang, Fangyuan Luo, Jun Wu, Xiangnan He, and Yidong Li. Lightfr: Lightweight federated recommendation with privacy-preserving matrix factorization. *ACM Transactions on Information Systems*, 41(4):1–28, 2023.

Hongyi Zhang, Moustapha Cisse, Yann N Dauphin, and David Lopez-Paz. mixup: Beyond empirical risk minimization. In *International Conference on Learning Representations*, 2018.

Zilong Zhao, Aditya Kunar, Robert Birke, and Lydia Y Chen. Ctab-gan: Effective table data synthesizing. In *Asian conference on machine learning*, pp. 97–112. PMLR, 2021.

Yuli Zheng, Zhenyu Wu, Ye Yuan, Tianlong Chen, and Zhangyang Wang. Pcal: A privacy-preserving intelligent credit risk modeling framework based on adversarial learning. *CoRR*, 2020.

A USS OF LLMS

During the experimental process, we utilized large language models (LLMs) to assist with tasks such as code implementation, debugging, and visualization. In the course of writing the paper, LLMs were mainly employed for literature translation, summarization, and correcting formatting issues.

B KTGEN

B.1 VAE FOR TABULAR DATA

To facilitate learning in the latent space with diffusion models, we first employ a Variational Autoencoder (VAE) to map raw tabular data into a latent representation.

Feature Embedding. Each column of a tabular dataset corresponds to a distinct feature, which can be either categorical or numerical. Since these features differ in semantics and distributions, it is necessary to process them separately. Inspired by the embedding strategy in Transformer-based tabular prediction models (Vaswani et al., 2017; Gorishniy et al., 2021), we map each feature value of a sample $\boldsymbol{x}$ into a d-dimensional embedding.

For a categorical feature, we learn a 8-dimensional embedding vector for each possible category; For a numerical feature, we learn a linear mapping that projects each feature value into a 8-dimensional vector:

$$\boldsymbol{e}_j = \begin{cases} x_j^{\text{oh}} \boldsymbol{A}_j^{\text{cat}} + \boldsymbol{b}_j^{\text{cat}}, & \text{if feature } j \text{ is categorical feature,} \\ x_j^{\text{num}} \boldsymbol{a}_j^{\text{num}} + \boldsymbol{b}_j^{\text{num}}, & \text{if feature } j \text{ is numerical feature,} \end{cases} \tag{9}$$

where $\boldsymbol{A}_j^{\text{cat}} \in \mathbb{R}^{k\times d}$, $\boldsymbol{a}_j^{\text{num}}, \boldsymbol{b}_j^{\text{cat}}, \boldsymbol{b}_j^{\text{num}} \in \mathbb{R}^{1\times d}$ are learnable parameters. $x_j^{\text{oh}} \in \mathbb{R}^{1\times k}$ is the one-hot embedding of categorical feature x_j^{cat}, k represent the total number of possible categories it can take. For all columns, feature embedding sequence is stocked as:

$$\boldsymbol{E} = \text{stock}[\boldsymbol{e}_1, \boldsymbol{e}_2, \dots, \boldsymbol{e}_n] \in \mathbb{R}^{n\times d} \tag{10}$$

Encoder and Decoder. In the VAE structure, the encoder takes the feature embedding sequence $\boldsymbol{E}$ as input and employs two Transformer modules to output the mean $\hat{\mu} \in \mathbb{R}^{n\times d}$ and log-variance $\log \hat{\sigma}^2 \in \mathbb{R}^{n\times d}$ of the latent distribution. Using the reparameterization trick to obtain latent embeddings $\boldsymbol{Z} \in \mathbb{R}^{n\times d}$. It can be decoded to reconstructed feature embedding sequence $\hat{\boldsymbol{E}} \in \mathbb{R}^{n\times d}$. Both the encoder and decoder consist of two-layer Transformer structures, each with a single attention head.

Data Reconstruction. To perform data generation, each embedding in the feature embedding sequence $\hat{\boldsymbol{E}}$ must be reconstructed back into its corresponding original feature value.

For a categorical feature, the reconstructed feature embedding $\hat{\mathbf{e}}_j$ is passed through a linear transformation to obtain logits over categories; For a numerical feature, a linear mapping directly produces a reconstructed nEumerical value:

$$\hat{x}_j^{\text{cat}} = \arg\max\left(\hat{x}_j^{\text{prob}}\right) = \arg\max\left(\hat{\boldsymbol{e}}_j^{\text{cat}} \hat{\boldsymbol{A}}_j^{\text{cat}} + \hat{\boldsymbol{b}}_j^{\text{cat}}\right), \hat{x}_j^{\text{num}} = \hat{\boldsymbol{e}}_j^{\text{num}} \hat{\boldsymbol{a}}_j^{\text{num}} + \hat{b}_j^{\text{num}}, \tag{11}$$

where $\hat{\boldsymbol{A}}_j^{\text{cat}} \in \mathbb{R}^{d\times k}$, $\hat{\boldsymbol{b}}_j^{\text{cat}} \in \mathbb{R}^{1\times k}$, $\hat{\boldsymbol{a}}_j^{\text{num}} \in \mathbb{R}^{d\times 1}$, and $\hat{b}_j^{\text{num}} \in \mathbb{R}^{1\times 1}$ are learnable parameters of reconstruction part. Thus, the reconstructed sample is $\hat{\boldsymbol{x}}_i = (\hat{x}_1, \hat{x}_2, \dots, \hat{x}_n)$.

VAE Training. We adopt the β-VAE (Higgins et al., 2017) training objective, which consists of a reconstruction loss and a KL-divergence term:

$$\mathcal{L}_{\text{vae}} = \text{CE}\left(\boldsymbol{X}^{\text{cat}}, \hat{\boldsymbol{X}}^{\text{prob}}\right) + \text{MSE}\left(\boldsymbol{X}^{\text{num}}, \hat{\boldsymbol{X}}^{\text{num}}\right) + \frac{\beta}{nd}\sum_{p,q} D_{\text{KL}}(\mathcal{N}(\hat{\mu}_{p,q}, \hat{\sigma}_{p,q}^2) \| \mathcal{N}(0,1)) \tag{12}$$

The first and second terms correspond to the reconstruction losses for categorical and numerical features, respectively, while the third term serves as a regularization on the mean and variance of the latent space. The coefficient β is introduced to balance these losses. Since an additional diffusion process is employed to learn the latent space distribution, we do not strictly enforce the latent variables to follow a Gaussian prior. During training, β is gradually decreased to emphasize more accurate data reconstruction. This strategy is demonstrated to be effective (Zhang et al., 2024).

B.2 Diffusion in Latent Space

On top of the latent space, we employ a score-based diffusion model (Song et al., 2021; Karras et al., 2022) to enable sampling from the noise space into the latent space. After the VAE model is trained, we extract the latent embeddings $\boldsymbol{Z}$ from the encoder. First, the latent embeddings $\boldsymbol{Z}$ is flattened to $\boldsymbol{z}$. To learn the underlying distribution of latent embeddings $p(\boldsymbol{z})$, we consider the following forward diffusion and reverse denoising processes.

The forward process gradually perturbs the latent variable by injecting Gaussian noise:

$$\boldsymbol{z}_t = \boldsymbol{z}_0 + \sigma(t)\epsilon, \quad \epsilon \in \mathcal{N}(0, I) \tag{13}$$

where $\boldsymbol{z}_0 = \boldsymbol{z}$, $\sigma(t)$ represents the noise level, and $\boldsymbol{z}_t$ is the noisy embedding at time step t. Follow previous work (Zhang et al., 2024), we set the noise level $\sigma(t) = t$.

The diffusion model is trained to learn a denoising function f_θ that estimates the added noise ϵ from the noise embedding $\boldsymbol{z}_t$ and the corresponding time step t:

$$\mathcal{L}_{\text{diff}} = \mathbb{E}_{\boldsymbol{z}_0 \sim p(\boldsymbol{z})}\mathbb{E}_{t\sim p(t)}\mathbb{E}_{\epsilon\sim\mathcal{N}(0,I)}\|f_\theta\left(\boldsymbol{z}_t, t\right) - \epsilon\|. \tag{14}$$

Based on the estimated noise, the score function of $\boldsymbol{z}_t$ can be approximated as

$$\nabla_{\boldsymbol{z}_t} \log p(\boldsymbol{z}_t) = -\frac{f_\theta\left(\boldsymbol{z}_t, t\right)}{\sigma(t)}, \tag{15}$$

The reverse denoising process then enables sampling from the latent space distribution:

$$d\boldsymbol{z}_t = -2\,\dot{\sigma}(t)\,\sigma(t)\,\nabla_{\boldsymbol{z}_t} \log p(\boldsymbol{z}_t)\,dt + \sqrt{2\,\dot{\sigma}(t)\,\sigma(t)}\,d\omega_t, \tag{16}$$

where ω_t denotes the standard Wiener process, $\dot{\sigma}(t)$ denotes the derivative of $\sigma(t)$ with respect to time step t. After the diffusion model is trained, synthetic latent embeddings can be generated by iteratively applying the reverse process. The denoising network consists of a 3-layer MLP with residual connections.

B.3 Correction Network

The detailed implementation of the Correction Network is provided in Section 4.2. Here, we focus on its architecture, which consists of a 2-layer MLP with residual connections.

C Datasets

Table 4: Statistics of Datasets

	Rows	Cols	Target	Cat Cols	Num Cols
abalone	4177	9	Regression	1	8
adult	48842	15	Classification	9	6
california	20640	9	Regression	0	9
credit	1000	21	Classification	14	7
default	30000	24	Classification	2	22
diabetes	768	9	Classification	1	8
magic	19020	11	Classification	1	10
shopper	12330	18	Classification	4	14

Below is a detailed introduction to each dataset:

- **abalone**: Predicting the age of abalone from physical measurements. The age of abalone is determined by cutting the shell through the cone, staining it, and counting the number of rings through a microscope – a boring and time-consuming task. `https://archive.ics.uci.edu/dataset/1/abalone`

- **adult**: Predict whether annual income of an individual exceeds 50K/yr based on census data. Also known as ”Census Income” dataset. `https://archive.ics.uci.edu/dataset/2/adult`
- **california**: This dataset was derived from the 1990 U.S. census, using one row per census block group. A block group is the smallest geographical unit for which the U.S. Census Bureau publishes sample data (a block group typically has a population of 600 to 3,000 people). `https://inria.github.io/scikit-learn-mooc/python_scripts/datasets_california_housing.html`
- **credit**: This dataset classifies people described by a set of attributes as good or bad credit risks. Comes in two formats (one all numeric). `https://archive.ics.uci.edu/dataset/144/statlog+german+credit+data`
- **default**: This research aimed at the case of customers' default payments in Taiwan. From the perspective of risk management, the result of predictive accuracy of the estimated probability of default will be more valuable than the binary result of classification - credible or not credible clients. `https://archive.ics.uci.edu/dataset/350/default+of+credit+card+clients`
- **diabetes**: Diabetes patient records were obtained from two sources: an automatic electronic recording device and paper records. The automatic device had an internal clock to timestamp events, whereas the paper records only provided ”logical time” slots (breakfast, lunch, dinner, bedtime). `https://archive.ics.uci.edu/dataset/34/diabetes`
- **magic**: The data are MC generated (see below) to simulate registration of high energy gamma particles in a ground-based atmospheric Cherenkov gamma telescope using the imaging technique. `https://archive.ics.uci.edu/dataset/159/magic+gamma+telescope`
- **shopper**: Of the 12,330 sessions in the dataset, 84.5% (10,422) were negative class samples that did not end with shopping, and the rest (1908) were positive class samples ending with shopping. `https://archive.ics.uci.edu/dataset/468/online+shoppers+purchasing+intention+dataset`

D Bias Data Sampling

For a table matrix $\boldsymbol{X} \in \mathbb{R}^{m \times n}$. We sequentially traverse each column of the table. For the j-th column $\boldsymbol{c}_j$, if the corresponding feature is categorical and has k possible values (encoded as ordinal values 0 to $k-1$), with proportions $p_0, p_1, \ldots, p_{k-1}$. We can compute a weight for each sample as:

$$\boldsymbol{w}_j = \gamma \left(p_{\boldsymbol{X}_{1,j}}, p_{\boldsymbol{X}_{2,j}}, \ldots, p_{\boldsymbol{X}_{m,j}} \right), \tag{17}$$

where $p_{\boldsymbol{X}_{i,j}}$ denotes the proportion of the value at row i, column j within the corresponding discrete column. And γ is a parameter controlling the degree of bias. A larger γ amplifies the difference between classes, giving higher weights to majority class and making them more likely to be selected. Conversely, as γ approaches 0, the weights of all samples converge, resulting in nearly random sampling.

If the feature is numerical, let c_{max}, c_{min}, c_{mean}, and c_{std} denote the maximum, minimum, mean, and standard deviation of the column $\boldsymbol{c}_j$, respectively. We consider three different weighting schemes:

$$\boldsymbol{w}_j = \gamma \frac{\boldsymbol{c}_j - c_{\text{min}}}{c_{\text{max}} - c_{\text{min}}}, \boldsymbol{w}_j = \gamma \frac{c_{\text{max}} - \boldsymbol{c}_j}{c_{\text{max}} - c_{\text{min}}}, \boldsymbol{w}_j = \exp\left(-\frac{(\boldsymbol{c}_j - \hat{c})^2}{2\left(\frac{c_{\text{std}}}{\gamma}\right)^2} \right), \tag{18}$$

The first scheme assigns higher weights to larger values and the second scheme assigns higher weights to smaller values. The parameter γ controls the magnitude of the weight differences. In the third scheme, $\hat{c}$ is sampled from a Gaussian distribution with mean c_{mean} and variance c_{std}^2. This scheme favors values around the $\hat{c}$, assigning them higher weights. The parameter γ controls the differences in weights across positions; when γ is large, the weight difference between values near

$\hat{c}$ and those at the extremes becomes significant. When γ approaches 0, all positions in $\boldsymbol{w}_j$ converge to similar values, resulting in almost no differences in weights.

Weights can be computed in this manner for all columns, and the weights across all columns are then aggregated:

$$\boldsymbol{w} = \prod_{j=1}^{n} \boldsymbol{w}_j. \tag{19}$$

We split the data into candidate and test sets with a ratio of 8:2. The candidate set is used to extract auxiliary information. Subsequently, training samples are drawn from this candidate set based on the aggregated weights $\boldsymbol{w}$. We perform multiple biased sampling iterations on each training set. For each iteration, we first sample a bias magnitude γ , and then generate a fixed-size sample set following the procedure. For each dataset, this sampling process is repeated 100 times to obtain 100 sample sets. Due to the stochasticity of the sampling process, we additionally compute the distributional similarity of each sample set relative to the training set. Specifically, for categorical features we calculate the KL divergence, and for numerical features we compute the Wasserstein distance. Each resulting value d_j is strictly positive. We transform them to distributional similarity:

$$s = \frac{1}{n} \sum_{j=1}^{n} \frac{1}{1 + d_j} \tag{20}$$

From the 100 sample sets, we select 4 with the smallest similarity as the high-bias sample sets, 4 with median similarity as the medium-bias sample sets, and another 4 randomly sampled sets as the unbiased sample sets.

E BASELINES

Below is a detailed introduction and implementation of the baseline methods used in this paper:

- **SMOTE** (Chawla et al., 2002)

  Introduction: Synthetic Minority Over-sampling Technique generates new samples for minority classes via interpolation. It helps balance imbalanced datasets and improves classifier performance on underrepresented classes.

  Implementation: Use the open-source implementation of SMOTE from the python library Imbalanced-learn (LemaÃŽtre et al., 2017). `https://imbalanced-learn.org/stable/`.

  Hyperparameter Space:

  k: integer, choices $\{1, 3, 5\}$

- **Mixup** (Zhang et al., 2018)

  Introduction: Creates virtual training samples by linearly interpolating random pairs of examples and their labels. This regularizes models and improves generalization by encouraging smoother decision boundaries.

  Implementation: We manually implement the Mixup technique, generating virtual samples by linearly interpolating randomly selected pairs of training examples and their labels.

- **TVAE** (Xu et al., 2019):

  Introduction: A Variational Autoencoder designed for tabular data that captures feature dependencies in a latent space. It generates realistic synthetic samples while preserving correlations among columns.

  Implementation: Use the open-source implementation in the python library Synthcity (Qian et al., 2023). `https://github.com/vanderschaarlab/synthcity/tree/main`.

  Hyperparameter Space:

  n_iter: integer, choices $\{100, 200, 300, 400, 500\}$

  lr: float, choices $\{0.0001, 0.0002, 0.001\}$

  decoder_n_layers_hidden: integer, range $[1, 5]$

weight_decay: float, choices $\{0.0001, 0.001\}$
batch_size: integer, choices $\{64, 128, 256, 512\}$
n_units_embedding: integer, range $[50, 500]$ step 50
decoder_n_units_hidden: integer, range $[50, 500]$ step 50
decoder_nonlin: categorical, choices $\{\text{elu}, \text{leaky\_relu}, \text{relu}, \text{tanh}\}$
decoder_dropout: float, range $[0.0, 0.2]$
encoder_n_layers_hidden: integer, range $[1, 5]$
encoder_n_units_hidden: integer, range $[50, 500]$ step 50
encoder_nonlin: categorical, choices $\{\text{elu}, \text{leaky\_relu}, \text{relu}, \text{tanh}\}$
encoder_dropout: float, range $[0.0, 0.2]$

- **CTGAN** (Xu et al., 2019):

  Introduction: A GAN-based model for tabular data that uses conditional sampling to handle discrete columns. It effectively models mixed-type tables and generates high-quality synthetic data.

  Implementation: Use the open-source implementation in the python library Synthcity.

  Hyperparameter Space:

  generator_n_layers_hidden: integer, range $[1, 4]$
  generator_n_units_hidden: integer, range $[50, 150]$, step 50
  generator_nonlin: categorical, choices $\{\text{elu}, \text{leaky\_relu}, \text{relu}, \text{tanh}\}$
  n_iter: integer, range $[100, 1000]$, step 100
  generator_dropout: float, range $[0.0, 0.2]$
  discriminator_n_layers_hidden: integer, range $[1, 4]$
  discriminator_n_units_hidden: integer, range $[50, 150]$, step 50
  discriminator_nonlin: categorical, choices $\{\text{elu}, \text{leaky\_relu}, \text{relu}, \text{tanh}\}$
  discriminator_n_iter: integer, range $[1, 5]$
  discriminator_dropout: float, range $[0.0, 0.2]$
  lr: float, choices $\{0.0001, 0.0002, 0.001\}$
  weight_decay: float, choices $\{0.0001, 0.001\}$
  batch_size: integer, choices $\{100, 200, 500\}$
  encoder_max_clusters: integer, range $[2, 20]$

- **TabDDPM** (Kotelnikov et al., 2023):

  Introduction: A diffusion-based generative model that denoises samples in data or latent space. It gradually transforms noise into realistic tabular samples using a learned denoising process.

  Implementation: Use the open-source implementation in the python library Synthcity.

  Hyperparameter Space:

  lr: log-uniform, range $[10^{-5}, 0.1]$
  batch_size: integer log-uniform, range $[256, 4096]$
  num_timesteps: integer, range $[10, 1000]$
  n_iter: integer log-uniform, range $[1000, 10000]$

- **TABSYN** (Zhang et al., 2024):

  Introduction: Diffusion-based method combining continuous and discrete features for realistic tabular synthesis. It can capture complex dependencies and generate samples consistent with real data distributions.

  Implementation: Use the open-source implementation in GitHub. `https://github.com/amazon-science/tabsyn`.

  Hyperparameter: Use the default parameters in the paper

- **ARF** (Watson et al., 2023):

  Implementation: Use the open-source implementation in the python library Synthcity.

Introduction: Adversarial Random Forests is a non-parametric method for density estimation and synthetic data generation. It can model intricate feature interactions without assuming a parametric form.

Hyperparameter Space:

num_trees: integer, range $[10, 100]$, step 10
delta: float, range $[0.0, 0.5]$
max_iters: integer, range $[1, 5]$
early_stop: categorical, choices $\{\text{False}, \text{True}\}$
min_node_size: integer, range $[2, 20]$, step 2

- **BN** (Ankan & Textor, 2024):

  Introduction: Bayesian Network-based generator models variable dependencies via a directed acyclic graph. New samples are generated by sampling from the joint probability distribution encoded by the network.

  Implementation: Use the open-source implementation in the python library Synthcity.

  Hyperparameter Space:

  struct_learning_search_method: categorical, choices $\{\text{hillclimb}, \text{pc}, \text{tree\_search}\}$
  struct_learning_score: categorical, choices $\{\text{bdeu}, \text{bds}, \text{bic}, \text{k2}\}$

- **TabPFGen** (Ma et al., 2023):

  Introduction: Leverages the tabular foundation model TabPFN combined with energy-based modeling. It generates synthetic data by performing probabilistic inference informed by both model priors and data statistics.

  Implementation: Use the open-source implementation in the python library TabPFGen. `https://github.com/sebhaan/TabPFGen`.

- **TabEBM** (Margeloiu et al., 2024):

  Implementation: Use the open-source implementation in the python library TabEBM. `https://github.com/andreimargeloiu/TabEBM`.

  Introduction: Combines TabPFN with energy-based models to synthesize high-quality tabular data. This approach balances flexibility and accuracy by leveraging energy-based likelihood estimation.

- **TabPFN** (Hollmann et al., 2025):

  Introduction: A tabular foundation model that performs density estimation and probabilistic prediction using in-context learning. Perform density estimation on tabular data using TabPFN, and generate synthetic data based on the estimated distribution.

  Implementation: Use the open-source implementation in the python library tabpfn-extensions. `https://github.com/priorlabs/tabpfn-extensions`.

F DOWNSTREAM MODEL

Below is a detailed introduction and implementation of the downstream model used in this paper:

- **XGBoost** (Chen & Guestrin, 2016)

  Introduction: A scalable and efficient gradient boosting framework for supervised learning. It constructs an ensemble of decision trees to optimize prediction performance while controlling overfitting.

  Implementation: Use the open-source implementation in the python library xgboost. `https://xgboost.ai/`

  Hyperparameter Space:

  alpha: float, $[10^{-8}, 100]$ (log scale)
  colsample_bylevel: float, $[0.5, 1.0]$
  colsample_bytree: float, $[0.5, 1.0]$
  gamma: float, $[10^{-8}, 100]$ (log scale)
  lambda: float, $[10^{-8}, 100]$ (log scale)

learning_rate: float, $[10^{-4}, 0.3]$ (log scale)
max_depth: integer, $[3, 10]$
min_child_weight: float, $[10^{-2}, 100]$ (log scale)
subsample: float, $[0.5, 1.0]$

- **Random Forest** (Breiman, 2001)

  Introduction: An ensemble method that builds multiple decision trees and aggregates their predictions. It is robust to overfitting and can capture complex feature interactions.

  Implementation: Use the open-source implementation in the python library scikit-learn (Pedregosa et al., 2011). `https://scikit-learn.org/stable/index.html`

  Hyperparameter Space:
  min_samples_split: integer, $[2, 10]$ **min_samples_leaf**: integer, $[1, 10]$

- **TabPFN** (Hollmann et al., 2025)

  Introduction: A tabular foundation model that performs in-context learning for classification and regression tasks. It can estimate predictive distributions without explicit training on the downstream dataset.

  Implementation: Use the open-source implementation in the python library tabpfn. `https://github.com/PriorLabs/TabPFN`.

- **Linear Regression or Logistic Regression** (Cox, 1958)

  Introduction: Classical parametric models for regression and classification. Linear regression models continuous outcomes, while logistic regression models binary outcomes using a sigmoid function.

  Implementation: Use the open-source implementation in the python library scikit-learn.

G Experimental Results

Downstream Model Performance.

Table 5: **abalone**.

		high-bias				medium-bias				unbias			
		XGB	RF	PFN	LR	XGB	RF	PFN	LR	XGB	RF	PFN	LR
20 samples	Basic	1.2489	1.1638	1.2036	2.1150	1.0963	1.1286	1.1202	1.4425	0.9843	0.9407	0.7921	1.0519
	SMOTE	1.2921	1.1922	1.2273	2.1691	1.0782	1.1058	1.0918	1.8927	0.8827	0.9365	0.8017	1.3134
	Mixup	1.2519	1.1979	1.2696	2.0779	0.9975	1.0469	1.0884	1.2701	0.9066	0.9564	0.8483	1.0100
	TVAE	1.2665	1.2409	1.3005	1.3315	1.0566	1.0462	1.1494	1.3861	0.9697	0.9049	1.0250	0.9096
	CTGAN	1.2949	1.2690	1.2859	1.1259	1.1936	1.1675	1.2387	1.3496	0.9458	0.9073	1.0748	0.9044
	TabDDPM	1.2940	1.2524	1.2379	1.0924	1.1222	1.1216	1.2772	1.3002	1.3276	1.3388	1.2637	1.5956
	TABSYN	1.2424	1.1815	1.2599	0.9656	1.0584	1.0778	1.0759	1.4604	0.9338	0.8684	0.8939	0.8928
	ARF	1.2570	1.2033	1.2832	1.1006	1.1628	1.1723	1.2685	1.3539	0.9501	0.9091	0.9515	0.9344
	BN	1.2364	1.1952	1.3129	1.0984	1.0598	1.0911	1.1355	1.3609	0.9374	1.0219	0.8974	0.9366
	TabPFGen	1.2789	1.1656	1.1984	1.5064	1.0228	1.0977	1.2535	1.1108	0.9036	0.8689	0.8172	0.8455
	TabEBM	1.2513	1.1462	1.2086	1.4229	1.0619	1.0079	1.0998	1.0992	0.9107	0.9163	0.8780	0.8494
	TabPFN	1.2158	1.1523	1.2609	1.7931	1.1444	1.1980	1.1053	1.4641	0.8913	0.9120	0.9470	0.8770
	KTGen$_b$	1.2624	1.1845	1.2373	3.2123	1.1000	1.1763	1.2189	1.2826	0.9096	0.9162	0.9634	0.9347
	KTGen$_c$	1.0677	0.9929	1.0624	0.9965	0.9667	0.9669	1.0166	1.4591	0.8622	0.8405	0.8390	0.7920
50 samples	Basic	1.1859	1.1748	1.2066	1.4604	1.5202	1.4204	1.1014	1.5834	0.8522	0.8372	0.7452	0.7674
	SMOTE	1.3040	1.3785	1.2672	1.4947	1.5102	1.6756	1.1337	2.2439	0.8773	0.9085	0.7835	1.0207
	Mixup	1.2012	1.2493	1.3472	1.5541	1.4755	1.6976	1.6866	1.2783	0.7913	0.7909	0.7590	0.7928
	TVAE	1.1832	1.2202	1.2869	1.4578	1.2744	1.2062	1.1350	1.1217	0.8620	0.8252	0.9582	0.7912
	CTGAN	1.1639	1.2161	1.3143	1.9017	1.2029	1.2818	1.1337	1.1156	1.2118	0.8958	1.0411	0.9435
	TabDDPM	1.4331	1.6842	1.3413	1.8359	0.9819	0.9877	1.7576	1.0214	1.3276	1.3388	1.2637	1.5956
	TABSYN	1.1722	1.1651	1.2034	1.2256	1.4638	1.5101	1.0516	1.0705	0.8760	0.8351	0.8620	0.8296
	ARF	1.2090	1.2146	1.2772	1.0669	1.2561	1.1470	1.1250	1.0558	0.8570	0.8137	0.8509	0.8143
	BN	1.1919	1.2478	1.2788	1.2131	1.5771	1.4152	1.4327	1.0202	0.8166	0.8316	0.8358	0.7722
	TabPFGen	1.1871	1.1596	1.2251	1.1814	1.4417	1.3896	1.2847	0.8150	0.8308	0.7899	0.7556	0.7640
	TabEBM	1.1604	1.1473	1.1475	1.2566	1.1341	1.1722	1.0451	0.8771	0.7946	0.7485	0.7261	0.7510
	TabPFN	1.1857	1.1765	1.2607	2.0221	1.3200	1.2457	1.8819	2.0822	0.8132	0.7997	0.8117	0.7747
	KTGen$_b$	1.1083	1.1597	1.1391	1.8301	1.4760	1.3697	2.0305	1.4015	0.7989	0.7798	0.7900	0.7558
	KTGen$_c$	0.9709	0.9658	1.2226	0.9300	0.9368	0.8955	1.1040	0.9162	0.8237	0.8002	0.7746	0.7557
100 samples	Basic	1.1871	1.1912	1.2725	1.0976	1.1527	1.1065	1.0645	1.2656	0.8191	0.7856	0.7320	0.7269
	SMOTE	1.1864	1.1555	1.2536	1.3062	1.2227	1.4157	1.1430	2.1584	0.8252	0.8794	0.7899	0.8458
	Mixup	1.2024	1.2430	1.3230	1.0061	1.1461	1.2743	1.1579	1.1644	0.7910	0.8173	0.7305	0.7288
	TVAE	1.2775	1.1821	1.2164	0.8646	1.0904	1.1840	1.1533	1.3047	0.8745	0.8472	0.9048	0.8638
	CTGAN	1.1899	1.1524	1.2807	1.0153	1.1456	1.1781	1.2936	1.3079	0.8551	0.8156	0.8488	0.8112
	TabDDPM	1.2882	1.2552	1.2657	1.1363	1.3276	1.3388	1.2637	1.5956	0.8510	0.8504	0.7345	1.0756
	TABSYN	1.3289	1.2079	1.3127	0.9190	1.0818	1.1155	1.1901	1.1236	0.8610	0.8281	0.8311	0.8192
	ARF	1.1464	1.1965	1.2394	0.9490	1.0483	1.0278	1.0948	1.4482	0.7466	0.7459	0.7326	0.7472
	BN	1.2875	1.2682	1.3378	1.0364	1.0770	1.0638	1.3570	1.1492	0.8180	0.8134	0.8271	0.7154
	TabPFGen	1.1951	1.1603	1.2675	1.0328	1.1090	1.0951	1.3851	0.9828	0.8402	0.8081	0.7785	0.7740
	TabEBM	1.2047	1.1692	1.2432	0.9675	1.0583	1.0360	1.2197	1.0711	0.7274	0.7035	0.6797	0.7122
	TabPFN	1.1864	1.1720	1.3191	1.3116	0.9921	0.9477	1.3714	1.1983	0.7621	0.7431	0.7389	0.7615
	KTGen$_b$	1.2296	1.1659	1.2316	1.1359	1.0237	1.0026	1.8164	1.3401	0.7750	0.7548	0.7257	0.7746
	KTGen$_c$	0.9276	0.9299	1.1210	0.8942	0.8991	0.8754	1.1964	0.8765	0.7986	0.7814	0.7352	0.7263

Table 6: **adult**.

		high-bias				**medium-bias**				**unbias**			
		XGB	RF	PFN	LR	XGB	RF	PFN	LR	XGB	RF	PFN	LR
20 samples	Basic	0.7005	0.7265	0.7440	0.7161	0.6318	0.6790	0.7095	0.7217	0.7947	0.8193	0.8216	0.8171
	SMOTE	0.6558	0.6969	0.6720	0.7073	0.6746	0.7293	0.7187	0.7478	0.7689	0.7864	0.8201	0.7793
	Mixup	0.6425	0.6591	0.6129	0.6594	0.6603	0.7071	0.6996	0.7316	0.7170	0.7298	0.7437	0.7399
	TVAE	0.6157	0.6323	0.6571	0.6063	0.5954	0.6266	0.6275	0.5759	0.7662	0.7680	0.7657	0.7903
	CTGAN	0.6463	0.6334	0.5926	0.6070	0.5914	0.6393	0.6587	0.6487	0.7412	0.7412	0.6245	0.7341
	TabDDPM	0.6173	0.6322	0.6670	0.6079	0.6029	0.6235	0.6207	0.6457	0.6169	0.7016	0.7256	0.5680
	TABSYN	0.6076	0.6613	0.6879	0.7004	0.5697	0.5994	0.6266	0.6184	0.8060	0.7729	0.8190	0.8077
	ARF	0.6962	0.7174	0.6914	0.7453	0.6649	0.6553	0.6337	0.6676	0.7493	0.7418	0.7175	0.7590
	BN	0.6491	0.6940	0.6983	0.7022	0.7359	0.7184	0.6648	0.7325	0.7564	0.7922	0.7941	0.8007
	TabPFGen	0.6535	0.6936	0.6810	0.7069	0.6723	0.6601	0.6904	0.7112	0.7499	0.8082	0.7995	0.8183
	TabEBM	0.7638	0.7895	0.7744	0.7779	0.7573	0.8154	0.7930	0.7953	0.8388	0.8498	0.8445	0.8535
	TabPFN	0.6187	0.6434	0.6930	0.6666	0.6244	0.6303	0.6877	0.7017	0.7737	0.7381	0.7959	0.7607
	KTGen$_b$	0.6641	0.6747	0.7225	0.6872	0.6140	0.6183	0.6776	0.6938	0.7789	0.7812	0.8135	0.7807
	KTGen$_c$	0.6717	0.7025	0.7479	0.7166	0.7115	0.7042	0.7146	0.7128	0.7937	0.7954	0.8175	0.8208
50 samples	Basic	0.7968	0.7979	0.8071	0.7826	0.7958	0.8149	0.8330	0.8292	0.8044	0.8436	0.8541	0.8287
	SMOTE	0.7842	0.7751	0.7353	0.7228	0.8148	0.8088	0.8133	0.8127	0.8352	0.8402	0.8445	0.8333
	Mixup	0.7522	0.7609	0.7010	0.7449	0.7715	0.7812	0.7446	0.8148	0.8018	0.8009	0.7846	0.8239
	TVAE	0.7472	0.7551	0.7836	0.7670	0.8021	0.8027	0.8065	0.7785	0.7590	0.7931	0.8098	0.7950
	CTGAN	0.6356	0.6936	0.6494	0.6318	0.7930	0.7937	0.8024	0.7883	0.7207	0.7546	0.7800	0.7072
	TabDDPM	0.7916	0.7758	0.7387	0.7716	0.7795	0.8201	0.8076	0.8019	0.8159	0.8371	0.8257	0.8179
	TABSYN	0.7471	0.7559	0.7798	0.7634	0.8057	0.8053	0.8067	0.7963	0.8028	0.8101	0.8437	0.8233
	ARF	0.7039	0.6993	0.7008	0.7114	0.7362	0.7174	0.6910	0.7264	0.8124	0.8130	0.8047	0.8215
	BN	0.7911	0.7766	0.7315	0.7077	0.8104	0.8011	0.7552	0.7953	0.8259	0.8261	0.8235	0.8229
	TabPFGen	0.8009	0.7938	0.7905	0.7850	0.8059	0.8049	0.8193	0.8309	0.8351	0.8280	0.8354	0.8307
	TabEBM	0.8009	0.7808	0.7821	0.7895	0.7573	0.8154	0.7930	0.7953	0.8388	0.8498	0.8445	0.8535
	TabPFN	0.7689	0.7589	0.7389	0.7542	0.8141	0.8036	0.7899	0.8037	0.8182	0.8206	0.8159	0.8284
	KTGen$_b$	0.7542	0.7542	0.7487	0.7231	0.8002	0.7878	0.7969	0.7914	0.8170	0.8142	0.8312	0.8068
	KTGen$_c$	0.7318	0.7479	0.7533	0.6825	0.7895	0.7885	0.8172	0.8221	0.8171	0.8265	0.8307	0.8310
100 samples	Basic	0.8341	0.8588	0.8664	0.8501	0.8312	0.8455	0.8576	0.8504	0.8326	0.8435	0.8692	0.8652
	SMOTE	0.8201	0.8352	0.8111	0.8220	0.8457	0.8328	0.8351	0.8235	0.8490	0.8503	0.8296	0.8558
	Mixup	0.8075	0.8210	0.7881	0.8357	0.8150	0.8027	0.7660	0.8165	0.8325	0.8393	0.8092	0.8591
	TVAE	0.8073	0.8190	0.8322	0.8159	0.8015	0.8055	0.8129	0.7951	0.8401	0.8427	0.8302	0.8168
	CTGAN	0.7760	0.7957	0.7480	0.7567	0.7791	0.7896	0.7808	0.7908	0.8160	0.8243	0.8409	0.8117
	TabDDPM	0.8280	0.8460	0.8286	0.7911	0.8093	0.8282	0.8125	0.7722	0.8204	0.8293	0.8465	0.7618
	TABSYN	0.8235	0.8381	0.8473	0.8181	0.8264	0.8255	0.8421	0.8247	0.8540	0.8512	0.8691	0.8534
	ARF	0.8097	0.8366	0.7894	0.8150	0.8048	0.8181	0.7866	0.8100	0.8476	0.8511	0.8257	0.8520
	BN	0.8260	0.8319	0.7969	0.7997	0.8288	0.8269	0.7983	0.8132	0.8429	0.8480	0.8057	0.8415
	TabPFGen	0.8457	0.8539	0.8541	0.8457	0.8294	0.8310	0.8432	0.8354	0.8462	0.8586	0.8520	0.8713
	TabEBM	0.8290	0.8451	0.8437	0.8469	0.8388	0.8498	0.8445	0.8535	0.8591	0.8655	0.8714	0.8829
	TabPFN	0.8149	0.8200	0.7984	0.7983	0.8187	0.8206	0.8009	0.8157	0.8446	0.8421	0.8372	0.8313
	KTGen$_b$	0.8138	0.8255	0.8137	0.8143	0.8214	0.8126	0.8046	0.7973	0.8378	0.8401	0.8398	0.8496
	KTGen$_c$	0.8267	0.8435	0.8279	0.8106	0.8317	0.8288	0.8198	0.7981	0.8341	0.8438	0.8590	0.8533

Table 7: **california**.

		high-bias				**medium-bias**				**unbias**			
		XGB	RF	PFN	LR	XGB	RF	PFN	LR	XGB	RF	PFN	LR
20 samples	Basic	1.3160	1.4231	1.3082	3.7761	1.2063	1.2155	1.1348	1.5143	0.8494	0.8409	0.7304	1.4925
	SMOTE	1.2784	1.3858	1.3619	3.8253	1.1252	1.1559	1.1323	1.5396	0.9491	0.8671	0.7106	1.7952
	Mixup	1.3473	1.1991	1.2399	3.7072	1.1392	1.1552	1.2915	1.4890	0.8379	0.7792	0.6254	1.5518
	TVAE	1.2790	1.1907	1.2385	1.4377	1.1753	1.1992	1.0714	1.8850	0.8428	0.8020	0.7408	1.2111
	CTGAN	1.3875	1.3648	1.3190	1.3869	1.2335	1.2818	1.2476	1.7435	0.8965	0.8606	0.8520	1.4285
	TabDDPM	1.4699	1.5672	1.8390	1.5181	1.2566	1.2340	1.2404	1.2502	0.9283	0.9471	0.8596	1.2008
	TABSYN	1.5572	1.5600	1.4310	1.7990	1.2929	1.2451	1.2296	1.2858	0.9440	0.9011	0.8851	1.0505
	ARF	1.4323	1.4798	1.5304	1.7413	1.1982	1.1981	1.1263	1.9405	0.8995	0.9286	0.8099	1.1705
	BN	1.4904	1.3110	1.4203	1.4568	1.1335	1.1399	1.1249	1.1872	0.8563	0.8389	0.7968	0.7524
	TabPFGen	1.3782	1.3314	1.3685	1.3570	1.2733	1.2218	1.1973	1.4703	0.8428	0.7972	0.7387	1.1850
	TabEBM	1.4184	1.3784	1.3596	1.2922	1.1955	1.1914	1.2215	1.4192	0.7994	0.7184	0.6724	1.1562
	TabPFN	1.3152	1.3045	1.3269	3.7408	1.2243	1.2211	1.1100	2.0470	0.8826	0.8457	0.7829	1.6428
	KTGen$_b$	1.3927	1.3417	1.1300	1.7636	1.2237	1.2370	1.1436	1.3947	0.8879	0.8521	0.7728	1.4676
	KTGen$_c$	1.2121	1.1230	1.2661	1.0145	1.1977	1.0964	1.2047	0.8977	0.8363	0.7750	0.7961	0.7068
50 samples	Basic	1.3951	1.4334	1.3656	2.4224	0.9390	0.9569	0.9464	1.7225	0.7535	0.7632	0.6266	0.8890
	SMOTE	1.2495	1.4453	1.2004	2.4547	0.8699	0.9223	0.8833	1.7421	0.7600	0.7550	0.6477	1.1170
	Mixup	1.3461	1.2824	1.3613	2.5387	0.8870	0.9058	0.8961	1.7643	0.7205	0.7211	0.5640	0.8320
	TVAE	1.6017	1.5264	1.5507	2.5256	1.0318	0.9654	0.9524	1.6140	0.8146	0.8199	0.7565	0.8917
	CTGAN	1.5869	1.4203	1.6994	2.3314	0.9991	1.0299	0.9409	2.3011	0.8888	0.8833	0.8835	0.9808
	TabDDPM	1.7510	1.8468	1.6716	2.6257	0.9377	0.9117	0.9246	1.2550	0.7579	0.7757	0.6362	0.9103
	TABSYN	1.5960	1.5434	1.4724	1.9979	1.0896	0.9941	1.0261	1.3096	0.8479	0.8219	0.8107	0.8849
	ARF	1.3695	1.4301	1.3234	1.8458	1.0094	0.9809	0.9797	1.6618	0.8177	0.8284	0.7990	0.9403
	BN	1.3922	1.3090	1.4090	2.0209	0.9366	1.0653	1.0266	1.1747	0.7488	0.7444	0.6883	0.6555
	TabPFGen	1.3219	1.3590	1.4985	2.3720	0.9476	0.8760	0.8476	1.6323	0.7465	0.7201	0.5715	0.7350
	TabEBM	1.3755	1.4362	1.3539	2.0373	0.8589	0.8922	0.9564	1.5547	0.6916	0.6350	0.5702	0.7211
	TabPFN	1.4577	1.4355	1.4605	3.9013	1.0115	1.1349	0.9700	1.5916	0.7603	0.7460	0.6957	0.8076
	KTGen$_b$	1.4320	1.4807	1.3893	4.3607	0.9739	1.0511	1.0635	1.9210	0.7414	0.7263	0.6099	0.8150
	KTGen$_c$	1.2693	1.2058	1.1645	1.2709	0.9266	0.8983	1.1366	0.7769	0.7637	0.7591	0.7515	0.6443
100 samples	Basic	1.2419	1.1435	1.0728	1.5256	0.9064	0.9180	0.8424	1.2342	0.6617	0.6543	0.5449	0.8105
	SMOTE	1.1691	1.1556	1.2027	1.3094	0.9424	1.0322	0.9316	1.4766	0.6393	0.6734	0.5619	1.1468
	Mixup	1.2142	1.1686	1.0163	1.4790	0.8924	0.9416	0.9017	1.1995	0.6114	0.6427	0.5588	0.8704
	TVAE	1.2576	1.1789	1.0899	1.4001	0.9056	0.9286	1.0536	1.3462	0.6617	0.6642	0.5991	0.9799
	CTGAN	1.3399	1.2626	1.2055	2.0532	0.9531	0.9367	0.9310	1.6229	0.7360	0.7378	0.6939	0.9249
	TabDDPM	1.1389	1.0968	1.0030	1.3520	0.9438	0.9480	0.9091	1.4592	0.6194	0.6463	0.5875	0.9255
	TABSYN	1.2677	1.1815	1.1405	1.4950	0.9368	0.9186	0.8988	1.1631	0.7134	0.7186	0.6710	0.7905
	ARF	1.4749	1.4191	1.3104	2.1456	1.0094	0.9809	0.9797	1.6618	0.8177	0.8284	0.7990	0.9403
	BN	1.1841	1.0933	1.1443	1.1813	0.9091	0.9609	0.9533	1.0037	0.6570	0.6684	0.6530	0.6442
	TabPFGen	1.3065	1.1998	1.0801	1.5254	0.9013	0.9523	0.9716	1.1728	0.6126	0.6322	0.5339	0.8325
	TabEBM	1.1573	1.1473	1.0458	1.3984	0.8997	0.9455	0.8830	1.1573	0.5587	0.5813	0.5235	0.8625
	TabPFN	1.2046	1.1529	1.0149	1.5624	0.8890	0.9190	0.8855	1.6971	0.6405	0.6592	0.6032	0.9182
	KTGen$_b$	1.2531	1.1583	0.9461	1.3714	0.8908	0.9329	0.8645	1.4603	0.6360	0.6359	0.6062	0.8401
	KTGen$_c$	1.0425	1.0055	0.9873	0.7953	0.9028	0.8826	0.8680	0.7596	0.6600	0.6723	0.6730	0.6293

Table 8: **credit**.

		high-bias				medium-bias				unbias			
		XGB	RF	PFN	LR	XGB	RF	PFN	LR	XGB	RF	PFN	LR
20 samples	Basic	0.6040	0.5973	0.6719	0.6454	0.6205	0.6207	0.7154	0.6238	0.6410	0.6535	0.6259	0.6310
	SMOTE	0.6553	0.6695	0.6551	0.6432	0.6126	0.6521	0.6657	0.6314	0.6787	0.6828	0.6910	0.6645
	Mixup	0.5577	0.5829	0.5998	0.6045	0.5631	0.5616	0.5601	0.5749	0.6336	0.6655	0.6005	0.6496
	TVAE	0.5509	0.5936	0.5956	0.5321	0.5753	0.5909	0.6027	0.5751	0.6294	0.6655	0.6430	0.6212
	CTGAN	0.5618	0.6170	0.5992	0.5747	0.5777	0.6569	0.6243	0.5913	0.6020	0.6010	0.6043	0.5674
	TabDDPM	0.5888	0.5974	0.6287	0.5708	0.6776	0.6907	0.6967	0.6415	0.7088	0.7077	0.7020	0.6802
	TABSYN	0.5624	0.6103	0.5911	0.5826	0.5190	0.5324	0.5707	0.5153	0.5988	0.6099	0.5797	0.6011
	ARF	0.5753	0.5972	0.5983	0.5810	0.6044	0.6283	0.6147	0.6225	0.5982	0.6178	0.5928	0.6154
	BN	0.6669	0.6698	0.6775	0.6404	0.6226	0.6722	0.6701	0.6346	0.6534	0.6773	0.6721	0.6600
	TabPFGen	0.6393	0.6594	0.6837	0.6503	0.6077	0.6419	0.6876	0.6276	0.6847	0.6969	0.6925	0.6985
	TabEBM	0.6039	0.6356	0.6529	0.6277	0.6630	0.6787	0.6914	0.6575	0.7209	0.7380	0.7319	0.7158
	TabPFN	0.6243	0.6549	0.6577	0.6506	0.5940	0.6435	0.6201	0.5979	0.6338	0.6402	0.6499	0.6211
	$KTGen_b$	0.5861	0.6441	0.6539	0.6294	0.5833	0.6131	0.6298	0.5928	0.6988	0.6911	0.6882	0.6584
	$KTGen_c$	0.6177	0.6829	0.6703	0.6530	0.6282	0.6746	0.6636	0.6369	0.6643	0.6888	0.6721	0.6601
50 samples	Basic	0.6698	0.6793	0.6508	0.6555	0.6978	0.6908	0.7097	0.6627	0.6926	0.7205	0.7201	0.6722
	SMOTE	0.6541	0.6653	0.6452	0.6653	0.6968	0.7090	0.6662	0.6403	0.6879	0.6737	0.6536	0.6618
	Mixup	0.6185	0.6276	0.5979	0.6227	0.5850	0.6179	0.5762	0.6236	0.6276	0.6299	0.6135	0.6299
	TVAE	0.5985	0.6225	0.6114	0.5862	0.6622	0.6849	0.7077	0.6661	0.6173	0.6626	0.6979	0.6760
	CTGAN	0.6110	0.6369	0.6210	0.5824	0.6871	0.7002	0.7000	0.6497	0.5866	0.6570	0.6204	0.5896
	TabDDPM	0.6571	0.6700	0.6549	0.6512	0.6776	0.6907	0.6967	0.6415	0.7088	0.7077	0.7020	0.6802
	TABSYN	0.6543	0.6609	0.6523	0.6259	0.6271	0.6587	0.6761	0.5981	0.5958	0.6232	0.6693	0.6340
	ARF	0.6445	0.6483	0.6150	0.6410	0.6376	0.6498	0.6065	0.5800	0.6087	0.6157	0.5933	0.5876
	BN	0.6499	0.6594	0.6700	0.6522	0.6979	0.7096	0.6816	0.6217	0.6820	0.6718	0.6682	0.6489
	TabPFGen	0.6638	0.6760	0.6495	0.6699	0.6264	0.6398	0.6687	0.6366	0.5925	0.6245	0.6552	0.6007
	TabEBM	0.6449	0.6539	0.6345	0.6426	0.6630	0.6787	0.6914	0.6575	0.7209	0.7380	0.7319	0.7158
	TabPFN	0.6649	0.6742	0.6824	0.6691	0.6673	0.6841	0.6717	0.6283	0.6725	0.6821	0.6551	0.6443
	$KTGen_b$	0.6327	0.6448	0.6639	0.6401	0.6582	0.6729	0.6787	0.6256	0.6762	0.6905	0.6672	0.6551
	$KTGen_c$	0.6984	0.6965	0.6993	0.6701	0.6888	0.7071	0.7067	0.6632	0.7023	0.7239	0.7073	0.6750
100 samples	Basic	0.7024	0.7162	0.7191	0.7039	0.7346	0.7421	0.7404	0.7080	0.7268	0.7514	0.7305	0.6719
	SMOTE	0.6869	0.7090	0.6910	0.6924	0.7247	0.7318	0.7073	0.7016	0.7426	0.7559	0.7209	0.7176
	Mixup	0.6676	0.6820	0.6506	0.6825	0.6962	0.7050	0.6687	0.6847	0.7059	0.7253	0.6826	0.6702
	TVAE	0.6875	0.7161	0.7004	0.6821	0.6912	0.7078	0.7245	0.6905	0.7191	0.7505	0.7422	0.7015
	CTGAN	0.6810	0.7087	0.6930	0.6662	0.6940	0.7057	0.7078	0.6882	0.6976	0.7182	0.7237	0.6623
	TabDDPM	0.6776	0.6907	0.6967	0.6415	0.7088	0.7077	0.7020	0.6802	0.7019	0.7264	0.6885	0.6119
	TABSYN	0.7077	0.7316	0.7366	0.6843	0.7075	0.7185	0.7225	0.6965	0.7040	0.7087	0.7100	0.6642
	ARF	0.6977	0.7146	0.6806	0.6920	0.6845	0.7115	0.6964	0.7085	0.7129	0.7401	0.7061	0.7142
	BN	0.6788	0.6943	0.6735	0.6777	0.7231	0.7276	0.6839	0.6849	0.7346	0.7501	0.6926	0.6953
	TabPFGen	0.7044	0.7029	0.7133	0.7074	0.7220	0.7239	0.7383	0.7208	0.6893	0.7098	0.7002	0.6771
	TabEBM	0.6927	0.7049	0.7023	0.6921	0.7209	0.7380	0.7319	0.7158	0.6824	0.7214	0.6955	0.6776
	TabPFN	0.6786	0.6984	0.6796	0.6769	0.6916	0.7144	0.7038	0.6876	0.7040	0.7234	0.6983	0.6556
	$KTGen_b$	0.6885	0.6876	0.6962	0.6793	0.6898	0.6954	0.6986	0.6790	0.7145	0.7462	0.7197	0.6993
	$KTGen_c$	0.7152	0.7255	0.7049	0.7051	0.7260	0.7328	0.7339	0.7148	0.7418	0.7725	0.7304	0.7258

Table 9: **default**.

		high-bias				medium-bias				unbias			
		XGB	RF	PFN	LR	XGB	RF	PFN	LR	XGB	RF	PFN	LR
20 samples	Basic	0.6293	0.6321	0.6251	0.6141	0.5264	0.5360	0.5472	0.5963	0.5400	0.5721	0.6106	0.6263
	SMOTE	0.6078	0.6171	0.5917	0.6092	0.5313	0.5410	0.5585	0.5752	0.5740	0.5998	0.5725	0.5736
	Mixup	0.6055	0.6347	0.6170	0.6004	0.5472	0.5799	0.5411	0.5583	0.6052	0.6267	0.6093	0.5640
	TVAE	0.6410	0.6527	0.6669	0.6466	0.5306	0.5240	0.5465	0.5460	0.6033	0.6067	0.6084	0.5916
	CTGAN	0.5777	0.5815	0.5928	0.5759	0.4805	0.4796	0.4661	0.4189	0.5732	0.5748	0.5711	0.5993
	TabDDPM	0.5481	0.5712	0.5574	0.5391	0.5223	0.5416	0.5444	0.5086	0.5721	0.5981	0.5523	0.5471
	TABSYN	0.5749	0.5910	0.6067	0.5919	0.5248	0.5472	0.5432	0.5319	0.5832	0.6100	0.5822	0.5636
	ARF	0.6318	0.6469	0.6152	0.5976	0.5646	0.5815	0.6115	0.5748	0.5699	0.5823	0.5619	0.5426
	BN	0.6061	0.6128	0.6209	0.6042	0.5688	0.5858	0.5956	0.5776	0.6098	0.6085	0.6350	0.5769
	TabPFGen	0.6119	0.6199	0.6339	0.6168	0.5110	0.5088	0.5123	0.5470	0.6512	0.6496	0.6203	0.5666
	TabEBM	0.6183	0.6257	0.6013	0.6083	0.5485	0.5490	0.5328	0.5482	0.6347	0.6223	0.6331	0.5998
	TabPFN	0.6170	0.6298	0.6173	0.5874	0.5119	0.5409	0.5566	0.5352	0.6225	0.6239	0.5765	0.5617
	KTGen_b	0.6207	0.6243	0.6036	0.5707	0.5016	0.5272	0.5684	0.5494	0.5947	0.6220	0.5993	0.5528
	KTGen_c	0.6571	0.6967	0.6539	0.6760	0.6913	0.6846	0.6162	0.6495	0.6816	0.6998	0.6680	0.6934
50 samples	Basic	0.6107	0.6413	0.6560	0.5923	0.5835	0.6413	0.6396	0.6243	0.6679	0.6982	0.6990	0.6662
	SMOTE	0.6165	0.6258	0.6054	0.5685	0.6127	0.6240	0.5863	0.5888	0.6731	0.6780	0.6708	0.6162
	Mixup	0.6171	0.6304	0.6213	0.5654	0.6364	0.6654	0.6225	0.6005	0.6838	0.6912	0.6757	0.6270
	TVAE	0.5727	0.6021	0.5801	0.5832	0.5730	0.5919	0.5676	0.5529	0.6507	0.6614	0.6692	0.6722
	CTGAN	0.5507	0.5777	0.5363	0.5480	0.5854	0.6161	0.6060	0.5863	0.5979	0.6262	0.6288	0.6429
	TabDDPM	0.5880	0.5955	0.6046	0.5197	0.5987	0.6277	0.6378	0.5354	0.6937	0.6942	0.6883	0.6441
	TABSYN	0.5925	0.5964	0.6010	0.5368	0.6024	0.6320	0.6593	0.6513	0.6369	0.6526	0.6653	0.6631
	ARF	0.5963	0.5869	0.5974	0.5229	0.5951	0.5929	0.5866	0.5536	0.6836	0.6880	0.6767	0.6277
	BN	0.6075	0.6304	0.6424	0.5643	0.6355	0.6380	0.6142	0.5982	0.6698	0.6807	0.6759	0.6206
	TabPFGen	0.6164	0.6186	0.6360	0.5821	0.6542	0.6605	0.6473	0.6147	0.7055	0.7036	0.6586	0.6415
	TabEBM	0.6549	0.6757	0.6396	0.5957	0.6398	0.6536	0.6421	0.6369	0.6952	0.6994	0.6783	0.6800
	TabPFN	0.5949	0.6083	0.5974	0.5683	0.6343	0.6501	0.6245	0.5882	0.6716	0.6897	0.6516	0.6265
	KTGen_b	0.5954	0.5984	0.6065	0.5713	0.6450	0.6535	0.6182	0.6042	0.6846	0.7068	0.6810	0.6425
	KTGen_c	0.6493	0.6893	0.6756	0.6560	0.6950	0.7066	0.6670	0.6944	0.7075	0.7305	0.7052	0.6909
100 samples	Basic	0.6723	0.6859	0.6859	0.6332	0.6356	0.6459	0.6880	0.6442	0.6841	0.6807	0.6910	0.6096
	SMOTE	0.6621	0.6607	0.6379	0.6312	0.6401	0.6415	0.6142	0.6377	0.6919	0.6921	0.6757	0.6367
	Mixup	0.6726	0.6760	0.6584	0.6232	0.6657	0.6656	0.6621	0.6287	0.7097	0.7065	0.6876	0.6500
	TVAE	0.6127	0.6203	0.6249	0.5814	0.6267	0.6334	0.6604	0.6215	0.6563	0.6697	0.6778	0.6305
	CTGAN	0.5930	0.6183	0.6283	0.6237	0.6406	0.6521	0.6667	0.6315	0.6810	0.6766	0.6772	0.6385
	TabDDPM	0.6395	0.6426	0.6888	0.5852	0.6605	0.6606	0.6816	0.5535	0.6786	0.6858	0.6775	0.5767
	TABSYN	0.6403	0.6517	0.6691	0.6173	0.6459	0.6524	0.6667	0.6421	0.6368	0.6515	0.6638	0.6254
	ARF	0.6239	0.6105	0.6054	0.5461	0.5951	0.5929	0.5866	0.5536	0.6836	0.6880	0.6767	0.6277
	BN	0.6738	0.6720	0.6286	0.6344	0.6648	0.6636	0.6366	0.6278	0.6930	0.6978	0.6789	0.6324
	TabPFGen	0.6916	0.6855	0.6788	0.6392	0.6777	0.6808	0.6838	0.6545	0.7122	0.7147	0.6768	0.6632
	TabEBM	0.6812	0.6877	0.6690	0.6564	0.6830	0.6870	0.6826	0.6533	0.7191	0.7219	0.7026	0.6774
	TabPFN	0.6744	0.6813	0.6444	0.6374	0.6755	0.6767	0.6476	0.6211	0.7029	0.7179	0.6823	0.6346
	KTGen_b	0.6621	0.6577	0.6475	0.6220	0.6770	0.6988	0.6577	0.6195	0.6902	0.7145	0.6879	0.6327
	KTGen_c	0.7158	0.7242	0.6915	0.6719	0.7092	0.7124	0.6969	0.6685	0.7194	0.7325	0.7009	0.6790

Table 10: **diabetes**.

		high-bias				medium-bias				unbias			
		XGB	RF	PFN	LR	XGB	RF	PFN	LR	XGB	RF	PFN	LR
20 samples	Basic	0.6249	0.6967	0.7023	0.7129	0.6547	0.7369	0.7513	0.7471	0.7449	0.7519	0.7288	0.7247
	SMOTE	0.6197	0.6478	0.6262	0.7012	0.7204	0.7437	0.7100	0.7330	0.7094	0.7329	0.7408	0.7299
	Mixup	0.6537	0.6686	0.6154	0.7024	0.7252	0.7400	0.6986	0.7389	0.6954	0.6983	0.7247	0.7095
	TVAE	0.5930	0.6321	0.6896	0.6612	0.6941	0.7273	0.7170	0.7283	0.7209	0.7378	0.7327	0.7405
	CTGAN	0.6344	0.6948	0.6520	0.6694	0.6727	0.6550	0.6949	0.6545	0.6418	0.6332	0.6196	0.5581
	TabDDPM	0.5637	0.6281	0.5152	0.6227	0.6324	0.6543	0.6360	0.6912	0.6428	0.6493	0.6388	0.6560
	TABSYN	0.6164	0.6566	0.6107	0.6501	0.6898	0.7127	0.7146	0.7419	0.7081	0.7207	0.6953	0.7002
	ARF	0.6410	0.6603	0.5827	0.6310	0.6111	0.6170	0.5974	0.6129	0.6397	0.6557	0.6523	0.6770
	BN	0.6679	0.6797	0.6601	0.7017	0.7181	0.7224	0.7071	0.7343	0.7138	0.7189	0.7142	0.7106
	TabPFGen	0.6795	0.6872	0.6965	0.7245	0.6856	0.6725	0.6649	0.7240	0.6765	0.7021	0.7206	0.7200
	TabEBM	0.6697	0.6871	0.6957	0.7089	0.6966	0.7039	0.7295	0.7594	0.7087	0.7121	0.7230	0.6948
	TabPFN	0.6757	0.7039	0.6573	0.7039	0.7089	0.7038	0.6562	0.6765	0.6948	0.7221	0.7005	0.7019
	KTGen$_b$	0.6686	0.6926	0.6525	0.7231	0.7028	0.7151	0.7041	0.7131	0.6773	0.6924	0.7071	0.7073
	KTGen$_c$	0.7449	0.7635	0.7300	0.7950	0.7687	0.7682	0.7472	0.7764	0.7737	0.7840	0.7608	0.7775
50 samples	Basic	0.7297	0.7474	0.7687	0.7491	0.7518	0.7647	0.7720	0.7800	0.7397	0.7517	0.7737	0.7621
	SMOTE	0.7034	0.7176	0.6754	0.7377	0.7364	0.7524	0.7310	0.7773	0.7243	0.7438	0.7711	0.7944
	Mixup	0.7169	0.7338	0.7181	0.7316	0.7288	0.7418	0.7380	0.7770	0.7136	0.7266	0.7583	0.7858
	TVAE	0.7215	0.7286	0.7461	0.7372	0.7176	0.7447	0.7501	0.7136	0.7201	0.7368	0.7620	0.7625
	CTGAN	0.6879	0.7459	0.7537	0.7366	0.6942	0.7106	0.7237	0.7363	0.6950	0.7025	0.7391	0.7638
	TabDDPM	0.6675	0.7078	0.7391	0.7075	0.7152	0.7387	0.7222	0.6103	0.7385	0.7428	0.7284	0.6606
	TABSYN	0.7136	0.7444	0.7463	0.7312	0.6753	0.7070	0.7278	0.7164	0.7182	0.7340	0.7579	0.7395
	ARF	0.7169	0.7521	0.6825	0.7152	0.7180	0.7271	0.7194	0.7431	0.7330	0.7354	0.7498	0.7871
	BN	0.7271	0.7290	0.6978	0.7248	0.7391	0.7506	0.7091	0.7797	0.7269	0.7381	0.7330	0.7914
	TabPFGen	0.7539	0.7547	0.7444	0.7713	0.7146	0.7231	0.7394	0.7687	0.7107	0.7212	0.7610	0.7821
	TabEBM	0.7400	0.7599	0.7619	0.7656	0.7383	0.7409	0.7709	0.7750	0.7299	0.7324	0.7682	0.7838
	TabPFN	0.7169	0.7350	0.7087	0.7422	0.7294	0.7362	0.7087	0.7496	0.7279	0.7397	0.7552	0.7844
	KTGen$_b$	0.6994	0.7194	0.6966	0.7385	0.7125	0.7247	0.7139	0.7442	0.7180	0.7262	0.7434	0.7725
	KTGen$_c$	0.7744	0.7901	0.7746	0.7754	0.7604	0.7598	0.7624	0.7784	0.7611	0.7664	0.7780	0.7910
100 samples	Basic	0.7660	0.7631	0.7887	0.7945	0.7902	0.7847	0.8066	0.7955	0.7611	0.7609	0.8003	0.7939
	SMOTE	0.7642	0.7694	0.7415	0.7921	0.7888	0.7958	0.7882	0.7902	0.7788	0.7838	0.7945	0.8044
	Mixup	0.7347	0.7357	0.7526	0.7786	0.7751	0.7799	0.7817	0.7888	0.7693	0.7543	0.7865	0.8039
	TVAE	0.7378	0.7726	0.7889	0.7990	0.7461	0.7537	0.7751	0.7751	0.7745	0.7687	0.7913	0.7906
	CTGAN	0.7108	0.7377	0.7616	0.7592	0.7555	0.7487	0.7681	0.7426	0.7838	0.7603	0.7885	0.7892
	TabDDPM	0.7126	0.7417	0.7802	0.6911	0.7505	0.7726	0.7865	0.7400	0.7395	0.7656	0.7845	0.7047
	TABSYN	0.7181	0.7377	0.7669	0.7538	0.7703	0.7796	0.7973	0.7759	0.7705	0.7600	0.7867	0.7820
	ARF	0.7554	0.7625	0.7262	0.7695	0.7843	0.8038	0.7707	0.7839	0.7924	0.7725	0.7849	0.8020
	BN	0.7499	0.7488	0.7303	0.7887	0.7779	0.7835	0.7692	0.7803	0.7774	0.7702	0.7705	0.8076
	TabPFGen	0.7429	0.7498	0.7827	0.7963	0.7845	0.7846	0.8037	0.7809	0.7625	0.7545	0.8156	0.8029
	TabEBM	0.7411	0.7468	0.7791	0.7881	0.7831	0.7800	0.8013	0.7975	0.7536	0.7532	0.8002	0.8014
	TabPFN	0.7516	0.7642	0.7301	0.7775	0.7813	0.7931	0.7760	0.7848	0.7753	0.7628	0.7831	0.8064
	KTGen$_b$	0.7241	0.7316	0.7291	0.7782	0.7712	0.7823	0.7736	0.7771	0.7892	0.7681	0.7835	0.8143
	KTGen$_c$	0.7518	0.7720	0.7606	0.7931	0.7838	0.7920	0.7948	0.7928	0.7765	0.7705	0.7914	0.8048

Table 11: **magic**.

		high-bias				**medium-bias**				**unbias**			
		XGB	RF	PFN	LR	XGB	RF	PFN	LR	XGB	RF	PFN	LR
20 samples	Basic	0.6711	0.6727	0.7028	0.7212	0.6571	0.6483	0.7102	0.6563	0.6194	0.6844	0.7555	0.7430
	SMOTE	0.6230	0.6390	0.6330	0.7032	0.6653	0.6728	0.6850	0.6059	0.7495	0.6938	0.7956	0.7204
	Mixup	0.6410	0.6653	0.6771	0.7004	0.7184	0.6897	0.7032	0.5883	0.7854	0.7571	0.7915	0.7200
	TVAE	0.5840	0.5468	0.5962	0.5555	0.6348	0.6306	0.6183	0.6369	0.6332	0.6331	0.6240	0.5750
	CTGAN	0.6260	0.6126	0.5989	0.5778	0.6505	0.6249	0.5965	0.5383	0.6048	0.6011	0.6888	0.5887
	TabDDPM	0.6530	0.6771	0.6847	0.6087	0.6189	0.6509	0.6515	0.6170	0.5835	0.5685	0.6972	0.4763
	TABSYN	0.6408	0.6474	0.6332	0.6596	0.6225	0.6138	0.5691	0.5519	0.5489	0.6042	0.5949	0.4432
	ARF	0.6464	0.6489	0.6581	0.6740	0.6323	0.6270	0.5757	0.5402	0.6823	0.6656	0.7338	0.5817
	BN	0.6718	0.6653	0.6735	0.7110	0.6950	0.7039	0.7278	0.6001	0.7592	0.7370	0.7744	0.7193
	TabPFGen	0.6816	0.6742	0.6874	0.6966	0.6673	0.6817	0.7047	0.6416	0.7140	0.7554	0.7819	0.7400
	TabEBM	0.6957	0.6846	0.7007	0.6956	0.6627	0.6830	0.6987	0.6357	0.7034	0.7471	0.7664	0.7107
	TabPFN	0.6460	0.6541	0.6746	0.6863	0.6710	0.6685	0.7359	0.6721	0.6777	0.6907	0.7359	0.6703
	KTGen_b	0.6730	0.6844	0.6869	0.6835	0.6627	0.6756	0.6964	0.6636	0.7064	0.7075	0.7418	0.6515
	KTGen_c	0.6928	0.6885	0.7530	0.8120	0.7875	0.7620	0.8092	0.8037	0.7676	0.7862	0.8039	0.8339
50 samples	Basic	0.8009	0.7733	0.8403	0.8095	0.7133	0.6789	0.8223	0.7732	0.7473	0.8171	0.8788	0.8168
	SMOTE	0.7930	0.7846	0.7941	0.7932	0.7857	0.7951	0.7681	0.7508	0.8032	0.8048	0.8759	0.7503
	Mixup	0.8190	0.8136	0.8276	0.8090	0.7867	0.7853	0.7978	0.7299	0.7473	0.8052	0.8577	0.7506
	TVAE	0.7593	0.7693	0.7960	0.7244	0.7098	0.7092	0.7340	0.6937	0.6965	0.7410	0.7738	0.6175
	CTGAN	0.7700	0.7786	0.7702	0.7457	0.6625	0.6593	0.6834	0.6382	0.6007	0.6843	0.7262	0.6822
	TabDDPM	0.7613	0.7573	0.8296	0.6694	0.7079	0.7033	0.7426	0.6059	0.7985	0.8230	0.8415	0.7316
	TABSYN	0.7287	0.7492	0.7331	0.7032	0.6729	0.6734	0.6848	0.7270	0.7642	0.7797	0.7930	0.7938
	ARF	0.8030	0.8007	0.7961	0.7729	0.7704	0.7727	0.7624	0.7074	0.7301	0.7682	0.7603	0.6928
	BN	0.8124	0.8101	0.8109	0.7902	0.7843	0.7905	0.7478	0.7601	0.7618	0.7968	0.8136	0.7325
	TabPFGen	0.8002	0.7928	0.8284	0.8186	0.7720	0.7727	0.7931	0.7822	0.7417	0.7914	0.8422	0.7810
	TabEBM	0.8161	0.8106	0.8352	0.8184	0.7644	0.7654	0.7923	0.7867	0.7533	0.7994	0.8182	0.7808
	TabPFN	0.8064	0.8086	0.8123	0.8099	0.7722	0.7691	0.7794	0.7546	0.7856	0.7906	0.7963	0.7755
	KTGen_b	0.8226	0.8204	0.8324	0.8061	0.7794	0.7653	0.8023	0.7203	0.7302	0.7760	0.8271	0.7785
	KTGen_c	0.7671	0.7697	0.8306	0.8230	0.7601	0.7533	0.8204	0.8276	0.7325	0.7556	0.8622	0.8181
100 samples	Basic	0.8243	0.8310	0.8525	0.8164	0.7950	0.7991	0.8723	0.8221	0.8725	0.8708	0.9011	0.8273
	SMOTE	0.8053	0.8125	0.8099	0.8040	0.8235	0.8370	0.8014	0.8034	0.8855	0.8848	0.8968	0.8291
	Mixup	0.8189	0.8192	0.8004	0.8156	0.8359	0.8452	0.8462	0.8061	0.8867	0.8882	0.8914	0.8256
	TVAE	0.7658	0.7672	0.7623	0.7520	0.7753	0.7934	0.8227	0.7662	0.8140	0.8233	0.8280	0.7857
	CTGAN	0.6909	0.7157	0.7300	0.7026	0.7196	0.7456	0.8100	0.6892	0.8456	0.8510	0.8351	0.7702
	TabDDPM	0.7391	0.7824	0.8410	0.6059	0.7205	0.7463	0.8071	0.5636	0.8613	0.8562	0.8768	0.6568
	TABSYN	0.7783	0.8020	0.8384	0.8065	0.7747	0.7766	0.8061	0.7651	0.8478	0.8526	0.8787	0.8332
	ARF	0.8091	0.8032	0.8053	0.7841	0.7704	0.7727	0.7624	0.7074	0.7301	0.7682	0.7603	0.6928
	BN	0.8179	0.8293	0.7805	0.8032	0.8366	0.8383	0.8076	0.8098	0.8809	0.8789	0.8598	0.8242
	TabPFGen	0.8047	0.8108	0.8195	0.7944	0.8320	0.8314	0.8458	0.8058	0.8811	0.8805	0.8998	0.8259
	TabEBM	0.8260	0.8299	0.8363	0.8241	0.8370	0.8364	0.8576	0.8091	0.8842	0.8812	0.9020	0.8231
	TabPFN	0.8171	0.8342	0.8028	0.8095	0.8276	0.8402	0.8247	0.7558	0.8800	0.8801	0.8911	0.8229
	KTGen_b	0.7978	0.8102	0.8124	0.8054	0.8249	0.8435	0.8525	0.7681	0.8851	0.8836	0.8987	0.8232
	KTGen_c	0.7915	0.7829	0.8488	0.8291	0.7719	0.7971	0.8700	0.8295	0.8295	0.8283	0.8864	0.8333

Table 12: **shopper**.

		high-bias				**medium-bias**				**unbias**			
		XGB	RF	PFN	LR	XGB	RF	PFN	LR	XGB	RF	PFN	LR
20 samples	Basic	0.6306	0.6872	0.6988	0.6981	0.7575	0.7549	0.8109	0.7525	0.6734	0.7262	0.7746	0.7071
	SMOTE	0.6720	0.7200	0.7167	0.6870	0.7875	0.8087	0.7845	0.7535	0.8189	0.8156	0.8189	0.7582
	Mixup	0.6836	0.7096	0.7045	0.6782	0.7856	0.7903	0.7565	0.7472	0.8238	0.8160	0.8175	0.7358
	TVAE	0.5822	0.6146	0.6304	0.5934	0.6568	0.7013	0.7107	0.6926	0.7619	0.7768	0.7542	0.7307
	CTGAN	0.6250	0.6871	0.6396	0.6967	0.6213	0.6340	0.7186	0.6334	0.6803	0.6897	0.6679	0.5855
	TabDDPM	0.5835	0.5867	0.5839	0.5284	0.5657	0.6034	0.5721	0.5595	0.6919	0.7315	0.7023	0.7159
	TABSYN	0.5968	0.6498	0.6074	0.6865	0.6415	0.6814	0.7273	0.6756	0.6967	0.7262	0.7374	0.7460
	ARF	0.6320	0.6357	0.6177	0.6678	0.6864	0.7190	0.7852	0.7304	0.7598	0.7396	0.7560	0.7013
	BN	0.6840	0.7016	0.7036	0.6890	0.8008	0.7938	0.7463	0.7602	0.8408	0.8434	0.8216	0.7487
	TabPFGen	0.6367	0.6527	0.7451	0.7129	0.7812	0.7902	0.7757	0.7551	0.8174	0.8315	0.8216	0.7481
	TabEBM	0.6926	0.7063	0.7096	0.7254	0.7939	0.8011	0.8128	0.8138	0.8064	0.8206	0.8237	0.8240
	TabPFN	0.5758	0.6222	0.6506	0.6246	0.7097	0.7273	0.7085	0.6878	0.7465	0.7579	0.7440	0.6775
	KTGen_b	0.6300	0.6505	0.6587	0.6564	0.7170	0.7365	0.7554	0.6955	0.7586	0.7611	0.7605	0.6795
	KTGen_c	0.7276	0.7383	0.6944	0.7050	0.7632	0.7779	0.7994	0.7730	0.7847	0.8068	0.8010	0.7676
50 samples	Basic	0.7575	0.7897	0.8228	0.7448	0.7763	0.7835	0.8164	0.7405	0.8425	0.8211	0.8623	0.7623
	SMOTE	0.7907	0.8130	0.7896	0.7210	0.7920	0.8165	0.7924	0.7092	0.8516	0.8467	0.8667	0.7928
	Mixup	0.7590	0.7711	0.7146	0.6969	0.7659	0.7879	0.7344	0.6958	0.8349	0.8314	0.8415	0.8008
	TVAE	0.7753	0.7900	0.7821	0.7091	0.7176	0.7347	0.7352	0.7187	0.8195	0.7970	0.7998	0.7735
	CTGAN	0.7707	0.7695	0.7831	0.7570	0.6709	0.6805	0.6897	0.6822	0.7868	0.7824	0.8114	0.7258
	TabDDPM	0.5990	0.6343	0.6509	0.6231	0.6790	0.6843	0.7531	0.6218	0.8080	0.8279	0.8566	0.7119
	TABSYN	0.7630	0.7996	0.7829	0.7114	0.7028	0.7246	0.7243	0.6653	0.7800	0.7884	0.7802	0.7398
	ARF	0.7542	0.7418	0.7396	0.7139	0.8215	0.8393	0.8422	0.7888	0.8289	0.8119	0.8314	0.7928
	BN	0.7867	0.8026	0.7812	0.7293	0.7719	0.7768	0.7335	0.7164	0.8144	0.8271	0.8215	0.7858
	TabPFGen	0.7704	0.7882	0.7961	0.7525	0.7665	0.7893	0.7761	0.6930	0.8437	0.8530	0.8509	0.7970
	TabEBM	0.7876	0.7838	0.7996	0.7792	0.8243	0.8208	0.8109	0.7594	0.8503	0.8468	0.8620	0.8238
	TabPFN	0.7590	0.7783	0.7594	0.7471	0.7141	0.7140	0.6993	0.6720	0.7880	0.8011	0.8264	0.7850
	KTGen_b	0.7305	0.7500	0.7225	0.7188	0.7389	0.7385	0.6955	0.6774	0.8179	0.8174	0.8356	0.7885
	KTGen_c	0.8047	0.7649	0.7752	0.7391	0.8090	0.8183	0.7658	0.6985	0.8283	0.8435	0.8392	0.7428
100 samples	Basic	0.8316	0.8277	0.8514	0.7680	0.8745	0.8683	0.8951	0.7908	0.8381	0.8568	0.8639	0.8084
	SMOTE	0.8336	0.8396	0.8042	0.7620	0.8703	0.8735	0.8333	0.7633	0.8735	0.8826	0.8563	0.7993
	Mixup	0.8012	0.8087	0.7736	0.7489	0.8383	0.8544	0.7985	0.7715	0.8611	0.8638	0.8403	0.8144
	TVAE	0.7999	0.8117	0.8102	0.7118	0.8191	0.8378	0.8169	0.7456	0.8221	0.8433	0.8511	0.8146
	CTGAN	0.6904	0.6969	0.6160	0.5895	0.8379	0.8463	0.8374	0.7804	0.8345	0.8472	0.8586	0.8067
	TabDDPM	0.6926	0.7134	0.7333	0.6416	0.8018	0.8042	0.8459	0.5719	0.8518	0.8461	0.8417	0.6193
	TABSYN	0.8004	0.7969	0.8103	0.7525	0.8389	0.8602	0.8681	0.7783	0.8469	0.8565	0.8705	0.7858
	ARF	0.8355	0.8354	0.8172	0.8022	0.8732	0.8768	0.8522	0.8087	0.8384	0.8552	0.8616	0.8332
	BN	0.8178	0.8066	0.7587	0.7571	0.8643	0.8720	0.8161	0.7700	0.8499	0.8622	0.8380	0.8055
	TabPFGen	0.8123	0.8249	0.8215	0.7456	0.8774	0.8783	0.8734	0.8045	0.8546	0.8520	0.8469	0.8141
	TabEBM	0.8178	0.8494	0.8340	0.8122	0.8667	0.8896	0.8821	0.8446	0.8681	0.8663	0.8849	0.8611
	TabPFN	0.7454	0.7633	0.7227	0.7193	0.8370	0.8259	0.8027	0.7715	0.8304	0.8178	0.8158	0.7779
	KTGen_b	0.7424	0.7710	0.7661	0.7154	0.8383	0.8423	0.8303	0.7644	0.8390	0.8442	0.8413	0.8065
	KTGen_c	0.7921	0.8080	0.8328	0.7632	0.8428	0.8585	0.8729	0.7653	0.8546	0.8645	0.8669	0.7819