CTSYN: A FOUNDATIONAL MODEL FOR CROSS TABULAR DATA GENERATION

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ABSTRACT

Generative Foundation Models (GFMs) have achieved remarkable success in producing high-quality synthetic data for images and text. However, their application to tabular data presents significant challenges due to the heterogeneous nature of table features. Current cross-table learning frameworks struggle with the absence of a generative model backbone and a mechanism to decode heterogeneous feature values. To address these challenges, we propose the Cross-Table Synthesizer (CTSyn), a diffusion-based foundational model for tabular data generation. CTSyn features two key components: an Autoencoder network that consolidates diverse tables into a unified latent space and dynamically reconstructs table values based on the provided table schema embedding, adapting to heterogeneous datasets; and a conditional latent diffusion model that samples from this learned latent space. Through large-scale pre-training, CTSyn not only outperforms existing table synthesizers on standard tabular data generation benchmarks in terms of utility and diversity, but also uniquely enhances the performance of downstream machine learning tasks, surpassing what is achievable with real data in low data regime. This establishes CTSyn as a new paradigm for synthetic table generation and a foundation for achieving large-tabular model.

1 INTRODUCTION

Generative Foundation Models (GFMs) have revolutionized fields such as Computer Vision (CV) and Natural Language Processing (NLP)(Bommasani et al., 2021; He et al., 2016; OpenAI, 2023; Touvron et al., 2023; Ramesh et al., 2022; Rombach et al., 2022). Trained on vast datasets (Merity et al., 2016; Deng et al., 2009; Schuhmann et al., 2022) and with versatile model backbones (Vaswani et al., 2017; Ho et al., 2020), these models excel across a diverse range of domains and tasks. They can generate valuable synthetic training examples to boost performances of various downstream applications (Kirillov et al., 2023; Li et al., 2023; Moor et al., 2023; Trabucco et al., 2023; Zhang et al., 2023a).

GFMs also hold immense potential for generating tabular data, a modality integral to core real-world applications (Dash et al., 2019; Borisov et al., 2022; Shwartz-Ziv & Armon, 2022). Despite the ubiquity of tables, modeling often encounters a shortage of high-quality samples. Although tabular data synthesizers have increasingly gained attention (Xu et al., 2019; Kotelnikov et al., 2023; McKenna et al., 2022), they bring little performance gains in downstream models (Elor & Averbuch-Elor, 2022; Manousakas & Aydöre, 2023).This limitation stems from a fundamental constraint: literally synthesizers cannot add information not included in the original training data. Tabular GFMs has the potential of overcoming that limitation by leveraging diverse pre-training data.

Despite such opportunities, the implementation of tabular GFMs remains particularly challenging and largely overlooked, due to the heterogeneity between column structures, features sets and ranges of values (Onishi et al., 2023; Huang et al., 2020; Borisov et al., 2022; Zhu et al., 2023; van Breugel & van der Schaar, 2024). Existing methods for transferable tabular learning either model tables with language models (Ye et al., 2024; Wang & Sun, 2022; Hegselmann et al., 2023; Yan et al., 2024), or attempt to learn a unified latent space across datasets (Wang & Sun, 2022; Onishi et al., 2023; Zhu et al., 2023; Ye et al., 2023). They either lack generative capability, or rely on pre-trained language models that process table as unstructured sentences, distorting the structural information and metadata that are critical to effective tabular modeling.

In response to all these limitations, we propose *CTSyn*, a foundation model framework specifically designed for the generation of heterogeneous tables. *CTSyn* has the following main components:

- **Unified table representation and reconstruction:** We developed a cross-tabular variational autoencoder that tokenizes and embeds heterogeneous table rows, projects them into a unified latent space, and decode tabular values with guidance of table metadata. This approach facilitates the training of models across tabular formats, overcoming the barrier of data-specific structural needs while preserving structural information in table-compatible manner.
- **Generative foundation model:** Our versatile conditional diffusion transformer backbone efficiently samples from the unified latent spaces, allowing for improved flexibility and applicability across various tabular domains.
- **Cross-tabular pre-training** We perform extensive cross-tabular pre-training on a large-scale webdataset of 5 million rows. With diverse data domains covering common table applications, the pre-training serves as foundation for various downstream generation tasks.

Through extensive benchmarking with real-world datasets, we demonstrate that CTSyn extends the pre-train/fine-tuning paradigm to the tabular data generation and sets a new benchmark, surpassing the existing State-Of-The-Art (SOTA). Crucially, by effectively leveraging prior knowledge and incorporate of table metadata, our model unlocks unprecedented potential in synthetic tabular data generation, and can be extend to different tabular task such as regression/classification.

2 Related Work

2.1 Transferable Table Representation

Self-supervised learning can significantly enhance the informativeness of representations for various downstream tasks (Gururangan et al., 2020; Yuan et al., 2021b; Wei et al., 2021; Chen et al., 2024). In the tabular domain, methods like VIME (Yoon et al., 2020) train an encoder using a combination of supervised reconstruction loss and mask-array prediction loss, and SCARF (Bahri et al., 2022) employs contrastive loss by utilizing randomly corrupted feature vectors as positive pairs. Subtab (Ucar et al., 2021) and SSP (Chitlangia et al., 2022) integrates contrastive and reconstruction losses. However, these approaches do not produce transferable representations across tables as they rely on data-specific feature encoding and structures. Xtab (Zhu et al., 2023) and TabRet (Onishi et al., 2023) introduce transformer-based backbones with separate data-specific featurizer or projection heads for each downstream task. These models achieve transferability at the expense of high model complexity that grows with the number of datasets and tasks.

Pre-trained Language Models (PLMs) can be used to unify representation dimensions of heterogeneous features. TransTab (Wang & Sun, 2022) extends Subtab's methodology by tokenizing and then encoding column names and categories, creating a latent space that can be shared across tables. Combining tokenization with masked-value-prediction objective, transformer-based models can be trained to perform predictive task across tables (Ye et al., 2024; Yak et al., 2023; Yang et al., 2024; Yan et al., 2024). However, such methods include neither a generative model backbone, nor a fixed-dimensional row representation and decoder that could be integrated with other generative models.

Another line of research involving PLMs converts tabular features to sentences and model regression/classification problems as NLP tasks (Dinh et al., 2022; Hegselmann et al., 2023; Borisov et al., 2023; Liu et al., 2022; Zhang et al., 2023c;b). Despite enabling transfer learning, these methods face challenges with accurately modeling continuous values and tend to overlook the intrinsic structural properties of tables (van Breugel & van der Schaar, 2024).

2.2 Synthetic Tabular Data Generation

Synthetic Tabular Data Generation(STDG) has long been studied by statisticians (Nowok et al., 2016; Reiter, 2005; Chawla et al., 2002). Recent success of deep generative models significantly advanced its boundary (Che et al., 2017; Kim et al., 2021; Figueira & Vaz, 2022). In particular, CTGAN and TVAE (Xu et al., 2019) combines conditional generation with Generative Adversarial

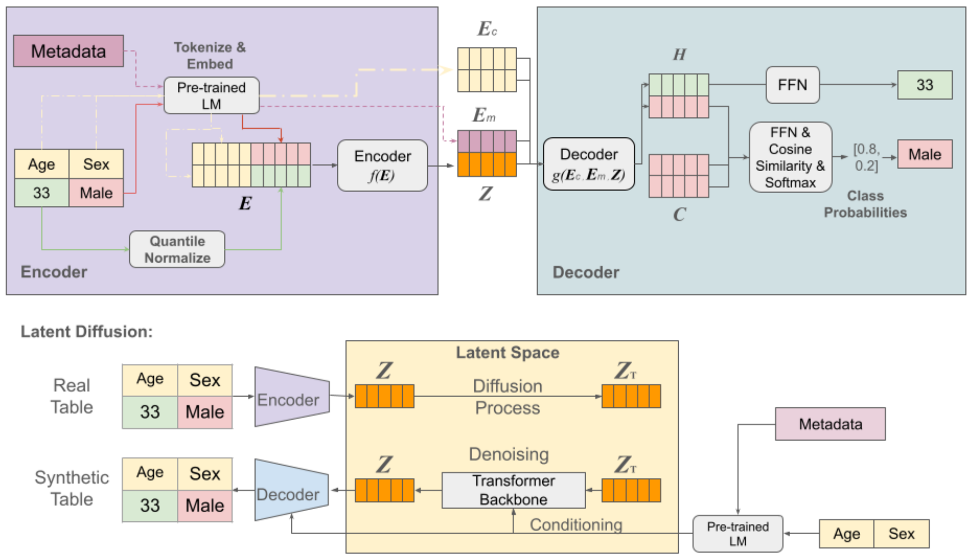


Figure 1: Overview of the proposed CTSyn framework.

Network(GAN) / Variational Autoencoder(VAE) and model-speicif normalization to model highly imbalanced and non-Gaussian columns. CtabGAN+(Zhao et al., 2021; 2024) proposed a solution for mixed-type and long-tailed variable problems. Autodiff (Suh et al., 2023) and Tabsyn (Zhang et al., 2024) used a combination of latent-diffusion and data-specific autoencoder structure, which is the most similar work to ours but missing the critical transferable encoding/decoding ability. TabDDPM (Kotelnikov et al., 2023) achieved the current state-of-the-art in tabular generation with separate diffusion process for numerical and categorical columns. Some models also synthesizes data with Differential Privacy guarantee (Jordon et al., 2018; Zhang et al., 2017; McKenna et al., 2022) Despite their effectiveness in modeling column distributions, none of the above methods is able to effectively boost the training of machine learning models with synthesized data, greatly limiting their usage in data augmentation (Manousakas & Aydöre, 2023).

GReaT (Borisov et al., 2023) and Tabula (Zhao et al., 2023) generate tables with PLMs, by treating tables rows as natural language text. Despite showing evidences of transferrability, they do not consider cross-table pre-training and generation, introduce risk of producing out-of-bound examples due to their unconstrained sampling of output token, and face the well-known challenge of modeling numeracy in discrete token space (Wallace et al., 2019).

3 METHODOLOGY

In this section, we outline *CTSyn*, our solutions to the challenges involved in creating a tabular GFM. Figure 1 provides an overview of the proposed framework.

3.1 FEATURE EMBEDDING

Let an observation (row) in a mixed-type table be represented as $\boldsymbol{x} = [c_1, x_1, c_2, x_2, \ldots, c_p, x_p]$, where c_i for $i = 1, 2, \ldots, p$ are the feature names, and x_i for $i = 1, 2, \ldots, p$ are the corresponding feature values, which can be either numerical or categorical. The parameter p denotes the number of features in this row. Let m_{meta} be the text metadata describing the context of the table.

To facilitate knowledge transfer across tables, it is crucial to develop a unified representation that preserves information at the cell, observation, and table levels. Featuring techniques such as one-hot encoding and mini max standardization losses such structural and contextual information: tables with completely different contents can have identical representation. Thus we tokenize and embed all levels of information into vectors of consistent dimensions to ensure smooth integration. The first step in this process is to consolidate all text metadata, column names, and categorical values, making sure that integer class labels and abbreviations are transformed into their full textual forms, reflecting their original meanings. Then we create embeddings as follows:

$$e_m = \mathbf{LM}(m), \quad e_{c_i} = \mathbf{LM}(c_i), \quad e_{x_i} = \begin{cases} \mathbf{LM}(x_i) & \text{if } x_i \text{ is categorical,} \\ \mathbf{1}(\text{Quantile}(x_i)) & \text{if } x_i \text{ is numerical} \end{cases}$$

where **LM** is a pre-trained language model used to encode text, and it is only invoked once for each unique category or column name. Quantile is a quantile transformer (Pedregosa et al., 2011) fitted on the dataset, which maps numerical values to a uniform distribution. Finally, we interleave all embeddings and flatten them into a sequence:

$$\boldsymbol{E} = [(e_{c_1}, e_{x_1}), (e_{c_2}, e_{x_2}), \ldots, (e_{c_p}, e_{x_p})] \in \mathbb{R}^{p \times 2M_{\text{LM}}}, \tag{1}$$

where M_{LM} is the dimensionality of the language model embeddings. Each step in the sequence is formed by concatenating the column name embedding e_{c_i} with the corresponding column value embedding e_{x_i}. This creates cell level representations, eliminate the need of learning relative position of column name/values, suiting the permutation invariant property of tabular data.

3.2 Autoencoder for heterogenous tables

Encoder: We use an encoder model f to compress the input sequence $\boldsymbol{E}$ into a fixed-dimensional latent vector $\boldsymbol{z} = f(\boldsymbol{E}) \in \mathbb{R}^{\ell \times M_{\text{agg}}}$, where ℓ is the number of latent parameters and M_{agg} is their dimensionality, to facilitate efficient learning for the diffusion model. The encoder follows a Perceiver Resampler (Yuan et al., 2021a) structure, comprising multi-head attention (MHA) blocks and linear layers. The learnable latent parameters serve as queries, while the concatenation of the latent queries and the flattened input sequence $\boldsymbol{E}$ serves as the keys and values.

In each layer of the encoder, a cross-attention operation is performed where the latent queries iteratively attend to both the input sequence (in the first layer) and the latent representations (in subsequent layers). Formally, the output of one attention block is given by:

$$\boldsymbol{Z}^{(l+1)} = \text{FFN}\left(\boldsymbol{Z}^{(l)} + \text{MHA}(q = \boldsymbol{Z}^{(l)}, kv = \boldsymbol{Z}^{(l)})\right)$$

where $\boldsymbol{Z}^{(l)}$ is the latent representation at layer l, MHA$(\cdot)$ represents the multi-head attention operation, and FFN is a feedforward network. At the first layer ($l = 0$), the keys and values are the concatenation of the latent queries and the input sequence, i.e., $kv = [\boldsymbol{Z}^{(0)}; \boldsymbol{E}]$.

Following the variational autoencoder setting, we use two separate encoders, the output of each serves as the mean vector $\mu \in \mathbb{R}^{\ell \times d_{\text{LM}}}$ and the log-variance vector $\log \sigma^2 \in \mathbb{R}^{\ell \times d_{\text{LM}}}$ respectively. For each input, we sample the latent $\boldsymbol{z}$ with the repamaterization trick given predicted μ and $\log \sigma^2$

Decoder with Meta Guidance: To enable cross-tabular training, the decoder must handle varying column orders and combinations of mixed-type columns. Unlike traditional tabular autoencoders, which rely on fixed column orders, our approach uses a transformer-based decoder guided by explicit embeddings of the target column names. Instead of positional embeddings, we encode the column names using a pre-trained language model (PLM) as $\boldsymbol{E_c} = [e_{c_1}, e_{c_2}, \ldots, e_{c_p}]$, where each e_{c_i} represents the embedding of column c_i. These embeddings serve as queries for the decoder.

The table metadata embedding e_m is concatenated with the latent variables $\boldsymbol{z}$ (derived from the encoder) to form the keys and values. The decoder $g(\cdot)$ operates by cross-attend to $\boldsymbol{E_c}$ and $[e_m, \boldsymbol{z}]$. The order of the output from the decoder is thus determined by the order of of columns in $\boldsymbol{E}_c$, and model learns to extract cell information from row latent dynamically. The output of decoder model is $h = g(\boldsymbol{E}_c, [e_m; f(\boldsymbol{E})]) \in R^{p \times M_{\text{decoded}}}$. The decoded dimension is smaller than M_{LM} to allow flexibility in output embedding fine graining.

Table reconstruction The decoded embeddings are used to reconstruct the table cell values. For numerical variables, the decoding process transforms the embedding back into scalar values using a linear layer followed by softmax, resulting in the prediction $\hat{x}_i^{\text{num}}$. For categorical columns, we use a loss based on cosine similarity to handle unseen levels in real applications. Inspired by (Yak et al., 2023), we compute the cosine similarity by first fine-graining both the predicted and real category embeddings using a linear layer, then calculating the cosine similarity between these embeddings, applying softmax on the similarities, and using these as predicted class probabilities $\hat{P}(x_j^{\text{cat}})$. Formally:

$$\begin{cases} \hat{P}(x_j^{\text{cat}}) = \text{Softmax}\left(\text{CosineSim}\left(\text{Linear}(h_j), \text{Linear}(\boldsymbol{C})\right)\right) & \text{if } x_j \text{ is categorical,} \\ \hat{x}_i^{\text{num}} = \text{Softmax}(\text{Linear}(h_i)) \quad \text{if } x_i \text{ is numerical} \end{cases}$$

where h_i and h_j are the latent representations of the i-th numerical cell and j-th categorical cell, respectively, and $\boldsymbol{C}$ represents the set of embeddings for all possible categories in the column. These predicted probabilities and values are then used to reconstruct the original table by mapping the latent space to the appropriate categorical or numerical values for each cell.

Training VAE: Following the β-VAE setup (Higgins et al., 2017), the overall objective is the combination numerical and categorical reconstruction losses, and the KL-divergence $\mathcal{L}_{\text{KL}}$:

$$\mathcal{L} = \sum_{i=1}^{p} \mathcal{L}_{\text{num}}(x_i^{\text{num}}, \hat{x}_i^{\text{num}}) + \sum_{j=1}^{q} \mathcal{L}_{\text{cat}}(x_j^{\text{cat}}, \hat{P}(x_j^{\text{cat}})) + \beta \sum_{k=1}^{\ell} D_{\text{KL}}(\mathcal{N}(\mu_k, \sigma_k^2) \| \mathcal{N}(0, 1)),$$

where $\mathcal{L}_{\text{num}}$ is the MSE loss for numerical variables, $\mathcal{L}_{\text{cat}}$ is the cross-entropy loss for categorical variables, D_{KL} is the KL-divergence loss between the learned latent distribution $\mathcal{N}(\mu_k, \sigma_k^2)$ and the standard Gaussian $\mathcal{N}(0, 1)$, and β is the weight balancing the reconstruction and KL-divergence.

Implementation: We use two layers for both the encoder and decoder, with $\ell = 16$ and $M_{\text{agg}} = 64$. The models are trained using the AdamW optimizer with an initial learning rate of 0.0002. The learning rate is reduced by a factor of 0.7 if the validation loss does not improve for 10 consecutive epochs. We use a β-VAE setup, starting with $\beta_{\text{max}} = 10^{-2}$, and gradually decrease β by multiplying it with 0.7 when the reconstruction loss fails to improve for 5 consecutive epochs, down to a minimum value of 10^{-5}. We construct training batches to contain samples from the same source table, improving efficiency of training by eliminating contrast between examples from non-related domains that are not realistic in application.

3.3 Conditional Diffusion Model for Latent Vector Generation

For cross-tabular generation, a conditional latent diffusion model is preferred because table data can vary significantly across domains, with different column types and distributions. An unconditional model would struggle to generalize across these diverse formats, making it harder to fine-tune for domain-specific tasks. We follow the Denoising Diffusion Probabilistic Model(DDPM) formulation to train a conditional diffusion model with the objective specified below. The input latent variable z is derived from our VAE encoder. For denoising objective, we utilize the v-parameterization strategy, which is more effective for latent diffusion than classic noise prediction strategy. We condition the embedding generation on the embedding sequence $[e_m, E_c]$ which encompass schema of the desired table. The model is trained with the following loss function:

$$\mathcal{L}(\theta) = \mathbb{E}_{t,(z_{\text{src}}, z_{\text{trg}}),\epsilon} \left[\lambda_t \left\| \hat{z}_\theta \left(\sqrt{\alpha_t} z_{\text{trg}} + \sqrt{1-\alpha_t}\epsilon, t, [e_m, E_c]\right) - z_{\text{trg}} \right\|_2^2 \right],$$

where z_{trg} is the latent variable from the target sequence, α_t is the noise schedule. Classifier-free guidance is used to improve sample quality, with conditional and unconditional networks jointly trained, where conditioning is dropped with a probability of 0.1 during training. Following specification in Lovelace et al. (2024), our diffusion model a pre-LayerNorm transformer architecture with 12 layers, hidden dimension of 768, a learnable absolute positional encodings and GeGLU activations function. he noise level is conditioned via a sinusoidal time embedding, which is processed by an MLP and added to the input sequence. Adaptive layer normalization is applied to each feedforward layer, conditioned on the time embedding. To simply training, we pre-compute latent variables for all table observations prior to diffusion training. We use AdamW optimizer with learning rate 0.0001, with cosine annealing scheduler, batch size = 256, and sampling step = 250.

4 EXPERIMENT

4.1 TEST SETUP

In this section, we evaluate the performance of CTSyn in representing tables and generating informative and diverse synthetic tabular data. Our primary research questions are: **1. How effectively does CTSyn represent heterogeneous tables in its unified latent space? 2. Does pre-training on large, general datasets improve the quality of synthetic data generation for downstream tasks?**

Dataset Construction: We use a filtered version of the OpenTab (Ye et al., 2024) dataset for pre-training. The filtering process follows the strategy outlined in (Yan et al., 2024), and we exclude the following types of tables: duplicate tables, tables containing free-text, date-time, or personally identifiable information (PII) columns, tables with fewer than 10,000 rows, and tables with categorical columns in integer label format that cannot be mapped back to their original string representations. After filtering, the pre-training dataset consists of 86 tables with a total of 5.01 million observations.

For downstream benchmarks, we use eleven real-world datasets that are commonly evaluated in tabular synthesis literature (Suh et al., 2023; Kotelnikov et al., 2023; Zhang et al., 2024), as detailed in Table 1. To avoid data leakage, we ensure that no dataset included in pre-training is used for downstream evaluation. Further details on the pre-training and downstream datasets can be found in Appendix D.

Baselines: We compared our method against a wide array of baselines in synthetic data generation. These include modified SMOTE (Chawla et al., 2002) CTGAN and TVAE (Xu et al., 2019) , TabDDPM (Kotelnikov et al., 2023) and TabSyn (Zhang et al., 2024) , AIM (McKenna et al., 2022) and PATE-CTGAN (Jordon et al., 2018), and GReaT (Borisov et al., 2023) . Implementation of baselines are detailed in section B.

Dataset	Rows	Target	Num Cols	Cate Cols
Faults	1941	Classification	34	0
Wilt	4839	Classification	5	1
HTRU2	17898	Classification	8	1
News	39644	Regression	60	0
Bean	13611	Classification	16	1
Obesity	2111	Classification	8	9
Titanic	714	Classification	6	2
Insurance	1338	Regression	4	3
Abalone	4177	Regression	8	1
Shoppers	12330	Classification	16	2
Indian Liver Patient	579	Classification	9	2

Table 1: Summary Statistics of Downstream Datasets

As methods that enable transfer learning, CTSyn and GReaT are first trained on the pre-train set, with the pre-trained checkpoint used as the common initialization for fine-tuning on all downstream tasks. Other baselines have structure specific to downstream tables, and are thus unable to learn from heterogeneous tables in the pre-training set. They only on the fine-tuning sets and then tested on the corresponding holdout test sets. For CTSyn, we pre-train the autoencoder for 300 epochs, diffusion model for 200000 steps. For fine-tuning CTSyn, we train the conditional diffusion model and decoder network of the autoencoder, while freezing the encoder part of the autoencoder to maintain alignment in the latent space. We finetune the decoder for 100 epochs and diffusion model for 10000 steps.

4.2 STATISTICAL FIDELITY

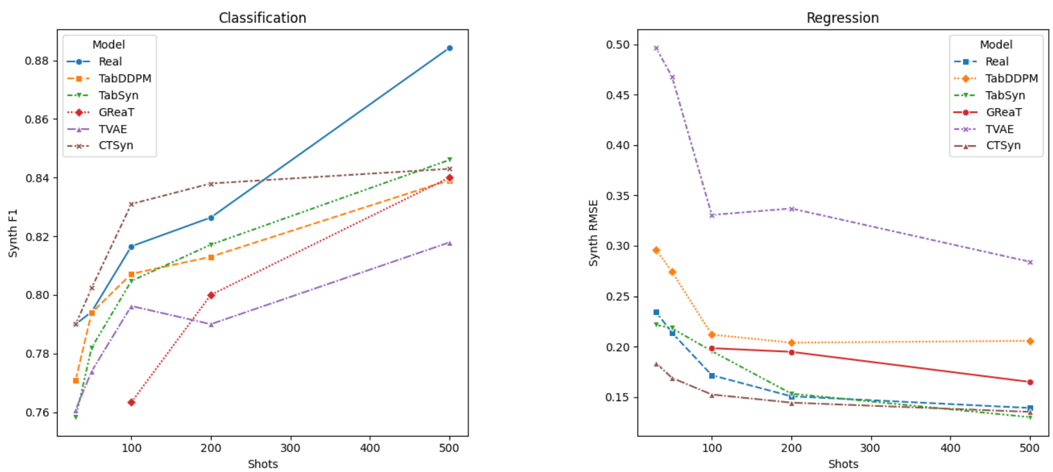
Model	Shape	Corr	Precision	Recall
SMOTE	0.96 (0.02)	0.91 (0.03)	0.68 (0.04)	0.02 (0.003)
CTGAN	0.81 (0.04)	0.73 (0.02)	0.57 (0.03)	0.014 (0.002)
TVAE	0.88 (0.03)	0.89 (0.04)	0.35 (0.02)	0.01 (0.001)
AIM	0.63 (0.05)	0.70 (0.02)	0.01 (0.001)	0.03 (0.003)
PATECTGAN	0.15 (0.01)	0.47 (0.03)	0.01 (0.001)	0.02 (0.002)
TabDDPM	0.93 (0.03)	0.93 (0.02)	0.59 (0.04)	0.027 (0.004)
TabSyn	**0.97** (0.01)	0.93 (0.02)	**0.69** (0.03)	0.003 (0.001)
GReaT	0.90 (0.03)	0.64 (0.04)	0.68 (0.03)	0.005 (0.001)
CTSyn	0.94 (0.02)	**0.95** (0.02)	0.64 (0.04)	**0.075** (0.006)

Table 2: Statistical Fidelity Metrics. Scores are averaged across tested datasets.

We evaluate the similarity between real and synthetic tables based on marginal column distributions, column-wise correlations, and sample-level coverage. For column distributions, we use Kolmogorov-Smirnov (KS) Test for numerical columns and Total Variation Distance (TVD) for categorical columns, and subtract them from one to let higher values indicating better similarity. For column-wise correlation, we apply Pearson's correlation for numerical columns, contingency similarity for categorical columns, and a combined method for mixed types. For sample-level coverage, we measure precision and recall to quantify overlaps between real and synthetic data (Alaa et al., 2022).

Table 2 presents the average similarity in column distribution and correlation across benchmark datasets. CTSyn consistently matches or exceeds state-of-the-art baselines. While methods like TabSyn and SMOTE excel in maintaining lower-order distribution similarity due to their focus on replicating training data distributions, CTSyn demonstrates superior performance in capturing complex relationships between columns. This is particularly evident in its higher correlation scores and significantly better recall, which indicates its ability to preserve important structural relationships within the data, as well as the regularization effect from pre-training.

4.3 Machine Learning Utility



(a) Classification F1-Scores

(b) Regression RMSE

Figure 2: Downstream Machine Learning Utility on Classification and Regrssion Datasets, on synthetic data from different generators.

To evaluate the utility of synthetic data for training machine learning models, we fit the following classifiers: logistic regression, Naive Bayes, decision tree, random forest, XGBoost (Chen & Guestrin, 2016), and CatBoost (Prokhorenkova et al., 2018), then evaluate on the holdout test set. To further explore the ability of each generator to generalize on small datasets, which is critical for real world data augmentation application, we create subsets of the training set with different number of examples(shots), use them to train generators and sample different synthetic tables. Synthetic data modeled from different subsets are all sampled 500 observations to ensure fair comparison, and are evaluated agains the same test set.

Figure 2 reports the average classification F1-score (for classification datasets) and regression root mean squared error(RMSE) across models and shots. For visibility, only the top five performing models are shown. We report scores of remaining models in appendix section E. We observe that for low-data regime (Seedat et al.) with $N \leq 100$, CTSyn consistently outperforms all baselines and even the real data on the corresponding scale. The gaps widen on the interval of 100-200 shots interval. This indicates the ability of CTSyn to leverage pre-training data to assist training in where real data is rare. Note that GReaT failed to generate text that follows table format for $N < 100$. However, as the data size further increases, the advantage of CTSyn fades. We conjecture that this phenomenon is due to ineffective transfer learning setup, and leave transfer learning of tabular GFM beyond simple pre-training/finetuning paradim to future work.

4.4 Diversity and Privacy

We evaluate the diversity and privacy of the synthesized data using two metrics: the Proportion of synthetic examples with L2 Distance closer to the test set (PCT) compared to the training set (Platzer & Reutterer, 2021), and authenticity scores (Alaa et al., 2022), which assess how likely a synthetic data point is a genuine generation rather than a memorization of real data. Lower PCT or authenticity values suggest that synthetic data points are too close to the training set, raising concerns about potential data copying. A powerful generator can easily memorize training data, achieving falsely high fidelity and utility without true generation, thus harming downstream model generalization and breaching individual privacy.

Model	PCT	Authenticity
SMOTE	0.82 (0.24)	0.88 (0.03)
CTGAN	0.84 (0.04)	0.91 (0.29)
TVAE	0.84 (0.01)	0.95 (0.31)
AIM	1.00 (0.00)	1.00 (0.00)
PATECTGAN	1.00 (0.00)	1.00 (0.06)
TabDDPM	0.85 (0.07)	0.87 (0.16)
TabSyn	0.80 (0.03)	0.93 (0.03)
GReaT	0.74 (0.21)	0.79 (0.03)
CTSyn	**0.90 (0.02)**	**0.97 (0.06)**

Table 3: Privacy scores of synthesized data. Best scores of non-DP synthesizers are bolded.

Table 3 presents the diversity scores. CTSyn achieved the highest PCT and authenticity scores compared to state-of-the-art models like TabDDPM and Tabsyn, indicating that CTSyn produces more distinct synthetic data. CTSyn's high PCT scores are comparable to AIM and PATE-CTGAN, which incorporate Differential Privacy (DP) mechanisms to reduce proximity to real data. However, these DP models demonstrated poor fidelity and utility in previous sections. CTSyn, by contrast, achieves a balance between data utility, diversity, and privacy, providing further evidence that pre-training acts as a form of regularization.

We further illustrate the diversity of synthesized data using a 2D-tSNE projection in Figure 3 for the Indian Liver Patient dataset. Among all synthesizers, CTSyn generates the most diverse data distribution convering wider regions around the test set. On the opposite, baseline models tend to overfit to regions surrounding certain data points. This diversity, facilitated by pre-training, explains CTSyn's superior utility, as the diverse pre-training data serves as implicit regularization, promoting better generalization.

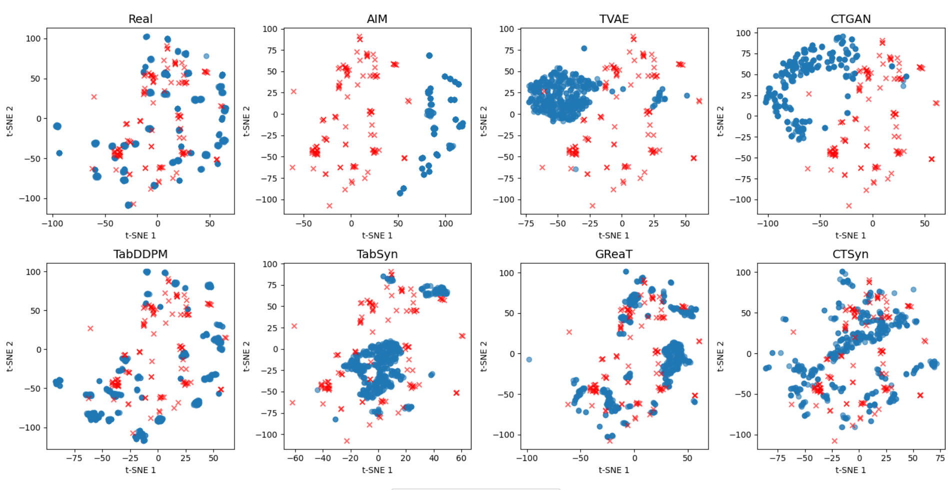


Figure 3: T-sne plot of Indian Liver Patient dataset from different synthesizers.

4.5 Ablation Study

Importance of Metadata. We evaluate key factors for effective cross-tabular representation and reconstruction by testing different autoencoder configurations: (1) removing column name embeddings from the encoder input $\boldsymbol{E}$; (2) removing both column name and metadata embeddings from

Variants	In-distribution		Unseen Columns		Perturbed Columns	
	MSE	Acc	MSE	Acc	MSE	Acc
Column & Meta	0.0004	0.94	0.0063	0.76	0.0005	0.94
Meta Only	0.0008	0.91	0.0082	0.61	0.0009	0.91
PE Only	0.006	0.87	0.07	0.54	0.08	0.67

Table 4: Reconstruction performance of different autoencoder settings.

$\boldsymbol{E}$ and the decoder input, while using positional encoding (PE) as a control for output order. The second setting replaces column name embeddings with PE to assess the impact of structural guidance. These models are trained on the same pre-training data and tested on three scenarios: (1) in-distribution data from the validation splits; (2) unseen data from downstream test datasets; and (3) perturbed data, where columns are randomly permuted.

Table 4 shows the results in terms of mean squared error (MSE) and categorical accuracy. Removing column names primarily affects categorical column reconstruction, emphasizing the need for contextual representation. The removal of all metadata, particularly in favor of PE, significantly worsens performance, especially when handling permuted column order. This highlights a fundamental distinction between tables and unstructured data like text: tables are permutation-invariant, and relying on positional information, as in PE, is ineffective. Metadata, on the other hand, plays a critical role in reconstructing and understanding tabular data structure, underscoring its importance in cross-tabular learning.

Model	Pretrained	Shape	Corr	Synth F1	Synth RMSE	PCT
CTSyn	✓	0.94	0.95	0.84	0.13	0.97
	×	0.96	0.90	0.80	0.17	0.90
GReaT	✓	0.90	0.71	0.79	3.75	0.88
	×	0.90	0.64	0.83	0.18	0.79
TabSyn	✓	0.88	0.82	0.75	0.23	0.90
	×	0.97	0.93	0.84	0.14	0.93

Table 5: Impact of transfer learning on different models.

Impact of pre-training: We compare different model‘s potential of leveraging pre-training data. We repeat the experiments for where CTSyn is not pre-trained, while GReaT and TabSyn are also pre-trained before training on downstream benchmarks. For GReaT we pool all pre-train data into one dataloader to train a pre-trained distiall GPT2, use the resulting model as initialization for downstream benchmark training. For TabSyn, since its model structure is data-specific, we first train separate VAE networks for *each* of the pre-training table, pool and zero-pad all embeddings to the same length and use them to train a latent diffusion model; during downstream training, the VAE embeddings are padded to the same dimension as in pre-training. As shown in table 5, the performance of CTSyn degrades without pre-training, though still on par with other State-of-the-art models across all dimensions. On the other hand, performance change on GReaT and Tabsyn with pre-training is mostly negative, indicating the inability of them to effectively translate knowledge across tabular domains, and further reinforce the need for a model that comprehensively encode tabular structure information like CTSyn.

5 Conclusion

In this paper, we introduced CTSyn, a pioneering framework within the realm of Generative Foundation Models (GFMs) for tabular data. Through extensive experimentation with real data, we demonstrated that CTSyn effectively leverages knowledge from diverse pre-trained tables to enhance synthetic data utility across various downstream datasets, particularly in low-data regime. To the best of our knowledge, our method is the first improve tabular generation performance through combination of latent diffusion and large-scale pre-training, thereby paving the way for overcoming significant challenges in tabular data augmentation using deep generative models.

References

Ahmed Alaa, Boris Van Breugel, Evgeny S Saveliev, and Mihaela van der Schaar. How faithful is your synthetic data? sample-level metrics for evaluating and auditing generative models. In *International Conference on Machine Learning*, pp. 290–306. PMLR, 2022.

Dara Bahri, Heinrich Jiang, Yi Tay, and Donald Metzler. Scarf: Self-supervised contrastive learning using random feature corruption. In *International Conference on Learning Representations*, 2022. URL `https://openreview.net/forum?id=CuV_qYkmKb3`.

Rishi Bommasani, Drew A Hudson, Ehsan Adeli, Russ Altman, Simran Arora, Sydney von Arx, Michael S Bernstein, Jeannette Bohg, Antoine Bosselut, Emma Brunskill, et al. On the opportunities and risks of foundation models. *arXiv preprint arXiv:2108.07258*, 2021.

Vadim Borisov, Tobias Leemann, Kathrin Seßler, Johannes Haug, Martin Pawelczyk, and Gjergji Kasneci. Deep neural networks and tabular data: A survey. *IEEE Transactions on Neural Networks and Learning Systems*, 2022.

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. URL `https://openreview.net/forum?id=cEygmQNOeI`.

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.

Zhengping Che, Yu Cheng, Shuangfei Zhai, Zhaonan Sun, and Yan Liu. Boosting deep learning risk prediction with generative adversarial networks for electronic health records. In *2017 IEEE International Conference on Data Mining (ICDM)*, pp. 787–792. IEEE, 2017.

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.

Xiaokang Chen, Mingyu Ding, Xiaodi Wang, Ying Xin, Shentong Mo, Yunhao Wang, Shumin Han, Ping Luo, Gang Zeng, and Jingdong Wang. Context autoencoder for self-supervised representation learning. *International Journal of Computer Vision*, 132(1):208–223, 2024.

Sharad Chitlangia, Anand Muralidhar, and Rajat Agarwal. Self supervised pre-training for large scale tabular data. 2022.

Sabyasachi Dash, Sushil Kumar Shakyawar, Mohit Sharma, and Sandeep Kaushik. Big data in healthcare: management, analysis and future prospects. *Journal of big data*, 6(1):1–25, 2019.

Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition*, pp. 248–255. Ieee, 2009.

Tuan Dinh, Yuchen Zeng, Ruisu Zhang, Ziqian Lin, Michael Gira, Shashank Rajput, Jy-yong Sohn, Dimitris Papailiopoulos, and Kangwook Lee. Lift: Language-interfaced fine-tuning for non-language machine learning tasks. *Advances in Neural Information Processing Systems*, 35:11763–11784, 2022.

Yotam Elor and Hadar Averbuch-Elor. To smote, or not to smote? *arXiv preprint arXiv:2201.08528*, 2022.

Alvaro Figueira and Bruno Vaz. Survey on synthetic data generation, evaluation methods and gans. *Mathematics*, 10(15):2733, 2022.

Suchin Gururangan, Ana Marasović, Swabha Swayamdipta, Kyle Lo, Iz Beltagy, Doug Downey, and Noah A Smith. Don't stop pretraining: Adapt language models to domains and tasks. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 8342–8360, 2020.

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 770–778, 2016.

Stefan Hegselmann, Alejandro Buendia, Hunter Lang, Monica Agrawal, Xiaoyi Jiang, and David Sontag. Tabllm: Few-shot classification of tabular data with large language models. In *International Conference on Artificial Intelligence and Statistics*, pp. 5549–5581. PMLR, 2023.

Irina Higgins, Loic Matthey, Arka Pal, Christopher P Burgess, Xavier Glorot, Matthew M Botvinick, Shakir Mohamed, and Alexander Lerchner. beta-vae: Learning basic visual concepts with a constrained variational framework. *ICLR (Poster)*, 3, 2017.

Jonathan Ho, Ajay Jain, and Pieter Abbeel. Denoising diffusion probabilistic models. *Advances in neural information processing systems*, 33:6840–6851, 2020.

Xin Huang, Ashish Khetan, Milan Cvitkovic, and Zohar Karnin. Tabtransformer: Tabular data modeling using contextual embeddings. *arXiv preprint arXiv:2012.06678*, 2020.

James Jordon, Jinsung Yoon, and Mihaela Van Der Schaar. Pate-gan: Generating synthetic data with differential privacy guarantees. In *International conference on learning representations*, 2018.

Jayoung Kim, Jinsung Jeon, Jaehoon Lee, Jihyeon Hyeong, and Noseong Park. Oct-gan: Neural ode-based conditional tabular gans. In *Proceedings of the Web Conference 2021*, pp. 1506–1515, 2021.

Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C Berg, Wan-Yen Lo, et al. Segment anything. *arXiv preprint arXiv:2304.02643*, 2023.

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.

Zhuoyan Li, Hangxiao Zhu, Zhuoran Lu, and Ming Yin. Synthetic data generation with large language models for text classification: Potential and limitations. In *The 2023 Conference on Empirical Methods in Natural Language Processing*, 2023.

Guang Liu, Jie Yang, and Ledell Wu. Ptab: Using the pre-trained language model for modeling tabular data. *arXiv preprint arXiv:2209.08060*, 2022.

Justin Lovelace, Varsha Kishore, Chao Wan, Eliot Shekhtman, and Kilian Q Weinberger. Latent diffusion for language generation. *Advances in Neural Information Processing Systems*, 36, 2024.

Dionysis Manousakas and Sergül Aydöre. On the usefulness of synthetic tabular data generation. *arXiv preprint arXiv:2306.15636*, 2023.

Ryan McKenna, Brett Mullins, Daniel Sheldon, and Gerome Miklau. Aim: an adaptive and iterative mechanism for differentially private synthetic data. *Proceedings of the VLDB Endowment*, 15 (11):2599–2612, 2022.

Stephen Merity, Caiming Xiong, James Bradbury, and Richard Socher. Pointer sentinel mixture models. *arXiv preprint arXiv:1609.07843*, 2016.

Michael Moor, Oishi Banerjee, Zahra Shakeri Hossein Abad, Harlan M Krumholz, Jure Leskovec, Eric J Topol, and Pranav Rajpurkar. Foundation models for generalist medical artificial intelligence. *Nature*, 616(7956):259–265, 2023.

Beata Nowok, Gillian M Raab, and Chris Dibben. synthpop: Bespoke creation of synthetic data in r. *Journal of statistical software*, 74:1–26, 2016.

Soma Onishi, Kenta Oono, and Kohei Hayashi. Tabret: Pre-training transformer-based tabular models for unseen columns. In *ICLR 2023 Workshop on Mathematical and Empirical Understanding of Foundation Models*, 2023.

OpenAI. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.

F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830, 2011.

Michael Platzer and Thomas Reutterer. Holdout-based empirical assessment of mixed-type synthetic data. *Frontiers in big Data*, 4:679939, 2021.

Liudmila Prokhorenkova, Gleb Gusev, Aleksandr Vorobev, Anna Veronika Dorogush, and Andrey Gulin. Catboost: unbiased boosting with categorical features. *Advances in neural information processing systems*, 31, 2018.

Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. Hierarchical text-conditional image generation with clip latents. *arXiv preprint arXiv:2204.06125*, 2022.

Jerome P Reiter. Using cart to generate partially synthetic public use microdata. *Journal of official statistics*, 21(3):441, 2005.

Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 10684–10695, 2022.

Christoph Schuhmann, Romain Beaumont, Richard Vencu, Cade Gordon, Ross Wightman, Mehdi Cherti, Theo Coombes, Aarush Katta, Clayton Mullis, Mitchell Wortsman, et al. Laion-5b: An open large-scale dataset for training next generation image-text models. *Advances in Neural Information Processing Systems*, 35:25278–25294, 2022.

Nabeel Seedat, Nicolas Huynh, Boris van Breugel, and Mihaela van der Schaar. Curated llm: Synergy of llms and data curation for tabular augmentation in low-data regimes. In *Forty-first International Conference on Machine Learning*.

Ravid Shwartz-Ziv and Amitai Armon. Tabular data: Deep learning is not all you need. *Information Fusion*, 81:84–90, 2022.

Namjoon Suh, Xiaofeng Lin, Din-Yin Hsieh, Merhdad Honarkhah, and Guang Cheng. Autodiff: combining auto-encoder and diffusion model for tabular data synthesizing. *CoRR*, abs/2310.15479, 2023. URL `https://doi.org/10.48550/arXiv.2310.15479`.

Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*, 2023.

Brandon Trabucco, Kyle Doherty, Max A Gurinas, and Ruslan Salakhutdinov. Effective data augmentation with diffusion models. In *The Twelfth International Conference on Learning Representations*, 2023.

Talip Ucar, Ehsan Hajiramezanali, and Lindsay Edwards. Subtab: Subsetting features of tabular data for self-supervised representation learning. *Advances in Neural Information Processing Systems*, 34:18853–18865, 2021.

Boris van Breugel and Mihaela van der Schaar. Why tabular foundation models should be a research priority. *arXiv preprint arXiv:2405.01147*, 2024.

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.

Eric Wallace, Yizhong Wang, Sujian Li, Sameer Singh, and Matt Gardner. Do nlp models know numbers? probing numeracy in embeddings. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pp. 5307–5315, 2019.

Zifeng Wang and Jimeng Sun. Transtab: Learning transferable tabular transformers across tables. *Advances in Neural Information Processing Systems*, 35:2902–2915, 2022.

Colin Wei, Sang Michael Xie, and Tengyu Ma. Why do pretrained language models help in downstream tasks? an analysis of head and prompt tuning. *Advances in Neural Information Processing Systems*, 34:16158–16170, 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.

Scott Yak, Yihe Dong, Javier Gonzalvo, and Sercan Arik. Ingestables: Scalable and efficient training of llm-enabled tabular foundation models. In *NeurIPS 2023 Second Table Representation Learning Workshop*, 2023.

Jiahuan Yan, Bo Zheng, Hongxia Xu, Yiheng Zhu, Danny Chen, Jimeng Sun, Jian Wu, and Jintai Chen. Making pre-trained language models great on tabular prediction. In *The Twelfth International Conference on Learning Representations*, 2024. URL `https://openreview.net/forum?id=anzIzGZuLi`.

Yazheng Yang, Yuqi Wang, Guang Liu, Ledell Wu, and Qi Liu. Unitabe: A universal pretraining protocol for tabular foundation model in data science. In *The Twelfth International Conference on Learning Representations*, 2024.

Chao Ye, Guoshan Lu, Haobo Wang, Liyao Li, Sai Wu, Gang Chen, and Junbo Zhao. Towards cross-table masked pretraining for web data mining. In *Proceedings of the ACM on Web Conference 2024*, pp. 4449–4459, 2024.

Han-Jia Ye, Qile Zhou, and De-Chuan Zhan. Training-free generalization on heterogeneous tabular data via meta-representation. 2023.

Jinsung Yoon, Yao Zhang, James Jordon, and Mihaela Van der Schaar. Vime: Extending the success of self-and semi-supervised learning to tabular domain. *Advances in Neural Information Processing Systems*, 33:11033–11043, 2020.

Lu Yuan, Dongdong Chen, Yi-Ling Chen, Noel Codella, Xiyang Dai, Jianfeng Gao, Houdong Hu, Xuedong Huang, Boxin Li, Chunyuan Li, et al. Florence: A new foundation model for computer vision. *arXiv preprint arXiv:2111.11432*, 2021a.

Xin Yuan, Zhe Lin, Jason Kuen, Jianming Zhang, Yilin Wang, Michael Maire, Ajinkya Kale, and Baldo Faieta. Multimodal contrastive training for visual representation learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 6995–7004, June 2021b.

Boyu Zhang, Hongyang Yang, Tianyu Zhou, Muhammad Ali Babar, and Xiao-Yang Liu. Enhancing financial sentiment analysis via retrieval augmented large language models. In *Proceedings of the Fourth ACM International Conference on AI in Finance*, pp. 349–356, 2023a.

Han Zhang, Xumeng Wen, Shun Zheng, Wei Xu, and Jiang Bian. Towards foundation models for learning on tabular data. *arXiv preprint arXiv:2310.07338*, 2023b.

Hengrui Zhang, Jiani Zhang, Zhengyuan Shen, Balasubramaniam Srinivasan, Xiao Qin, Christos Faloutsos, Huzefa Rangwala, and George Karypis. Mixed-type tabular data synthesis with score-based diffusion in latent space. In *The Twelfth International Conference on Learning Representations*, 2024. URL `https://openreview.net/forum?id=4Ay23yeuz0`.

Jun Zhang, Graham Cormode, Cecilia M Procopiuc, Divesh Srivastava, and Xiaokui Xiao. Privbayes: Private data release via bayesian networks. *ACM Transactions on Database Systems (TODS)*, 42(4):1–41, 2017.

Tianping Zhang, Shaowen Wang, YAN Shuicheng, Li Jian, and Qian Liu. Generative table pre-training empowers models for tabular prediction. In *The 2023 Conference on Empirical Methods in Natural Language Processing*, 2023c.

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.

Zilong Zhao, Robert Birke, and Lydia Chen. Tabula: Harnessing language models for tabular data synthesis. *arXiv preprint arXiv:2310.12746*, 2023.

Zilong Zhao, Aditya Kunar, Robert Birke, Hiek Van der Scheer, and Lydia Y Chen. Ctab-gan+: Enhancing tabular data synthesis. *Frontiers in big Data*, 6:1296508, 2024.

Bingzhao Zhu, Xingjian Shi, Nick Erickson, Mu Li, George Karypis, and Mahsa Shoaran. Xtab: cross-table pretraining for tabular transformers. In *Proceedings of the 40th International Conference on Machine Learning*, pp. 43181–43204, 2023.

A Broader Impact and Limitations

A foundational table generator like CTSyn can significantly enhance various application domains, especially where real data is scarce, sensitive, or expensive to obtain, by providing high-quality synthetic tabular data. In healthcare, for example, CTSyn can generate synthetic patient records that maintain statistical fidelity to real data, enhancing the robustness and generalization ability of machine learning models by augmenting datasets with synthetic data.

CTSyn also facilitates data collaboration between parties, such as advertising companies and social media websites. Through conditional generation, CTSyn can augment one party's dataset with essential columns for business analysis without violating privacy laws that prohibit linking individual data points across parties.

However, CTSyn's performance relies heavily on clean, large-scale tabular datasets. The quality of generated data depends on the training data, and any biases or errors can be propagated. This risk can be mitigated by carefully curating high-quality datasets for different domains. Additionally, despite pre-training reducing memorization of downstream data, individuals included in the pre-training data still face privacy risks, complicating the safe gathering of large datasets. This can be mitigated by properly anonymizing or adding noise to public pre-training datasets to ensure privacy before they are used for pre-training.

The requirement of semantically meaningful category names also present challenges for acquiriing large-scale training data, as normalized values must be carefully sanitized and converted back to raw form.

B Baselines Implementation

CTGAN: We use the official implementation at https://github.com/sdv-dev/CTGAN. We use embedding dimension =128, generator dimension=(256,256), discriminator dimension =(256,256), generator learning rate=0.0002, generator decay =0.000001, discriminator learning rate =0.0002, discriminator decay =0.000001, batch size=500, training epoch = 300, discriminator steps=1, pac size = 5.

TVAE: We used the official implementation at: https://docs.sdv.dev/sdv. We used default parameters: class dimensions =(256, 256, 256, 256), random dimensions=100, 64 channels, l2scale=1e-5, batch size=500, training epoch = 300.

TabDDPM: We used the official implementation at https://github.com/yandex-research/tab-ddpm. We used 2500 diffusion steps, 10000 training epochs, learning rate = 0.001, weight decay = 1e-05, batch size = 1024.

AIM: We use the code implementation at https://github.com/ryan112358/private-pgm, with default parameters: epsilon=3,delta=1e-9,max model size=80

PATE-CTGAN: We adapted the implementation posted at: https://github.com/opendp/smartnoise-sdk/blob/main/synth/snsynth, which combines the PATE Jordon et al. (2018) learning framework with CTGAN. We use epsilon = 3, 5 iterations for student and teacher network, and the same value for other parameters which are shared with CTGAN.

GReaT: We used the official implementation at `https://github.com/kathrinse/be_great/tree/main`. We used a batch size of 32. During pre-training, we began with a pre-trained distilgpt2 model and training for 2 millions steps on the combination of pre-training data. We train 200 epochs for each dataset during finetuning.

TabSyn: We use the official implementation at `https://github.com/amazon-science/tabsyn`, with default parameters. For pre-training with heterogeneous VAE embeddings, we train its VAE model for each pre-training dataset, zero-pad all embeddings to the same dimension, and then pre-train a diffusion model on such padded embeddings. During downstream training, the VAE embedding of the downstream datasets are padded to the same dimension as in the pre-training. The pre-trained TabSyn is loaded and diffusion training proceed with it as initialization.

SMOTE: The original SMOTE algorithm are designed to upsample minority classes. We extend it to perform interpolation for all classes. For each generation, we first randomly select one target class using empirical class frequency as probability. Then we randomly sample one example from the selected class, and generated interpolated examples using number of nearest neighbour $k = 5$. The interpolation weight $\alpha = 0.5$.

C PRETRAINING DATASETS

We show the OpenTab files included in our pre-training, as well as their summary statistics. The classification type dataset are shown in table 6, and regression datasets in table 7.

D DOWNSTREAM DATASETS

We provide the URL for the sources of each downstream benchmark set considered in the paper.

1. **abalone** (OpenML) : https://www.openml.org/search?type=data&sort=runs&id=183&status=active (Multi class)
2. **Bean** (UCI) : https://archive.ics.uci.edu/dataset/602/dry+bean+dataset (Multi class)
3. **faults** (UCI) : https://archive.ics.uci.edu/dataset/198/steel+plates+faults (Multi class)
4. **HTRU** (UCI) : https://archive.ics.uci.edu/dataset/372/htru2 (Binary class)
5. **indian liver patient** (Kaggle) : https://www.kaggle.com/datasets/uciml/indian-liver-patient-records?resource=download (Binary class)
6. **insurance** (Kaggle) : https://www.kaggle.com/datasets/mirichoi0218/insurance (Regression)
7. **News** (UCI) : https://archive.ics.uci.edu/dataset/332/online+news+popularity (Regression)
8. **Obesity** (Kaggle) : https://www.kaggle.com/datasets/tathagatbanerjee/obesity-dataset-uci-ml (Multi class)
9. **Shoppers** (Kaggle) : https://www.kaggle.com/datasets/henrysue/online-shoppers-intention (Binary class)
10. **Titanic** (Kaggle) : https://www.kaggle.com/c/titanic/data (Multi class)
11. **wilt** (OpenML) : https://www.openml.org/search?type=data&sort=runs&id=40983&status=active (Binary class)

File Name	N	Categorical Cols	Numerical Cols
2736_Shipping	10999	4	6
1366_bankmarketing	41188	11	10
0944_SensorDataResource	100000	1	25
0144_BNG(bridges_version1)	100000	9	4
0062_BNG(page-blocks,nominal,295245)	100000	10	1
0673_BNG(baseball)	100000	1	16
1046_jungle_chess_2pcs_raw_endgame _complete	44819	1	6
0677_COMET_MC_SAMPLE	89640	0	5
1681_Air-Traffic-Data	15007	12	4
1969_CPS1988	28155	4	3
pulsar_data_train	12528	0	9
0666_BNG(primary-tumor)	100000	18	0
0050_BNG(breast-cancer,nominal,1000000)	100000	9	1
0080_BNG(vote)	100000	17	0
1375_MAGIC-Gamma-Telescope-Dataset	19020	1	10
0063_BNG(credit-g,nominal,1000000)	100000	21	0
1431_Beijing-Multi-Site-Air-Quality	100000	2	16
bodyPerformance	13393	2	10
term_deposit_subscribed33	31647	9	8
1465_credit	16714	0	11
0077_BNG(heart-statlog,nominal,1000000)	100000	14	0
0761_BNG(autos,1000,10)	100000	10	16
0142_BNG(breast-w)	39366	1	9
0105_kropt	28056	4	3
campaign33	12870	10	6
2149_electricity	38474	1	8
2701_BitcoinHeist_Ransomware	24780	0	8
0772_BNG(lymph,5000,5)	100000	16	3
0059_BNG(colic,nominal,1000000)	100000	23	0
2750_letter-challenge-unlabeled.arff	10000	1	16
0639_jm1	10885	1	21
fusion_experiment	100000	2	17
1690_Malware-Analysis-Datasets-PE-Secti on-Headers	43293	0	5
0137_BNG(labor)	100000	9	8
1020_Run_or_walk_information	88588	0	7
0070_BNG(glass,nominal,137781)	100000	10	0
classifying_document_types_to_enhanc e_search_and_recommendations_in_dig ital_libraries_dataset	11539	2	5
0747_BNG(letter,5000,1)	100000	1	16
Warehouse_block	10999	4	7
1579_MagicTelescope	13376	1	10
0160_BNG(hepatitis)	100000	14	6
1981_Higgs	100000	0	25
1674_adult	48842	9	6
2687_Diabetes130US	71090	0	8
0057_BNG(mushroom)	100000	23	0
0074_BNG(tic-tac-toe)	39366	10	0
0078_BNG(vehicle,nominal,1000000)	100000	19	0
univ.ai_Test Data	28000	6	5
flight_delays_train	100000	7	2
bank	11162	10	7
Firewall_Rule_Classification	100000	1	11
Crop_Agriculture_Data_2	88858	5	4
0711_Stagger1	100000	4	0
0674_BNG(wine)	100000	0	14
1942_mushroom	12960	9	0
0968_BNG(segment)	100000	20	0
bank_customer_survey	45211	9	8

Table 6: Classification Task Files

File Name	N	Categorical Cols	Numerical Cols
1860_Worldwide-Crop-Production	21165	3	2
2711_medical_charges	100000	0	4
0690_BNG(breastTumor)	100000	6	4
2743_Tallo	100000	9	12
MAMe_dataset	37407	4	4
2664_diamonds	53940	3	7
2134_Brazilian_houses	10692	0	9
0693_BNG(wine_quality)	100000	0	12
1587_elevators	16599	0	17
2677_fifa	19178	1	28
0940_seattlecrime6	52358	5	3
1697_AMD-Stock-Prices-Historical-Data	10361	0	6
1905_New-Delhi-Rental-Listings	17890	5	9
1415_beijing-pm2.5	43824	1	11
1649_Tamilnadu-Crop-production	13266	4	3
stats	10000	1	9
1466_post-operative	65532	1	11
Airline_Delay_Cause	100000	4	17
1704_House-Rent-in-Indian-Cities-and-Lo calities	10692	5	8
credit_card_defaulter	10000	2	2
1781_SDSS-16	100000	1	17
2131_houses	20640	0	9
1595_Oranges-vs.-Grapefruit	10000	1	5
1140_exercises	15000	1	6
1245_Production-cross-sections-of-Inert -Doublet-Model	50625	0	13
2136_nyc-taxi-green-dec-2016	100000	0	10
0684_BNG(autoPrice)	100000	0	16
1904_Apple-Complete-Stock-Data1980-2020	10015	0	6
1107_rainfall_bangladesh	16755	2	2
2659_video_transcoding	68784	2	17

Table 7: Regression Task Files

E Numerical Results For Utility

Model	30	50	100	200	500	Full
Real	0.79	0.79	0.82	0.83	0.88	0.90
SMOTE	0.67	0.74	0.76	0.77	0.83	0.85
PATECTGAN	0.31	0.27	0.32	0.34	0.37	0.40
AIM	0.44	0.48	0.55	0.62	0.52	0.57
CTGAN	0.41	0.52	0.52	0.54	0.63	0.64
GReaT	-	-	0.76	0.80	0.84	0.85
TVAE	0.75	0.77	0.79	0.79	0.82	0.84
TabDDPM	0.77	0.79	0.81	0.81	0.84	0.85
TabSyn	0.76	0.78	0.81	0.82	0.85	0.86
CTSyn	0.79	0.81	0.83	0.84	0.84	0.86

Table 8: ML utility for classification benchmarks.Columns represent training examples(shots) provided.

Model	30	50	100	200	500	Full
Real	0.24	0.23	0.21	0.17	0.15	0.14
SMOTE	0.48	0.24	0.22	0.16	0.13	0.11
AIM	10274.55	$\gg$10k	$\gg$10k	$\gg$10k	$\gg$10k	110.14
PATECTGAN	$\gg$10k	$\gg$10k	$\gg$10k	$\gg$10k	$\gg$10k	$\gg$10k
CTGAN	0.97	0.25	0.28	0.19	0.21	0.20
TVAE	0.60	0.50	0.47	0.33	0.34	0.28
GReaT	0.30	0.25	0.23	0.20	0.19	0.16
TabDDPM	0.35	0.30	0.27	0.21	0.20	0.18
TabSyn	0.27	0.23	0.22	0.19	0.16	0.13
CTSyn	0.22	0.18	0.17	0.15	0.14	0.12

Table 9: ML utility for regression benchmarks. Columns represent training examples(shots) provided.

F Computation

Our training are completed on an Amazon AWS g5.12xlarge instance, with 192 GB system memory, 4 Nvidia A10G GPU with 4×24 GB GPU memory. The pre-training time of CTSyn, GReaT and TabSyn are shown in the table 10.

Model	**VAE**	**Generation**
CTSyn	12 hours	12 hours
GReaT	-	50 hours
TabSyn	$86 \times 0.5 = 43$ hours	24 hours

Table 10: Pre-training computation cost. Note that TabSyn requires training table-specific encoders.