**Synthetic Data Generation Open-source Python Libraries Comparison: SDV and Synthicity**

**Abstract**

High-quality training data is critical to the performance of machine learning models, particularly Large Language Models (LLMs). However, obtaining real, high-quality data can be challenging, especially for smaller organizations and early-stage startups. Synthetic data generators provide a promising solution by replicating the statistical and structural properties of real data while preserving privacy and scalability. This study evaluates the performance of six tabular synthetic data generators from two widely used open-source libraries: SDV (Gaussian Copula, CTGAN, TVAE) and Synthicity (Bayesian Network, CTGAN, TVAE). Using a real-world dataset from the UCI Machine Learning Repository, comprising energy consumption and environmental variables from Belgium, we simulate a low-data regime by training models on only 1,000 rows. Each generator is then tasked with producing synthetic datasets under two conditions: a 1:1 (1,000 rows) and a 1:10 (10,000 rows) input-output ratio. Evaluation is conducted using two criteria: statistical similarity, measured via classical statistics and distributional metrics; and predictive utility, assessed using a “Train on Synthetic, Test on Real” approach with four regression models. While statistical similarity remained consistent across models in both scenarios, predictive utility declined notably in the 1:10 case. The Bayesian Network from Synthicity achieved the highest fidelity in both scenarios, while TVAE from SDV performed best in predictive tasks under the 1:10 setting. Although no significant performance gap was found between the two libraries, SDV stands out for its superior documentation and ease of use, making it more accessible for practitioners.

1. **Introduction**

The performance of machine learning models, particularly in supervised learning tasks, is heavily dependent on the availability of large volumes of high-quality data [1]. However, real-world datasets are often limited due to privacy concerns, regulatory constraints, high labeling costs, or data sparsity, especially in domains such as healthcare, energy systems, and finance [2]. As a result, synthetic data generation has emerged as a promising alternative that can supplement or even replace real data in certain use cases [3]. While synthetic data has been widely explored in computer vision and natural language processing [4, 5], its application to structured, tabular data, common in many real-world business and scientific settings, has gained traction more recently. To support this growing need, several open-source tools and libraries have been developed. Among the most prominent are the Synthetic Data Vault (SDV) and Synthicity, both of which provide user-friendly APIs for generating synthetic tabular data using a variety of models, ranging from classical probabilistic approaches to modern deep generative networks.

Despite the growing popularity of these tools, few studies have systematically compared their performance under controlled, real-world conditions. This study aims to fill that gap by evaluating and comparing SDV and Synthicity in terms of both statistical fidelity and downstream predictive utility. Using a real-world energy consumption dataset, we generate synthetic data under two experimental conditions: one where the output data matches the input size (1:1), and another where it scales tenfold (1:10). We assess performance using both statistical similarity metrics and a Train-on-Synthetic, Test-on-Real (TSTR) predictive evaluation pipeline.

Our findings offer practical insights into the strengths and limitations of each library and provide guidance for researchers and practitioners selecting synthetic data generation tools for tabular data tasks.

**2. Literature Review**

In the past few years, Large Language Models (LLMs) have become prominent, and with the release of commercial models like ChatGPT by OpenAI in November 2022 [6], their power became available to anyone with internet access, greatly impacting many aspects of daily life [7].

A common belief behind the success of LLMs is the scaling law of computing, model size, and, perhaps most importantly, the high quality of pre-training data [8]. The biggest LLMs today are often pre-trained on trillions of tokens. For example, GPT‑3 was famously trained on nearly 500 billion tokens [9], from a mixture of web text, books, and other sources. GPT‑4 is rumored to have used well over a trillion tokens [10], and Anthropic’s Claude reportedly relies on a similarly large-scale corpus, likely in the hundreds of billions to trillions of tokens [11]. The exact numbers for GPT‑4 and Claude have not been officially disclosed by OpenAI and Anthropic, but external analyses report similar figures [12].

However, acquiring such a massive quantity of high-quality data has become more challenging [13]. Many sources are now gated behind paywalls, restricted by copyright, or filtered due to data quality concerns [14]. As the demand for high-quality training data grows, finding scalable solutions for future LLM development remains an open question.

As a remedy, synthetic data has been widely adopted in training LLMs, offering a more accessible and controllable alternative to real-world data [15, 16]. Chen et al. [8] conducted a study on the measurement of diversity in synthetic data and its impact on LLM performance. They examined how synthetic data diversity influences both pre-training and fine-tuning stages, introducing a new diversity metric called LLM Cluster-Agent, designed specifically to evaluate the diversity of synthetic datasets. They define LLM Cluster-Agent as “a diversity measure pipeline that leverages LLM’s ability to interpret semantic meanings and understand rich contexts of text samples for clustering”. This metric is particularly suited for text-based synthetic data, which is commonly used in the pre-training process of large LLMs, rather than for tabular data. Through a series of controlled experiments with 350M and 1.4B parameter models, Chen et al. demonstrated that higher diversity in synthetic data correlates positively with both pre-training and fine-tuning performance. Interestingly, their findings suggest that synthetic data diversity in pre-training has an even stronger effect on fine-tuning than on pre-training itself. Although this study differs from our goal of comparing tabular data generators rather than synthetic text data, it is still relevant because it highlights how synthetic data can be effectively leveraged in the pre-training of LLMs.

The use of synthetic data generators for training LLMs, however, is not their only application. In fact, synthetic data generation is now widely used across multiple domains. Lu et al. [17] presented a comprehensive review of existing studies on employing machine learning for synthetic data generation, highlighting applications spanning computer vision, speech, natural language processing, healthcare, and business domains. Their review categorizes existing approaches based on machine learning techniques, with a particular emphasis on deep generative models, including GANs, VAEs, and reinforcement learning-based methods. One of the key findings of their study is that the effectiveness of synthetic data depends on the application domain. In computer vision, synthetic datasets are frequently used to train models for object detection, facial recognition, and domain adaptation when real-world labeled data is scarce. In speech processing, synthetic data has proven valuable in speech synthesis and voice cloning, reducing the need for extensive manually labeled datasets. In natural language processing, it is used to augment training datasets for tasks such as language modeling and machine translation. In healthcare, synthetic data generation enables the use of privacy-preserving patient data, facilitating medical research and predictive modeling without compromising sensitive information. In business and finance, synthetic data is used to simulate market behaviors, detect fraudulent transactions, and improve risk assessment models. Beyond applications, Lu et al. also discuss key challenges in synthetic data generation, particularly issues of data fidelity and bias. They emphasize that while synthetic data can approximate real-world distributions, its utility depends on the balance between realism and generalization. Their study provides an important foundation for understanding the broad applicability of synthetic data generation, reinforcing its relevance across various fields where data limitations exist.

Since this study compares existing open-source Python packages for synthetic data generation, it is essential to review the technical aspects and identify the most suitable and widely used models. Various approaches exist for generating synthetic data, ranging from graph-based models and probabilistic methods to deep neural networks. To highlight some of the most well-known models, I refer to the work of Bauer et al. [18], which provides a comprehensive overview of synthetic data generation techniques. This section will not delve into the technical details of each model, as a more precise definition of the models used in the comparison will be presented in the Method section.

Starting with probabilistic and statistical models, one of the most widely implemented is the Gaussian Mixture Model (GMM). GMMs are density estimation algorithms primarily used for clustering, but they can also serve as generative probabilistic models. They are commonly applied to tabular data and time-series generation. A GMM consists of N Gaussian distributions, each representing a continuous, symmetric probability distribution. Another important probabilistic model is the Markov Chain, which is used for generating sequential data by modeling infinite sequences of symbols where the probability of each symbol depends only on the previous n symbols. These models are widely applied in text generation and time-series synthesis.

Bayesian Networks (BNs) offer a graphical approach to modeling dependencies between variables. They are structured as Directed Acyclic Graphs (DAGs), where nodes represent random variables, and edges define their conditional dependencies. Each variable follows either a continuous or a discrete probability distribution. Synthcity, one of the Python packages we will analyze, implements Bayesian Networks as they are particularly effective for structured synthetic data generation, including privacy-preserving applications. The second Python package in our study, SDV, utilizes another probabilistic model, the Gaussian Copula. A copula function represents the joint probability distribution of a continuous random vector by separating the individual marginal distributions from the dependency structure between variables. More details on Bayesian Networks and Gaussian Copulas will be provided in the Method section.

Even though probabilistic and statistical models are still widely used, deep learning methods have become the dominant approach for state-of-the-art synthetic data generation. Among them, one of the most well-known frameworks is Generative Adversarial Networks (GANs). GANs consist of two neural networks, a generator (G) that creates synthetic data from random noise and a discriminator (D) that determines whether a given sample comes from the generator or the real training data. The authors of the original GAN paper describe this system as a “minimax two-player game”, where the generator continuously improves its ability to fool the discriminator, while the discriminator becomes better at distinguishing real from fake data [19]. Over time, numerous variations of the classic GAN architecture, originally implemented with Multi-Layer Perceptrons (MLPs), have emerged to improve stability, control, and performance. Deep Convolutional GANs (DCGANs) [20] introduced the use of convolutional layers instead of fully connected layers, allowing the generator to better capture spatial hierarchies in data, significantly enhancing the quality of image generation. Conditional GANs (cGANs) [21] addressed the uncontrolled nature of GAN outputs by introducing conditioning variables, such as class labels or additional attributes, enabling the generator to produce targeted synthetic samples. Another major advancement came with Wasserstein GANs (WGANs) [22], which improved training stability by replacing the traditional Jensen-Shannon divergence with the Wasserstein distance, mitigating common issues such as mode collapse and leading to more reliable convergence.

Another widely used deep learning-based approach for synthetic data generation is Variational Autoencoders (VAEs). VAEs are probabilistic generative models designed for latent space learning, enabling the generation of high-dimensional synthetic data such as images and text. Unlike GANs, which learn to generate data through adversarial training, VAEs model the data distribution explicitly by encoding inputs into a latent space and then reconstructing them via a decoder [23]. While VAEs do not always produce sharper images compared to GANs, they offer greater control over latent variables, making them useful for tasks requiring structured and interpretable representations.

For image and text synthesis, powerful generative models are Diffusion Models [24]. These models operate as Markov chains, where data is incrementally noised in a forward process over T steps, and the model learns to reverse this process, gradually denoising the input back to the original data distribution. Diffusion models have gained attention for their ability to generate highly detailed images, surpassing GANs in certain text-to-image tasks.

Perhaps the most influential deep learning model in text synthesis, and beyond, is the Transformer architecture. First introduced in 2017 in the seminal paper “Attention Is All You Need” [25], Transformers gained widespread recognition following the release of LLMs such as ChatGPT, which are built upon Transformer-based architectures. At their core, Transformers are sequence-to-sequence transduction models structured with an encoder-decoder mechanism. Unlike previous recurrent architectures (RNNs and LSTMs), Transformers allow for full parallelization, drastically improving efficiency and scalability. The key innovation behind Transformers is the multi-head self-attention mechanism, which enables models to capture long-range dependencies in data with a constant number of sequential operations, rather than the sequential processing bottleneck of RNNs. This shift allowed Transformers to excel in language modeling, translation, and generative tasks, building the foundation for modern LLMs.

To narrow the scope and examine studies similar to this one, as the conclusion of this literature review, we will analyze research comparing synthetic data generation techniques in real-world applications. One such study was conducted by Akiya et al. [26], which evaluates various synthetic data generation methods for control group survival data in oncology clinical trials. The primary objective of their research was to determine the most suitable synthetic patient data (SPD) generation method for oncology trials, focusing specifically on progression-free survival (PFS) and overall survival (OS), key evaluation endpoints in clinical oncology. In their study, Akiya et al. compared four distinct synthetic data generation techniques, incorporating both probabilistic/statistical methods and deep learning-based approaches. The traditional methods included Classification and Regression Trees (CARTs) and Random Forest (RF), while more complex models consisted of Bayesian Networks (BNs) and Conditional Tabular Generative Adversarial Networks (CTGANs). To evaluate performance, the researchers generated 1,000 synthetic datasets per method and assessed their effectiveness based on both statistical similarity and visual analysis. The results indicated that traditional tree-based methods outperformed deep learning-based techniques, particularly when trained on relatively small datasets, which is common in clinical trials. CART and RF demonstrated superior performance, with CART emerging as the most effective method, as its synthetic data closely matched the statistical properties of real patient survival data. On the other hand, Bayesian Networks (BNs) and CTGANs did not perform well, mainly due to their higher data requirements. These models typically require larger training datasets to learn meaningful patterns and generate synthetic data that aligns well with real-world statistical distributions.

While the previous study provides insights into synthetic data generation techniques, comparisons between specific open-source Python packages remain scarce. This study aims to fill that gap in the literature by providing a comparative analysis of two of the most popular open-source Python libraries for synthetic data generation: SDV and Synthcity. To evaluate these two packages, we will compare different models available in each framework. For SDV, we will analyze the Gaussian Copula synthesizer, Conditional Tabular GAN (CTGAN), and Tabular Variational Autoencoder (TVAE). For Synthcity, we will evaluate the Bayesian Network synthesizer, as well as CTGAN and TVAE, to ensure a direct comparison between the shared models across both packages. The synthetic data will be generated using a dataset from a publicly available repository in the UCI Machine Learning repository. It was collected by continuously monitoring a low-energy house in Belgium for 137 days, capturing both electrical energy consumption and environmental data. To assess the quality and effectiveness of the generated data, we will employ two key evaluation metrics:

1. Statistical Difference: Measured by comparing synthetic and real data distributions using reliable statistical functions provided by SDV, along with custom statistical comparison methods.
2. Predictive Utility: Evaluated by training Machine Learning models on both real and synthetic data and comparing the performance metrics (e.g., accuracy, precision, recall) of the models trained on each dataset.

This study aims to identify the best-performing open-source package for synthetic data generation and provide a comprehensive comparison of the quality and utility of the data generated by SDV and Synthcity. By doing so, we hope to contribute valuable insights into the strengths and limitations of these tools, guiding researchers and practitioners in selecting the most suitable synthetic data generation framework for their needs.

1. **Methods**
   1. **Data Generators Description**

In this research, we'll use four different Data Generators with well-known mathematical properties: Gaussian Copula, Bayesian Networks, Conditional Tabular GAN (CTGAN), and Tabular Variational Autoencoder (TVAE). The first two are statistical methods, whereas the latter two are deep neural network techniques. Let's first examine the mathematical properties of the statistical methods.

Gaussian copula methods model the joint distribution of a table by combining each column’s marginal distribution with a copula function capturing inter-column dependencies. The foundation is Sklar’s theorem [27], which states that any multivariate distribution can be decomposed as

where are the marginals and is the copula describing their dependency structure. A Gaussian copula assumes this dependence is encoded by a multivariate normal distribution with a correlation matrix, while allowing arbitrary marginals. In practice, one first estimates each column’s CDF, then transforms the data into a latent space with uniform or Gaussian marginals. First, you estimate a CDF for each column of the real data. Then, transform the real data into uniform variables and fit a copula to capture their joint dependence, which for a Gaussian copula means computing the correlation matrix. Lastly, draw a synthetic sample from the copula model, and invert the transform by applying the inverse CDF for each column, This yields a synthetic data record in the original space.

Patki et al. [28] introduced the open-source package Synthetic Data Vault (SDV) by using Gaussian copulas to model tabular data. In their approach, all columns are converted to a standard normal scale to remove the effect of each column distribution shape, before estimating the covariance matrix of the joint Gaussian copula. After modeling the correlations, synthetic rows are sampled by drawing from the multivariate normal and then transforming back to each column’s domain. One limitation, however, is that purely categorical fields cannot be directly handled by the Gaussian copula, since the copula operates in a continuous space. The SDV work addressed this by encoding categories as ordinal values in the range [0,1] so that they could be treated like continuous variables in the copula model. In general, the key advantage of Gaussian copula models is that they are statistical methods, as opposed to neural networks, offering a relatively simple mathematical formulation and a stable fitting procedure, while still capturing complex dependencies through the copula. However, if the data contains many discrete variables or highly non-linear dependencies, a copula model, like the Gaussian copula, might struggle.

Another class of tabular synthesizers uses Bayesian networks (BN) to learn the joint distribution from the data. A Bayesian network consists of a directed acyclic graph, in which the nodes represent variables of the data (columns of a data frame), and a set of conditional probability distributions for each node given its parent nodes [29]. In essence, the BN factorizes the joint probability

into ,

Representing inter-column relationships as conditional dependencies. Once a BN is learned from the real dataset, generating synthetic data is simple: one can sample from the network by first sampling the root nodes, which are variables with no parents according to the learned graph, and then sampling descendant nodes conditional on their parents’ sampled values, propagating through the network until all variables have values. This produces a synthetic record that statistically mirrors the correlation captured in the BN.

An example of Bayesian Network usage can be found in the research by Zhang et al. [25], which introduces PrivBayes, a method utilizing Bayesian networks to generate synthetic data under differential privacy constraints. PrivBayes learns a dependency graph over the attributes (columns) and then draws synthetic tuples (rows) by sampling that Bayesian Network. In general, a learned BN can accurately reproduce multi-variable interactions present in the original data, especially for mixed categorical data. Therefore, BN have the advantage of being well-understood models in probability theory, and they inherently ensure that generated samples are consistent with the conditional distributions observed in the real data. On the other hand, Bayesian network generators face some practical challenges. In fact, they often require discretizing continuous variables or assuming parametric forms for continuous conditional distributions, which can introduce errors [30]. Moreover, learning the optimal network structure for high-dimensional data can be computationally expansive and may require prior knowledge.

On the other hand, compared to statistical models such as the Gaussian Copula and Bayesian networks, deep learning methods exist for generating tabular synthetic data. As previously stated, this study will utilize the Conditional Tabular GAN (CTGAN) and Tabular Variational Autoencoder (TVAE). CTGAN is a deep generative model specifically designed for tabular data, introduced by Lei Xu and colleagues in 2019 [31]. It extends the standard Generative Adversarial Network architecture, consisting of a generator that synthesizes data and a discriminator that attempts to distinguish between real and synthetic data. CTGAN introduces novel components to tackle particular challenges of tabular data, such as mixed data types, imbalanced categories, and complex distributions. Unlike GAN architectures commonly used in image generation, which typically rely on convolutional networks [32], CTGAN employs fully connected multilayer perceptrons for both its generator and discriminator.

Lei Xu et al. introduce three key technical innovations in the CTGAN framework: Mode-Specific Normalization, a Conditional Generator, and a Training-by-Sampling strategy. Mode-Specific Normalization refers to CTGAN’s use of variational Gaussian Mixture models to preprocess continuous columns. Rather than employing simple min-max scaling, as often seen in classic GAN implementations [33], each continuous column is modeled as a mixture of Gaussians. Each value is normalized according to the “mode” (Gaussian component) it most likely belongs to. This normalization strategy helps the generator learn multi-modal and non-Gaussian distributions by providing a richer and more expressive representation of the continuous data. Essentially, it maps a continuous variable into a higher-dimensional space (with dimensions corresponding to mixture components), effectively addressing issues related to non-Gaussian distributions.

Another significant innovation of CTGAN is the Conditional Generator. Unlike traditional methods that generate entire rows unconditionally, CTGAN conditions the generation process on specific discrete column values during training. For example, if a table has a categorical column labeled "Education" with categories such as "High School," "Bachelor," and "Master," the model may fix a specific category (e.g., "Master") during certain training iterations and train the generator to produce rows conditioned on this category. This conditioning is implemented by appending a one-hot vector to the generator's input to indicate the selected category and by filtering real data accordingly when updating the discriminator. Consequently, the GAN explicitly learns the conditional distributions for each category within a categorical column, significantly improving the fidelity of synthetic data for imbalanced categories.

Accompanying the conditional generator, CTGAN incorporates a Training-by-Sampling strategy to select training minibatches in a balanced manner. When conditioning on a particular discrete category, the method selects real data batches exclusively from rows containing that category to update the discriminator, rather than randomly sampling from the entire dataset. This targeted sampling approach aligns the generator’s conditioning with the discriminator’s data distribution, preventing the generator from being biased toward majority classes. Thus, the GAN effectively trains on one sub-population at a time, implementing a form of oversampling for rare categories.

Regarding its architecture, CTGAN employs the Wasserstein GAN objective with gradient penalty (WGAN-GP) to ensure stable training [34] and incorporates PacGAN [35], which modifies the discriminator to jointly evaluate multiple samples, thus further mitigating mode collapse. The architecture combines a noise input z with the aforementioned condition vector, feeding the generator to produce synthetic rows. The discriminator then attempts to distinguish between real and synthetic data. Thanks to Mode-Specific Normalization, the generator’s output for each continuous feature can be accurately mapped back to the real data space, preserving the original distributions.

In the same paper in which Xu et al. [31] introduced the CTGAN for the first time, they also presented a the Tabular Variational Autoencoder (TVAE), a deep generative model that applies Variational Autoencoder (VAE) framework to tabular data. TVAE adapts a standard variational autoencoder to handle mixed data types. In a VAE, there are two networks: an encoder that maps an input data sample (a row in the table) to a latent representation , and a decoder that tries to reconstruct the original data from the latent code. The model is trained by maximizing the evidence lower bound (ELBO), which consists of a reconstruction term, ensuring that the decoded output matches the input data, and a regularization term pushing the latent to follow a specific standard distribution, usually standard normal [36].

To make VAEs work for tabular data (TVAE) Xu et al. use similar data pre-processing as for CTGAN, for instance by converting categorical columns into one-hot vectors and using Mode-Specific Normalization for continuous columns, so that the encoder and decoder can effectively model them. The decoder network in TVAE outputs parameters sufficient to reconstruct each column: for continuous columns, it might output means/variances (if assuming a Gaussian output distribution), and for categorical columns, it can output logits for each category, i.e. softmax probabilities for one-hot output. On the other hand, the encoder network likewise must handle one-hot inputs for categorical columns and numeric inputs for continuous columns. With this implementation, TVAE is able to capture the joint distribution of heterogeneous tabular columns in its latent space. Once trained, synthetic data generation is done by sampling a latent vector from the prior (e.g. ) and feeding it into the decoder to produce a new synthetic row. Because the decoder was trained to produce realistic combinations of values, in order to match the real data distribution, the sample outputs resemble real records. Xu et al. also demonstrated that a “vanilla” VAE, when trained with the right loss functions and data encoding, can be competitive with GAN-based models for tabular data. TVAE’s mathematical formulation is essentially the VAE probabilistic model: it seeks to maximize

over the real data, thereby learning which can be sampled. Yadav, Parul, et al. [36] concisely summarize TVAE as “a novel VAE for tabular data using two neural networks (encoder and decoder) trained with ELBO loss”. In practice, TVAE offers a more straightforward training process than GANs, i.e. no adversarial game to balance, and can be easier to converge, though it may require careful tuning to get the decoder to model categorical distributions accurately [36].

* 1. **Real data brief description**

The dataset used in this experiment is publicly available from the UCI Machine Learning Repository. It was collected by continuously monitoring a low-energy house in Belgium for 137 days, capturing both electrical energy consumption and environmental conditions. Energy usage data for various household appliances were recorded every 10 minutes using m-bus energy meters, while environmental data, including temperature and humidity, were collected from different rooms via a wireless ZigBee sensor network. Additionally, meteorological data from a nearby airport (e.g., temperature, humidity, wind speed, visibility) were integrated into the dataset based on matching timestamps [37].

The complete dataset contains 19,735 records and 29 features. However, for this study, only a subset of these data was used. Specifically, this subset of real data serves as the initial input to synthetic data generators. The aim is to evaluate how effectively these generators can expand and generalize from a limited amount of real data, testing their ability to create larger synthetic datasets with similar statistical and predictive characteristics.

* 1. **Comparison process and methods**

The goal of this study is to compare the models and tools offered by two of the most widely used Python packages for synthetic data generation: SDV and Synthicity. A total of six models were selected, three from each package, to evaluate and compare their performance. From SDV, the models used were Gaussian Copula, CTGAN, and TVAE; while for Synthicity, the models included Bayesian Network, CTGAN, and TVAE. A detailed description of each model is provided in the preceding section.

To evaluate how well the synthetic data replicates the original data, two key metrics were used: statistical similarity and predictive utility. The statistical similarity was assessed using a custom scoring function that compares the real and synthetic datasets on a column-by-column basis. The function computes normalized differences in key statistical properties for numerical columns, namely mean, median, and standard deviation, as well as two distributional distance measures: the Kolmogorov–Smirnov (KS) statistic and the Wasserstein distance. For categorical features, similarity was assessed by comparing the mode of each column between the real and synthetic data. Each column score was computed as a weighted combination of these metrics, normalized between 0 and 1, where lower statistical divergence yields higher scores. The final dataset-level score is the average of all column scores, scaled to a 0–100 range, with 100 indicating a perfect match between the synthetic and real datasets.

The predictive utility was assessed using the Train on Synthetic, Test on Real (TSTR) paradigm [38], which evaluates how closely machine learning models trained on synthetic data resemble models trained on real data when both are tested on a separate subset of real data. To clearly illustrate this approach, consider two students studying for the same exam. If each student studies different materials but achieves similar results, it can reasonably be inferred that the two sets of study materials provided comparable knowledge. Similarly, if models trained on synthetic data produce results similar to models trained on real data, this suggests that the synthetic data closely replicates the predictive characteristics of the real data (Fig. 1).

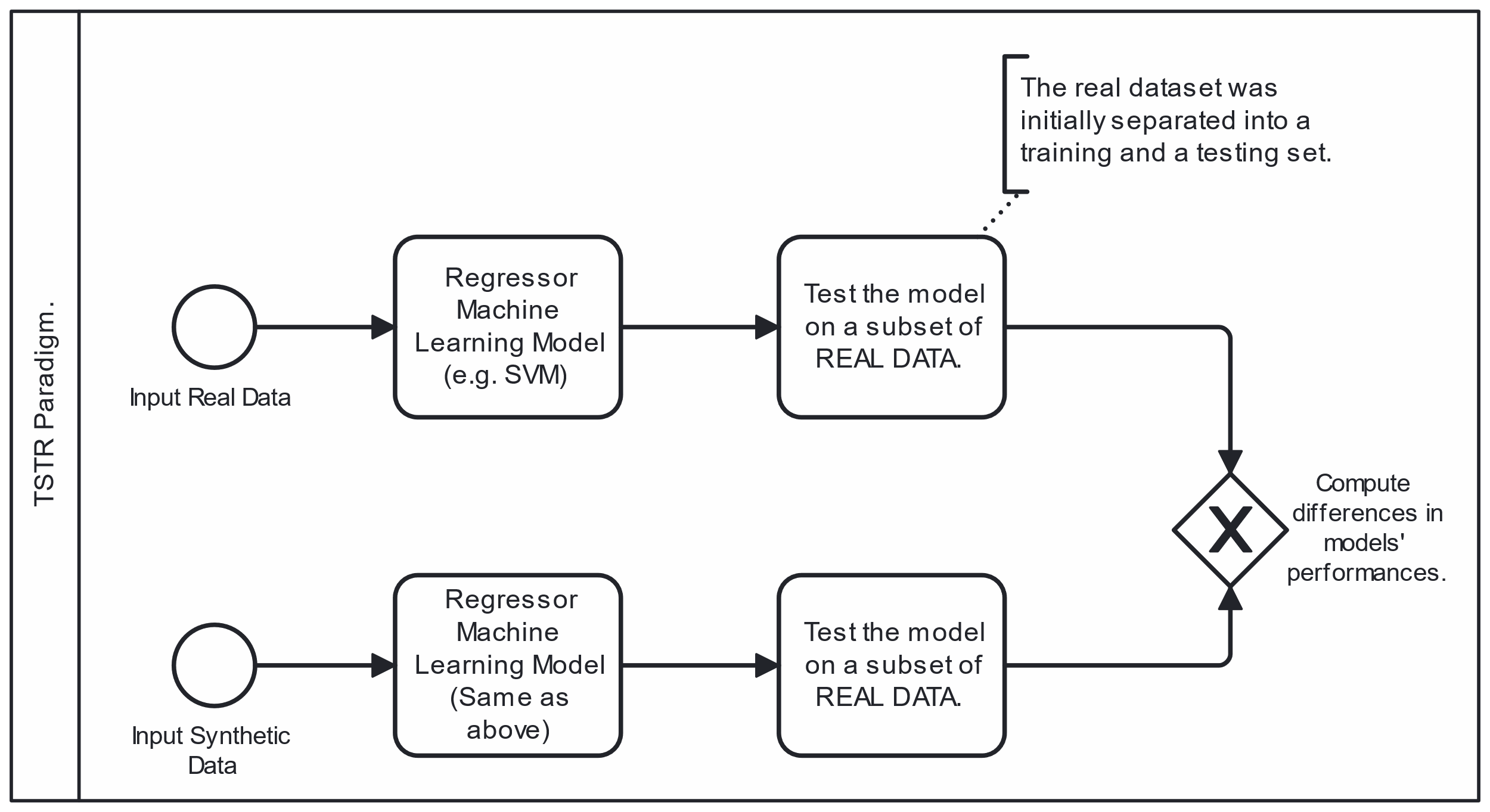


Figure 1. TSTR Paradigm Visually Explained.

To practically implement this approach, each synthetic dataset (generated by Gaussian Copula, CTGAN, and TVAE from SDV; Bayesian Network, CTGAN, and TVAE from Synthicity) was first scaled and then split into training subsets. These synthetic training subsets were then used to train four regression models: XGBRegressor, Random Forest Regressor, Support Vector Regressor (SVR), and Linear Regression. Critically, the trained models were tested only on subsets of the real data, ensuring a valid and realistic evaluation scenario. Multiple evaluation rounds were conducted using repeated holdout validation, each time varying the training-test split to obtain robust and statistically significant results. The predictive performance of these models was measured using three metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and the Coefficient of Determination (R²). These metrics were computed both for the models trained on synthetic datasets and for models trained directly on real data, averaged over multiple evaluation splits. To facilitate intuitive comparisons, absolute differences between synthetic-data-trained and real-data-trained model performances were calculated for each metric, and normalized relative to the performance of real-data-trained models. These normalized differences were converted into scores ranging from negative infinity to 1, with a score of 1 indicating identical performance to the real-data-trained models. Finally, an Overall Score was derived by averaging these metric-specific scores, providing an easily interpretable summary of each synthetic dataset's predictive utility.

To compare the models under different conditions, two experimental settings were designed. In the first experiment, all six synthetic data generators from the two packages were trained on the same subset of 1,000 rows from the real dataset (the energy data described in the section above). Each model was then asked to generate 1,000 synthetic rows, resulting in a 1:1 ratio between the input and the output (Fig. 2).

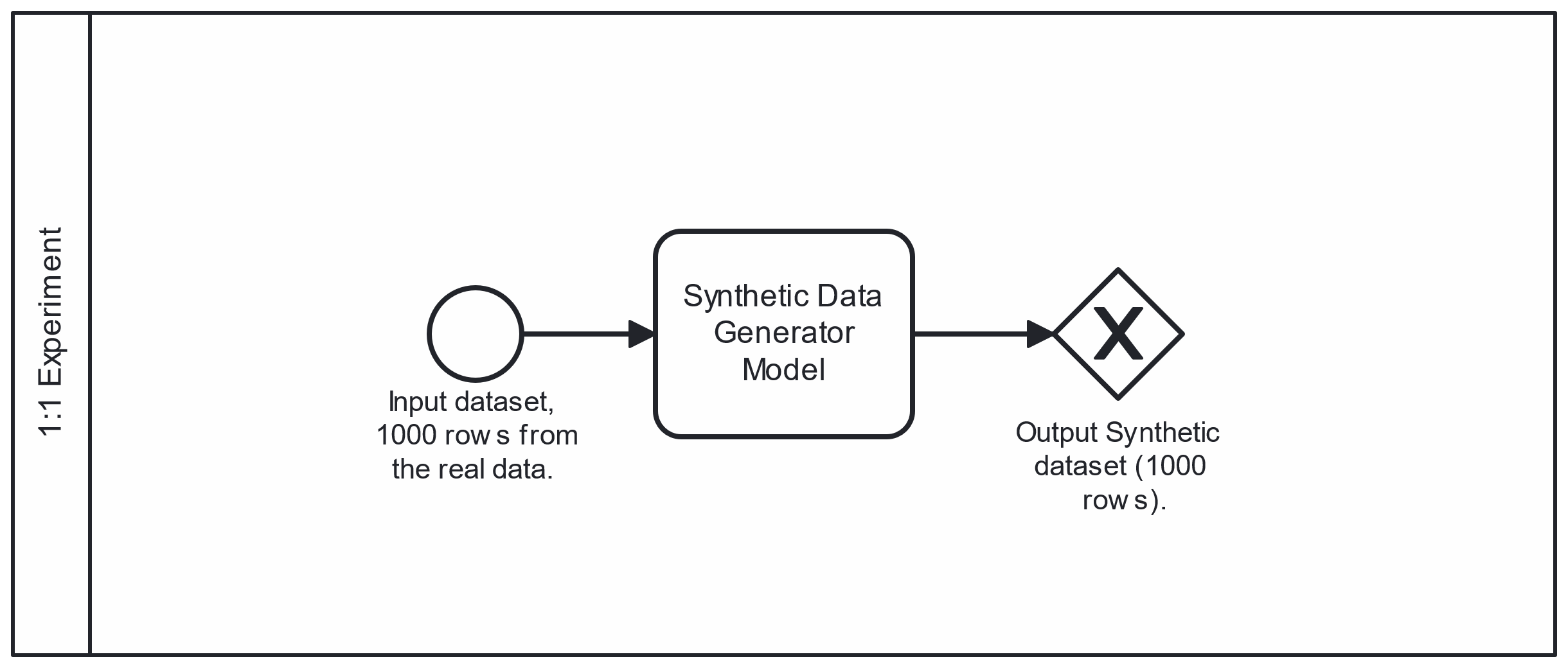


Figure 2. 1:1 Experiment Visualization.

This setup allowed us to evaluate how well each model could replicate the training data without having to extrapolate beyond the scale of the original dataset. In the second experiment, the same synthetic data generators were again trained on the same 1,000 real rows, but this time asked to generate 10,000 synthetic rows, creating a 1:10 ratio between the input and the generated output (Fig. 3). This second setting was meant to test the models’ ability to scale and generalize, specifically, their ability to generate significantly more data than the original input.

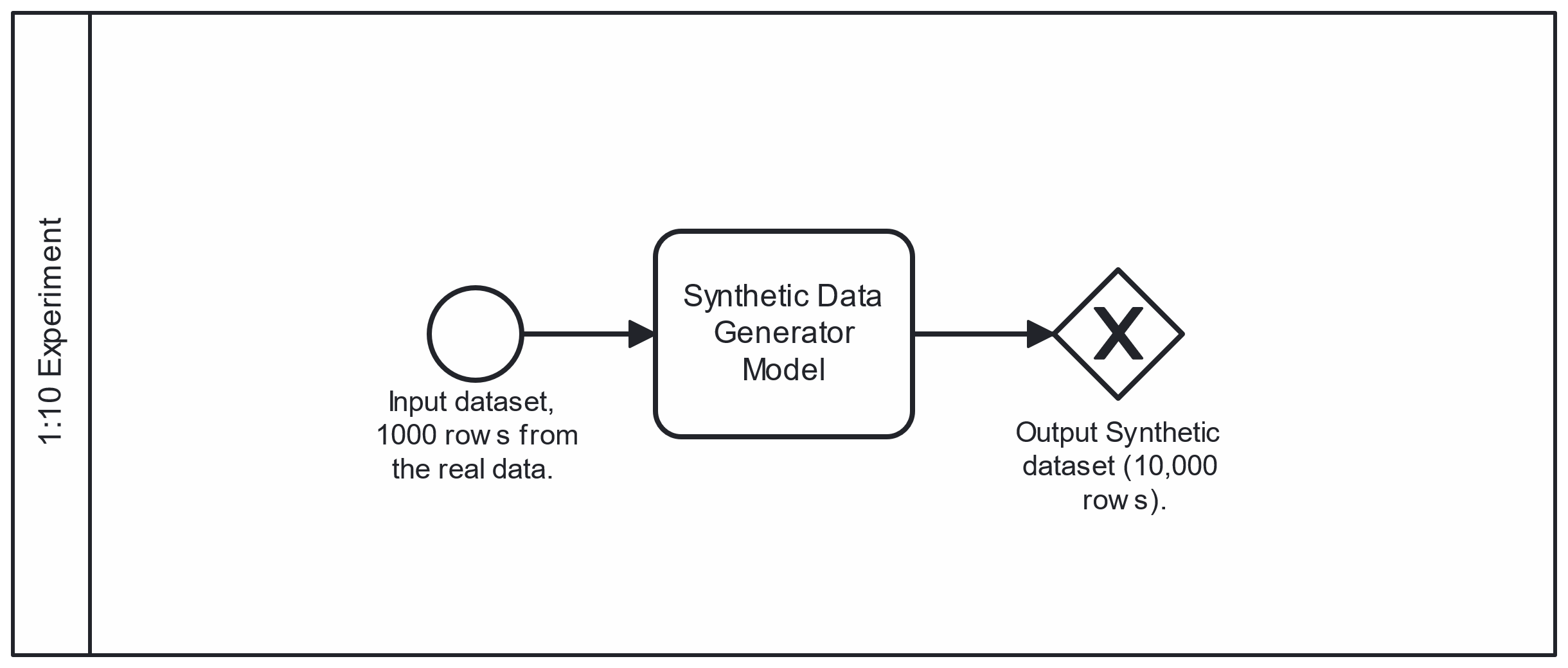


Figure 3. 1:10 Experiment Visualization.

From this process, a total of twelve synthetic datasets were produced: six from the 1:1 setting and six from the 1:10 setting. All synthetic datasets were then evaluated using the two previously described metrics: statistical similarity, which captures how closely the synthetic data matches the real data in terms of column-wise statistics and distributions; and predictive utility, which assesses how well machine learning models trained on synthetic data perform when tested on real data.

The full implementation and analysis are available in the accompanying [GitHub repository.](https://github.com/cris1618/syntheticData/blob/main/generate_synthetic_data.ipynb)

1. **Results**
   1. **Statistical Similarities**

In the 1:1 experiment (described above), six different synthetic datasets were generated: three from the SDV package and three from the Synthicity package. Each synthetic dataset was evaluated using the metric described in the method section, which measures how well the statistical properties of the synthetic data match those of the original real dataset on a column-by-column basis. This metric ranges from 0 to 100, with 100 indicating a perfect match, meaning the statistical properties are identical. In this setting, all models performed well, with scores ranging between 80 and 96. The best-performing model was the Bayesian Network from Synthicity, achieving a score of 96.53. The complete set of results for the 1:1 experiment is shown in Table 1.

Table 1. 1:1 Statistical Similarity Scores.

|  |  |  |  |
| --- | --- | --- | --- |
| Models | SDV Models | Synthicity  Models | |
| Gaussian Copula  CTGAN  TVAE  Bayesian Network | 91.98  80.28  87.38  - | -  88.37  86.26  96.53 |

The same evaluation process was applied to the synthetic datasets generated in the 1:10 experiment. In this case, the similarity scores were generally lower but still reasonably high, ranging from 70 to just under 80. Once again, the Bayesian Network from Synthicity was the best-performing model, achieving a similarity score of 78.25. The complete results for the 1:10 experiment are presented in Table 2.

Table 2. 1:10 Statistical Similarity Scores.

|  |  |  |  |
| --- | --- | --- | --- |
| Models | SDV Models | Synthicity  Models | |
| Gaussian Copula  CTGAN  TVAE  Bayesian Network | 77.07  71.89  73.29  - | -  75.23  76.17  78.25 |

* 1. **Predictive Utility**

The predictive utility of each synthetic dataset was evaluated using the method described in the previous section. In short, a custom scoring approach was implemented to quantify how closely the models trained on synthetic data resembled those trained on real data. This metric ranges from negative infinity to 1, where a score of 1 indicates that the synthetic data led to model performance identical to the real data, and lower values reflect greater divergence. To perform the evaluation, four regression models, XGBRegressor, Random Forest Regressor, Support Vector Regressor (SVR), and Linear Regression, were trained separately on both the real dataset and on each of the twelve synthetic datasets generated during the 1:1 and 1:10 experiments. For each model, we computed three standard regression metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and the Coefficient of Determination (R²). The results were then averaged across the four regression models to ensure robustness.

Table 3 presents the averaged model performances for the real dataset and the synthetic datasets generated in the 1:1 experiment.

Table 3. 1:1 ML models average performances.

|  |  |  |  |
| --- | --- | --- | --- |
| Dataset Used for Model Training | Average Mean Absolute Error (MAE) | Average Mean Squared Error (MSE) | Average Coefficient of Determination (R2) |
| Real Data | 58.78 | 11,649.10 | 0.32 |
| Gaussian Copula SDV | 71.48 | 16400.56 | 0.05 |
| Bayesian Network SYN | 57.60 | 11917.78 | 0.31 |
| CTGAN SDV | 118.06 | 23282.25 | -0.36 |
| CTGAN SYN | 96.32 | 18523.87 | -0.08 |
| TVAE SDV | 67.65 | 17335.38 | -0.002 |

Table 4 shows the corresponding results for the 1:10 experiment.

Table 4. 1:10 ML models average performances.

|  |  |  |  |
| --- | --- | --- | --- |
| Dataset Used for Model Training | Average Mean Absolute Error (MAE) | Average Mean Squared Error (MSE) | Average Coefficient of Determination (R2) |
| Real Data | 45.69 | 8177.29 | 0.29 |
| Gaussian Copula SDV | 73.91 | 12834.36 | -0.10 |
| Bayesian Network SYN | 103.30 | 20567.99 | -0.77 |
| CTGAN SDV | 148.06 | 30546.57 | -1.65 |
| CTGAN SYN | 115.63 | 21322.55 | -0.84 |
| TVAE SDV | 64.97 | 12150.86 | -0.04 |

**Note:** The performance scores on the real data differ between the 1:1 and 1:10 experiments because different amounts of real data were used for training. In the 1:1 experiment, only 1,000 rows of real data were used to train the regression models, matching the size of the synthetic datasets. In contrast, the 1:10 experiment used 10,000 rows of real data for training in order to ensure a fair comparison with the larger synthetic datasets generated in that setting.

In the 1:1 experiment, the synthetic datasets generated by the six synthetic data generators from the two packages performed reasonably well overall in terms of predictive utility (as measured by the custom score ranging from negative infinity to 1, described in the method section). The Bayesian Network from Synthicity achieved the highest score by far (0.97), followed by the Gaussian Copula from SDV (0.51). A score of 0.97 indicates that the performance of the regression models trained on the synthetic data generated by the Bayesian Network was nearly identical to the performance of the same models trained on the real data. This suggests that the synthetic data closely matched the underlying structure and distribution of the real dataset, an ideal outcome for synthetic data generation. The complete results for the 1:1 experiment are presented in Table 5.

Table 5. 1:1 Predictive Utility Scores.

|  |  |  |  |
| --- | --- | --- | --- |
| Models | SDV Models | Synthicity  Models | |
| Gaussian Copula  CTGAN  TVAE  Bayesian Network | 0.51  -0.37  0.45  - | -  0.17  0.45  0.97 |

The results were notably different in the 1:10 experiment. In this setting, overall performance dropped significantly, with predictive utility scores considerably lower than those observed in the 1:1 experiment. Moreover, the models that performed best in the 1:1 setting did not necessarily perform well here. In this case, the best-performing model was TVAE from SDV, which achieved a predictive utility score of 0.31, followed by the Gaussian Copula from SDV with a score of 0.15. All other models produced negative scores, indicating a substantial drop in performance and suggesting that the synthetic data they generated diverged significantly from the real data, an undesirable outcome in the context of synthetic data generation. The full set of results for the 1:10 experiment is shown in Table 6.

Table 6. 1:10 Predictive Utility Scores.

|  |  |  |  |
| --- | --- | --- | --- |
| Models | SDV Models | Synthicity  Models | |
| Gaussian Copula  CTGAN  TVAE  Bayesian Network | 0.15  -2.85  0.31  - | -  -1.33  -0.54  -1.13 |

1. **Discussion and Conclusion**

This study set out to compare synthetic data generators from two of the most prominent open-source Python packages: SDV and Synthicity. Our goal was to evaluate both usability and performance, and to determine whether one package consistently outperforms the other in generating high-quality synthetic data. Based on the results, there is no clear overall winner in terms of performance. When it comes to statistical similarity, all models from both packages performed reasonably well, with no significant distinction between the two. In terms of predictive utility, however, the Bayesian Network model from Synthicity clearly outperformed all others in the 1:1 experiment. Notably, SDV does not include an implementation of a Bayesian Network, which may explain part of the difference, especially considering that the structure of Bayesian Networks can be particularly effective for capturing dependencies in datasets like the one used in this study [39] (i.e., household energy consumption, as described in the method section).

Beyond raw performance, another important consideration is usability, including documentation quality and user experience. In this regard, SDV clearly stands out. It offers excellent documentation, a larger and more active community, and comprehensive tutorials that make the framework accessible, even to researchers and users with limited programming experience. The process of generating synthetic data with SDV is straightforward and well-supported. In contrast, Synthicity’s documentation is less complete and can be difficult to follow. During the course of this study, we encountered issues using Synthicity, particularly with larger datasets, and the troubleshooting process was not well-supported by the existing documentation. In conclusion, while both packages offer competitive performance, SDV excels in usability and support, making it a more user-friendly option. However, for users specifically interested in models like Bayesian Networks, Synthicity may be a better choice.

One of the main challenges in synthetic data generation lies in producing large amounts of realistic data from a small real dataset. The 1:1 and 1:10 experiments were specifically designed to explore this challenge. While the 1:1 scenario tests how well a generator can replicate what it has seen, the 1:10 scenario evaluates how well it can extend and generalize, an essential capability in low-data settings. The results clearly show that synthetic data generators performed significantly better in the 1:1 case. In this setting, most models achieved high statistical similarity scores, and predictive utility remained relatively strong, with the Bayesian Network from Synthicity reaching a near-perfect score of 0.97. This suggests that when the output size matches the input, generators are more capable of preserving the underlying data structure. In contrast, the 1:10 experiment revealed a marked drop in performance. While statistical similarity scores remained acceptable (between 70 and 80), predictive utility suffered noticeably. Only TVAE from SDV achieved a moderately positive score (0.31), while most other models, including the same ones that performed well in the 1:1 case, yielded negative utility scores. These results highlight the limitations of current synthetic data generators when tasked with generalizing beyond their input size. They also underscore the need for more robust generative models capable of scaling synthetic datasets without sacrificing predictive quality, a critical requirement in real-world scenarios where large datasets are needed but only small samples are available.

Another notable result that deserves further exploration is the observed performance disparity between statistical and deep learning-based methods across the two experimental settings. In the 1:1 experiment, statistical models such as Gaussian Copula and Bayesian Network outperformed deep learning-based models like CTGAN and TVAE in terms of predictive utility. This superior performance can be attributed to the nature of statistical models, which rely on explicit probabilistic assumptions and are well-suited for capturing the underlying distributions in smaller datasets. For instance, Bayesian Networks have demonstrated effectiveness in modeling complex dependencies in building energy consumption data, providing accurate predictions even with limited data [40].

Conversely, in the 1:10 experiment, where the synthetic data generators were tasked with producing ten times more data than the original input, deep learning-based models exhibited better performance. Specifically, TVAE from SDV achieved the highest predictive utility score among all models in this setting. Deep learning models like TVAE are designed to capture intricate, high-dimensional patterns in data, making them more adept at generalizing from limited inputs to generate larger synthetic datasets. However, it's important to note that while TVAE outperformed other models in the 1:10 experiment, its predictive utility score was still lower compared to the top-performing models in the 1:1 experiment, indicating challenges in maintaining data quality when scaling up synthetic data generation. Interestingly, CTGAN, another deep learning-based model, consistently underperformed in both experimental settings. This consistent underperformance suggests that CTGAN may have limitations in capturing the complex dependencies present in the energy consumption dataset used in this study. Previous research has also indicated that CTGAN's performance can vary depending on the dataset characteristics and that it may not always be the most effective choice for tabular data generation [41].

These findings suggest that the choice between statistical and deep learning-based synthetic data generation methods should consider the specific requirements of the task at hand, including the size of the available real dataset and the desired scale of the synthetic data. Statistical models may be more appropriate for scenarios with limited data and a need for high fidelity in replication, while deep learning models might be better suited for applications requiring the generation of larger synthetic datasets, albeit with potential trade-offs in data quality.

Finally, it's important to address why models with the same name, CTGAN and TVAE, showed different performances when implemented in the SDV and Synthicity packages. Although these models are conceptually based on the same architectures, the way each package implements them differs in key ways that can impact performance. For example, Synthicity uses deeper neural networks with more parameters and applies stronger regularization methods like dropout and weight decay, which can help prevent overfitting but may require more training data to work effectively [42]. In contrast, SDV’s versions tend to use smaller, simpler networks and rely on techniques like mode-specific normalization and PacGAN to improve learning from small datasets. Another factor is the training process itself. SDV uses a fixed number of training epochs with relatively conservative learning rates, while Synthicity uses more dynamic training strategies with longer training durations and early stopping. These choices can make Synthicity's models more flexible but also more sensitive to the nature of the input data. Furthermore, the way data is preprocessed before being fed into the models varies between the two frameworks. SDV uses its own transformation toolkit (RDT), which handles continuous and categorical columns differently from Synthicity’s internal preprocessing methods [43].

Together, these differences help explain why TVAE from SDV was the best-performing deep learning model in the 1:10 experiment, while its counterpart from Synthicity did not achieve the same level of utility. Likewise, CTGAN, despite being available in both packages, performed poorly across both settings, possibly due to its sensitivity to architectural and training hyperparameters, which differ significantly between the two environments [26].

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