**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 [1], their power became available to anyone with internet access, greatly impacting many aspects of daily life [2].

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 [3]. The biggest LLMs today are often pre-trained on trillions of tokens. For example, GPT‑3 was famously trained on nearly 500 billion tokens [4], from a mixture of web text, books, and other sources. GPT‑4 is rumored to have used well over a trillion tokens [5], and Anthropic’s Claude reportedly relies on a similarly large-scale corpus, likely in the hundreds of billions to trillions of tokens [6]. The exact numbers for GPT‑4 and Claude have not been officially disclosed by OpenAI and Anthropic, but external analyses report similar figures [7].

However, acquiring such a massive quantity of high-quality data has become more challenging [8]. Many sources are now gated behind paywalls, restricted by copyright, or filtered due to data quality concerns [9]. 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 [10, 11]. Chen et al. [3] 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. [12] 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. [13], 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 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 models and decomposes the joint probability distribution of a continuous random vector into a product of marginal distributions, capturing the dependencies between variables separately. 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 [14]. 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) [15] 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) [16] 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) [17], 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 [18]. 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 [19]. 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” [20], 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 is conducted by Akiya et al. [21], 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 Triplet-Based 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 large fraud detection dataset from a Kaggle competition, which contains millions of rows and over 300 features. 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.

**References**

[1] OpenAI. *ChatGPT.* 2022. Retrieved from <https://openai.com/index/chatgpt/>.

[2] A. Shaji George, & A. S. Hovan George. (2023). A Review of ChatGPT AI’s Impact on Several Business Sectors. *Partners Universal International Innovation Journal*, *1*(1), 9–23. <https://doi.org/10.5281/zenodo.7644359>

[3] Chen, Hao, et al. "On the Diversity of Synthetic Data and Its Impact on Training Large Language Models." *arXiv* preprint arXiv:2410.15226v2 [cs.CL], 22 Oct. 2024.

[4] Brown, Tom, et al. “Language Models Are Few-Shot Learners.” *Advances in Neural Information Processing Systems*, vol. 33, Curran Associates, Inc., 2020, pp. 1877–1901, <https://proceedings.neurips.cc/paper/2020/file/1457c0d6bfcb4967411061b3e5a3861b-Paper.pdf>.

[5] OpenAI. *GPT‑4 Technical Report.* 14 Mar. 2023, <https://cdn.openai.com/papers/GPT-4-System-Card.pdf>.

[6] Bai, Yuntao, et al. *Constitutional AI: Harmlessness from AI Feedback.* Anthropic, 2022, <https://arxiv.org/abs/2212.08073>.

[7] Bubeck, Sébastien, et al. “Sparks of Artificial General Intelligence: Early Experiments with GPT‑4.” *arXiv* preprint arXiv:2303.12712 [cs.LG], 2023.

[8] Pablo Villalobos, Jaime Sevilla, Lennart Heim, Tamay Besiroglu, Marius Hobbhahn, and Anson Ho. Will we run out of data? an analysis of the limits of scaling datasets in machine learning. arXiv. preprint arXiv:2211.04325, 2022.

[9] Perełkiewicz, Michał, and Rafał Poświata. "A Review of the Challenges with Massive Web-mined Corpora Used in Large Language Models Pre-Training." arXiv preprint arXiv:2407.07630 (2024).

[10] Lisa Bauer and Mohit Bansal. Identify, align, and integrate: Matching knowledge graphs to commonsense reasoning tasks. arXiv preprint arXiv:2104.10193, 2021

[11] Ruibo Liu, Jerry Wei, Fangyu Liu, Chenglei Si, Yanzhe Zhang, Jinmeng Rao, Steven Zheng, Daiyi Peng, Diyi Yang, Denny Zhou, et al. Best practices and lessons learned on synthetic data for language models. arXiv preprint arXiv:2404.07503, 2024.

[12] Lu, Yingzhou, et al. *Machine Learning for Synthetic Data Generation: A Review.* arXiv preprint, arXiv:2302.04062, 30 June 2024.

[13] Bauer, André, et al. *Comprehensive Exploration of Synthetic Data Generation: A Survey.* University of Chicago, University of Würzburg, University of Ulm, Argonne National Laboratory, 2024. arXiv preprint arXiv:2401.02524.

[14] Goodfellow, Ian, et al. "Generative adversarial nets." *Advances in Neural Information Processing Systems* (NeurIPS), vol. 27, 2014, pp. 2672–2680.

[15] Radford, Alec, Luke Metz, and Soumith Chintala. "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks." *arXiv preprint* arXiv:1511.06434, 2015.

[16] Mirza, Mehdi, and Simon Osindero. "Conditional generative adversarial nets." *arXiv preprint* arXiv:1411.1784, 2014.

[17] Arjovsky, Martin, Soumith Chintala, and Léon Bottou. "Wasserstein GAN." *arXiv preprint* arXiv:1701.07875, 2017.

[18] Kingma, Diederik P., and Max Welling. "Auto-Encoding Variational Bayes." *arXiv preprint* arXiv:1312.6114, 2013.

[19] Ho, Jonathan, Ajay Jain, and Pieter Abbeel. "Denoising diffusion probabilistic models." *Advances in Neural Information Processing Systems* (NeurIPS), vol. 33, 2020, pp. 6840–6851, arXiv:2006.11239.

[20] Vaswani, Ashish, et al. "Attention Is All You Need." *Advances in Neural Information Processing Systems* (NeurIPS), vol. 30, 2017, pp. 5998–6008.

[21] Akiya, Ippei, Takuma Ishihara, and Keiichi Yamamoto. "Comparison of Synthetic Data Generation Techniques for Control Group Survival Data in Oncology Clinical Trials: Simulation Study." JMIR Medical Informatics, vol. 12, 2024, e55118. https://doi.org/10.2196/55118.