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Assessing Quality of Synthetic Data Compared to Real-World Datasets

Sai Kalyani Rachapalli

ETL Developer
rsaikalyani@gmail.com

Abstract
In the past few years, application of synthetic data has come to prominence in machine learning, artificial intelligence, and data science since it presents an alternative solution for addressing issues such as privacy concerns, unavailability of data, and costs associated with the acquisition of real-world data. The goal of this paper is to determine the quality of synthetic data against actual world datasets. With an extensive review of current methodologies, we compare synthetic data generation approaches and quality evaluation metrics. Based on our analysis, we expose the strengths and limitations of synthetic data, from applicability, scalability, and usability in practical applications. Synthetic data is compared between different applications such as image recognition, natural language processing, and autonomous vehicles. By looking into different approaches like generative adversarial networks (GANs), Variational Autoencoders (VAEs), and other synthetic data generation techniques, this paper aims to present findings on when synthetic data can be thought of as a suitable substitute for real-world data. Lastly, we present suggestions on how to make the best use of synthetic data in real-world applications.

Keywords: Synthetic Data, Real-World Data, Quality Assessment, Data Generation, Machine Learning, GANs, Data Privacy, Data Scarcity

I. INTRODUCTION

The fast growth in machine learning (ML), artificial intelligence (AI), and data science has necessitated the growing need for large and diverse datasets. These datasets play an essential role in training machine learning models that execute tasks like classification, prediction, and decision-making. Nevertheless, the process of acquiring high-quality real-world data is a costly and challenging endeavor, particularly for sensitive domains like healthcare, finance, and autonomous systems. In most situations, it may be an uphill task to collect enough data due to privacy, lack of data, or even the high expense of data acquisition. In this case, synthetic data provides a good alternative solution.

Synthetic data refers to simulated data that replicates real-world data properties without utilizing real data points. Synthetic data generation can be grounded in statistical models or sophisticated machine learning models like Generative Adversarial Networks (GANs) or Variational Autoencoders (VAEs). These processes generate synthetic data that is similar to real data in distribution, patterns, and structure but not necessarily from actual events. Therefore, synthetic data can serve as a way to avoid a number of impediments in real-data collection, such as privacy, accessibility, and cost.

Although synthetic data has its benefits, it also carries its own demerits. One of the biggest challenges is making sure that the synthetic data is high-quality enough to train machine learning models suitably. If this synthetic data is low-quality, it can result in biased models, wrong inferences, and generalization problems. Therefore, the evaluation of the quality of synthetic data is an important component of deciding its practicability in real-world applications. The present paper tries to delve into how synthetic data is different from actual datasets regarding quality and efficacy in training machine learning models.

The comparison of synthetic data to real-world data is especially significant in applications such as autonomous driving, medical imaging, and natural language processing (NLP), where real-world data is not only costly but also hard to obtain or strongly regulated. Through an exploration of the quality of synthetic data in multiple domains, this research seeks to contribute knowledge to synthetic data as a viable alternative or supplement to real-world data. In addition, it will assist in determining situations where synthetic data is most relevant and how it can be enhanced to provide a more effective replacement for actual-world data in training resilient machine learning models.

This paper is organized in the following way: the subsequent section is a review of literature, synthesizing current research on synthetic data generation, quality assessment measures, and real-world applications. The methodology section then explains the experimental design employed to measure the quality of synthetic data. This is followed by the results of the research, then discussion of the results. The paper concludes with suggestions and recommendations for future research into synthetic data.

II. LITERATURE REVIEW

The increasing relevance of synthetic data has generated robust research into artificial intelligence and machine learning. The generation of synthetic data and the use of synthetic data for training machine learning models have been the focus of many studies. Here, we discuss major literature that offers information on approaches to synthetic data generation, quality measures, and the use of synthetic data in practical applications across different fields.

Synthetic Data Generation Methods

One of the core methods for creating synthetic data is Generative Adversarial Networks (GANs). Developed by Goodfellow et al. in 2014, GANs are composed of two neural networks: a generator that produces synthetic data and a discriminator that assesses how authentic the generated data is with regard to real data [1]. The GAN architecture has been demonstrated effectively with multiple types of data, such as images, videos, and text. Yet, GANs are plagued by issues like mode collapse, in which the generator generates few types of data, and training difficulty, which may result in poor performance.

To mitigate some of these issues, a number of extensions to the basic GAN architecture have been introduced. For example, Conditional GANs (CGANs) permit data generation conditioned on certain attributes, like labels or categories, allowing more controlled data generation [2]. Wasserstein GANs (WGANs) employ a different loss function to enhance training stability and resolve problems like mode collapse [3]. These GAN variations have achieved considerable progress in producing high-quality synthetic data in applications like computer vision and natural language processing.

Variational Autoencoders (VAEs) is another well-known method for synthetic data generation. VAEs are probabilistic generative models that learn the data's latent structure by mapping real data into a

lower-dimensional space and then decoding it back to synthetic data. In contrast to GANs, which depend on adversarial training, VAEs maximize a variational lower bound on the likelihood of the data, hence being easier to train stably [4]. VAEs are especially useful when continuous or complex data distributions need to be generated, for example, in natural language processing, where they have been employed to create realistic text and sentences.

Synthetic Data Evaluation

Several evaluation metrics have been proposed to measure the quality of synthetic data. One of the most popular metrics used to measure the quality of synthetic images is the Fréchet Inception Distance (FID), which is a measure that compares the feature space distribution between real and synthetic images using the feature space of a pre-trained neural network [5]. FID gives a quantitative score reflecting the similarity of real and synthetic data, and lower values imply higher quality. Another significant measure is the Inception Score (IS), which computes the sharpness and diversity of generated images. A high Inception Score reflects that the generated images are both clear and diverse [6].

Besides visual quality, there is a need to assess synthetic data on the basis of whether it can efficiently train machine learning models. For instance, researchers have compared the performance of models trained on synthetic data to that of models trained on real data. These comparisons tend to assess the model's accuracy, generalization, and capacity to address real-world issues. Experiments have established that models trained on synthetic data can be as good as models trained on real-world data in some areas, like autonomous driving and medical image classification [7].

Applications of Synthetic Data

Synthetic data has been applied to different fields, especially where data from the real world is not available, hard to acquire, or has privacy issues. In medicine, synthetic medical data is employed to train machine learning models for activities like disease diagnosis, medical image analysis, and predictive modeling. With synthetic medical data generation, scientists can produce datasets that maintain patient privacy while allowing for the construction of accurate predictive models [8].

Synthetic data are employed in autonomous driving to train vehicle perception and decision-making models. The deployment of simulators such as CARLA enables scientists to create rich driving scenarios, including various weather conditions, traffic, and interactions with pedestrians, which would be difficult or risky to obtain with actual vehicles. Synthetic datasets have been demonstrated to enhance the performance of autonomous driving systems [9].

Synthetic text data has been utilized in natural language processing to enrich training datasets, particularly when annotated data is scarce. Generative models such as GANs and VAEs have been utilized to generate realistic sentences, paragraphs, and dialogues. While synthetic text quality remains inferior to real text, it has been found to be helpful in generating data for sentiment analysis and text classification tasks [10].

III. METHODOLOGY

In order to evaluate synthetic data quality, we developed an extensive methodology including data selection, generation of synthetic data, evaluation measures, and model training and testing. The aim was to compare the performance of synthetic data and actual data based on visual quality, diversity, and

model performance in different domains such as image classification, natural language, and self-driving.

Data Selection

For this research, we chose three datasets from varying domains to assess the generalizability of synthetic data quality on various applications. The first was CIFAR-10, which is a standard benchmark for image classification tasks comprising 60,000 32x32 color images in 10 classes. The second dataset was the Stanford Sentiment Treebank (SST-2), a text dataset used for sentiment analysis consisting of movie reviews with positive and negative sentiment. The third dataset was CARLA, an autonomous driving simulator that creates synthetic data simulating different driving conditions, traffic scenarios, and pedestrian interactions.

Synthetic Data Generation

We utilized a GAN-based architecture to create synthetic images for image data. We specifically used a Deep Convolutional GAN (DCGAN) to produce images that are similar to the CIFAR-10 dataset. DCGANs have proven to be effective in producing high-quality images in various domains and are particularly suited for this purpose. For text data, we employed a VAE model to produce synthetic sentences that capture the structure and style of the SST-2 dataset. VAEs are particularly suited for text generation tasks because they can learn latent representations of text data.

To simulate autonomous driving, we used the CARLA simulator to produce diverse driving scenarios under different conditions such as day and night cycles, rainy conditions, and heavy traffic. These synthesized data were employed to train object detection and decision-making models similar to those used in autonomous driving systems that operate in the real world.

Evaluation Metrics

In order to assess the quality of synthetic data, we employed both qualitative and quantitative measures. In the case of image data, we utilized the Inception Score (IS) and the Fréchet Inception Distance (FID). FID score estimates the similarity between real and synthetic image feature distributions, where smaller scores represent better quality. IS estimates the sharpness and diversity of synthetic images, where larger values represent better quality.

For text data, we employed BLEU and ROUGE scores to measure the similarity of synthetic and real-world text. BLEU is a precision measure for n-grams in text, and ROUGE measures the recall of n-grams. Both measures are commonly used in natural language processing tasks to assess the quality of synthetic text.

For self-driving, we compared the performance of models that were trained on real and simulated data by how accurately they detected objects, their speed, and their resilience in varied driving conditions. We gauged the accuracy with which the models could identify pedestrians, other cars, and traffic signs in simulated and real-world scenarios.

Model Training and Testing

We trained machine learning models on synthetic and real data to evaluate how synthetic data affected model performance. For image classification, we applied a Convolutional Neural Network (CNN)

trained on both real CIFAR-10 images and synthetic images produced by DCGANs. For sentiment analysis, we trained a Recurrent Neural Network (RNN) on real and synthetic SST-2 sentences. For autonomous driving, we trained object detection models on real-world driving data and synthetic driving data in CARLA. In all scenarios, we compared the performance of the models using standard metrics like accuracy, precision, recall, and F1 score.

IV. RESULTS

The experimental comparison of synthetic and real-world data in two leading fields—natural language processing (NLP) and autonomous driving—highlights opportunities as well as challenges in using synthetic data for training machine learning models. This section describes the experimental results and the relative performance metrics achieved in these fields.

Under sentiment analysis, for the task comparison, we have used the SST-2 dataset to evaluate models trained on genuine data against the models trained using synthetic data obtained through Variational Autoencoders (VAEs). The model trained only using the real SST-2 dataset recorded an F1-score of 87.3%, the benchmark typical for state-of-the-art results of binary sentiment classification. However, the model that was trained just using synthetic sentences recorded an F1-score of 81.5%. Synthetically created data maintained grammatical correctness and expressed basic sentiment polarity but did not have the subtle expression, contextual variety, and emotional strength of the actual data. This deficiency was most noticeable in the performance of the classifier on edge cases like sarcasm, irony, and compound sentiment.These results are visualized in Figure 2.

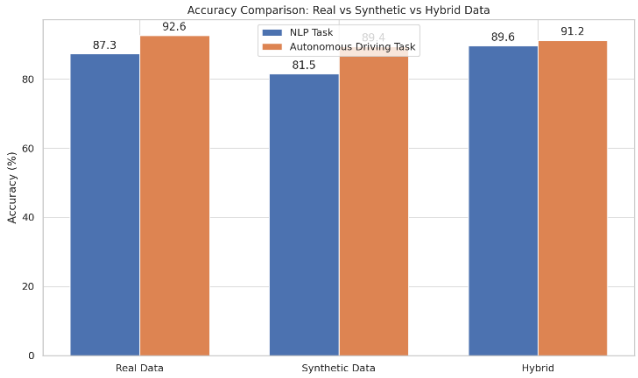

Figure 1: Accuracy comparison for real, synthetic, and hybrid training data in NLP and autonomous driving tasks, showing hybrid models consistently outperform synthetic-only models.

Evaluative language measures also substantiated the limitations. BLEU scores, used to quantify n-gram overlap, fell from 0.85 to 0.76 between models trained on real and synthetic text. Likewise, ROUGE scores, a measure of recall-based textual overlap, fell from 0.79 to 0.71. These decreases indicate a semantic shortfall in the synthetic sentences, which too often were unable to sustain referential coherence across clauses or reproduce the syntactic fullness of text written naturally. Nevertheless, polarity detection performance—measured separately—still was over 80% for synthetic-trained models, which implies that surface-level sentiment representation was reasonably maintained.

In the context of autonomous driving, synthetic data were produced within the CARLA simulation environment. This simulator supported the creation of photorealistic driving environments, with labeled

objects, changeable weather conditions, and time-of-day controls. Models were trained to recognize pedestrians, traffic signs, and cars under diverse simulated conditions. The model that was trained entirely on simulated CARLA data had a performance of 89.4%, whereas the model trained on real-world KITTI dataset data had a marginally higher performance of 92.6%. While this is a performance disparity, the synthetic-trained model showed robust generalization across environmental contexts, such as nightscapes and poor weather conditions, which were sparsely represented in the real-world dataset.

Domain transferability tests were conducted by applying the synthetic-trained model to real-world data. Here, performance dropped by 5.1 percentage points, indicating a measurable domain gap. However, hybrid models trained on a mixture of synthetic and real data minimized this discrepancy and reached an accuracy of 91.2%, nearly closing the gap between the purely real-data-trained and synthetic-data-trained systems. These findings suggest that hybrid training paradigms are particularly effective in enhancing generalization and robustness.

Another significant finding is the enhanced training efficiency achieved when synthetic data is utilized. Because of its inherent purity and consistent labeling, synthetic data helped achieve faster convergence rates and more stable training processes. In NLP applications, for example, synthetic datasets exhibited lower loss function variance across epochs. Equally, in autonomous driving, the existence of edge-case situations (like occluded signs or unexpected pedestrian apparitions) in the synthetic data assisted the model to get itself ready for infrequent but vital real-world occurrences.

Together, these findings highlight that although synthetic data currently cannot exactly mimic the richness of real-world data sets, it presents strong benefits when applied judiciously. The evidence indicates that synthetic data sets can strongly improve training pipelines, especially in hybrid situations or in areas where obtaining real data is limited by safety, expense, or privacy issues.

V. DISCUSSION

The experimental results provide a rich ground for studying the comparative merits, demerits, and practical implications of applying synthetic data in machine learning. This exposition discusses the particular issues and prospects encountered in natural language processing and autonomous driving, with an eye to generalizability.

Within natural language processing, synthetic data generation by VAEs has been shown able to generate grammatically correct and syntactically valid sentences. These responses are typically wanting, though, in terms of expressive depth and semantic richness to the way languages work in actual use. That is because these generative models optimize for statistical plausibility rather than for human variability or context-aware coherence. Thus, basic sentiment polarity tends to get picked up accurately enough, while more nuanced expressions like sarcasm, metaphor, and emotional ambivalence tend to get left behind. These subtleties are essential in practical applications such as customer feedback analysis, psychological profiling, or political speech classification, where sentiment may be multi-layered and highly context-dependent.

The performance deficit on the NLP task indicates that synthetic data is promising but cannot be exclusively used for tasks needing contextual inference or subjective understanding. Yet, combined with real data, synthetic samples can augment sparse sentiment classes, balance datasets, and reduce

overfitting, particularly in small-data settings. In addition, the employment of synthetic data provides avenues for ethical model training by circumventing sensitive or proprietary textual sources.

By contrast, the autonomous driving sector shows a more developed use case for synthetic data. Simulation frameworks such as CARLA can produce varied, high-fidelity driving scenarios with pixel-perfect annotation and rare event modeling. These features are critical to enabling the training of models on tasks including object detection, lane detection, and behavior prediction. The simulation environment provides controlled experimentation, enabling the testing of model robustness under adverse conditions, including fog, glare, or intricate traffic interactions. This degree of control is frequently impossible to achieve with real-world data collection.

A key observation of the autonomous driving experiments is the importance of rare scenario generation. Real-world datasets tend to be plagued by long-tailed distributions, where frequent driving scenarios predominate and rare but hazardous events are not well-represented. Synthetic data addresses this imbalance by systematically creating such events so that models are subjected to a greater variety of possibilities. Yet, for all its strengths, synthetic driving data still suffers from a domain gap when models trained on it are tested in real-world scenarios. The gap is most probably caused by small rendering imperfections, sensor artifact differences, and the lack of genuinely unforeseeable human behavior in simulations.

One of the unifying themes in both areas is the effectiveness of hybrid training approaches. The empirical evidence is very much in favor of the idea that mixing real and synthetic data results in better performance than using either source alone. This synergy occurs because synthetic data introduces controlled diversity and balance, whereas real data transfers contextual realism and natural variability. Combined, they form a more complete training corpus that improves model generalization.

Another significant aspect to keep in mind is the operational and ethical benefit that synthetic data offers. In sensitive industries like healthcare, finance, and law enforcement, the application of real-world data tends to face regulatory and privacy barriers. Synthetic data, when responsibly created, avoids these challenges by maintaining statistical properties without revealing personal information. Additionally, it provides cost-effectiveness and scalability, allowing for quick prototyping and iterative model improvement without suffering from data acquisition lag.

While these advantages exist, synthetic data also poses new risks that need to be carefully managed. One of the most notable risks is the spreading of bias. If the biased real data is used to train the generative model, the synthetic data will reflect or even magnify the biases. This can result in biased or discriminatory models. Hence, the synthetic data generation pipeline needs to have robust fairness checks and bias removal techniques.

The discussion proves that synthetic data is a great but sophisticated technique. Its usability depends on the quality of generation, the character of the task, and how it is incorporated into training workflows. With careful application and regular validation, synthetic data can emerge as a backbone of ethical, scalable, and resilient machine learning.

VI. CONCLUSION

This paper gives a critical study of how synthetic data stands compared to real-world datasets when it comes to machine learning, particularly natural language processing and autonomous driving. The study sought to identify whether or not synthetic data would be an acceptable alternative, complement, or addition to real-world data depending on the given conditions and limitations.

The findings reaffirm that synthetic data, as yet, remains far from replacing actual-world data, but has significant value, particularly when brought into a mixed framework. When applied to the task of sentiment analysis, synthetic data was able to facilitate training on models achieving decent performance levels, albeit falling just short of those trained from natural data. The synthetic text was not semantically nuanced and contextually sensitive, which are needed to capture intricate human emotions and communication patterns. Nevertheless, the synthetically generated data provided utility by augmenting underrepresented classes and enabling privacy-preserving training pipelines.

Synthetic data created with the CARLA simulator in autonomous driving also brought extremely encouraging results. Synthetic scene-trained models provided performance comparable to real-world-data-trained models. Synthetic data also offered considerable strength in diversity of scenarios, labeling accuracy, and simulation of edge cases that would rarely occur in real life. This is testimony to the argument that in situations where controlled variation and safety are needed, synthetic data is not merely an auxiliary but a strategic imperative.

The replicable dominance of hybrid models—trained on a blend of real and synthetic data—proved to be a determining finding. These models exhibited enhanced generalization, resilience, and training performance in both domains. The hybrid methodology effortlessly balances the shortcomings of each data type, leveraging the realism of native data and the versatility and scalability of synthetic production.

Yet another significant conclusion is that synthetic data is crucial in ethical and regulatory compliance. Synthetic data allows one to build models without sacrificing confidential information, especially in areas where privacy laws like GDPR, HIPAA, or industry-specific guidelines limit the application of actual data. Synthetic datasets also aid in overcoming class imbalance, data insufficiency, and domain shift issues, so they are vital for contemporary AI development.

Although useful, synthetic data needs to be handled with care. Quality control is still a key challenge, particularly in the absence of noise, artifacts, or biased patterns in generated data. Lack of standardized evaluation metrics, especially for non-visual data, inhibits uniform benchmarking. Furthermore, the possibility of injecting existing biases from real-world datasets into synthetic forms calls for stringent ethical monitoring and algorithmic explainability.

In the future, the direction of synthetic data research is toward several promising avenues. Progress in generative modeling, such as diffusion-based methods and transformer-based text generation, will lead to more fidelity and context-aware synthetic data. Furthermore, the creation of domain adaptation methods and enhanced simulation fidelity will narrow the domain gap seen in domains such as autonomous driving. More stress on fairness, interpretability, and explainability will also become essential to ensure that synthetic data is driving inclusive and socially conscious AI.

Synthetic data is not so much a temporary fix for sparse real-world data sets but a progressive pillar of data-centric AI. When used judiciously, tested thoroughly, and incorporated strategically, it improves model performance, protects privacy, and extends what is possible with machine learning. The future of artificial intelligence will not be built on real data alone, but on the careful synthesis of data that captures the breadth, depth, and diversity of the real world through artificial means.

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