

Generative Models for Synthetic Data: Transforming Data Mining in the GenAI Era

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Abstract

Generative models such as Large Language Models, Diffusion Models, and generative adversarial networks have recently revolutionized the creation of synthetic data, offering scalable solutions to data scarcity, privacy, and annotation challenges in data mining. This tutorial introduces the foundations and latest advances in synthetic data generation, covers key methodologies and practical frameworks, and discusses evaluation strategies and applications. Attendees will gain actionable insights into leveraging generative synthetic data to enhance data mining research and practice. More information can be found on our website: <https://syndata4dm.github.io/>.

CCS Concepts

- Computing methodologies → Natural language processing;
- Information systems → Data mining.

Keywords

Generative Models, Large Language Models, Data Synthesis, Data Mining

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1 INTRODUCTION

In the era of data-driven artificial intelligence (AI), access to large-scale, high-quality datasets has become a fundamental requirement for breakthroughs in data mining and machine learning. However, real-world data is often scarce, expensive to annotate, or restricted due to privacy and proprietary concerns. Synthetic data, algorithmically generated datasets that mimic the statistical properties and underlying patterns of real-world data, has emerged as a powerful solution to these challenges.

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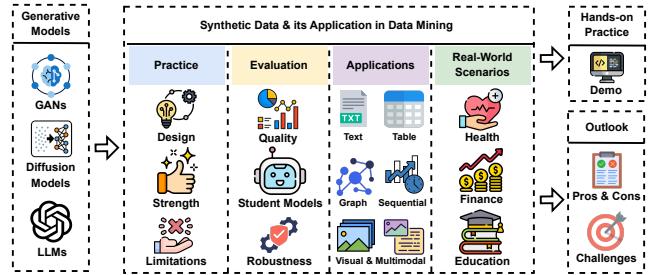


Figure 1: The overview of our tutorial.

Recent advances in generative models, such as Large Language Models (LLMs), Diffusion Models, and generative adversarial networks (GANs) have significantly enhanced our ability to generate realistic, diverse, and controllable synthetic data across a wide range of data types. Synthetic data powered by these generative models is revolutionizing the way we approach data mining, from augmenting training datasets and reducing annotation costs to enabling privacy-preserving analytics and fostering innovation in low-resource or long-tail scenarios.

This tutorial aims to provide an up-to-date overview of the foundations, methodologies, practical frameworks, evaluation techniques, and real-world applications of synthetic data generation using modern generative models. We will highlight both the opportunities and challenges in leveraging synthetic data for data mining, empowering researchers and practitioners to effectively apply these cutting-edge techniques in their own domains.

2 TARGET AUDIENCE, PREREQUISITES, AND BENEFITS

Target Audience. This tutorial is intended for researchers, practitioners, and graduate students in data mining, machine learning, natural language processing, and computer vision who are interested in using synthetic data to address challenges such as data scarcity, privacy, and generalization.

Prerequisites. Attendees are expected to have a basic understanding of machine learning and deep learning, and some familiarity with generative models such as Large Language Models and Diffusion Models. Prior exposure to NLP, computer vision, or multimodal tasks is helpful but not required.

Benefits. By the end of the tutorial, participants will have a clear overview of recent advances in synthetic data generation, learn how to apply existing tools to real-world problems, and understand the

practical considerations involved in evaluating and using synthetic data effectively.

3 OUTLINE of TUTORIAL

Our tutorial is designed as a half-day session, spanning 3 hours with a short break in between. The detailed agenda is as follows:

Part 1. Foundations of Synthetic Data (85 mins)

- Introduction & Background (15 mins)
- Core Generative Models for Data Generation (30 mins)
- Synthetic Data in Practice (20 mins)
- Evaluation and Benchmarking (20 mins)

Coffee Break. (15 mins)

Part 2. Applications and Future Directions (80 mins)

- Applications in Data Mining (30 mins)
- Real-world Scenarios (15 mins)
- Hands-on Practice (20 mins)
- Challenges, Future Directions, and Q&A (15 mins)

3.1 Introduction & Background

Definition & Motivation. In this section, we will first introduce the definition and motivation of synthetic data generation. In the broadest sense, it refers to the process of generating artificial data that algorithmically emulates the statistical properties and underlying patterns of a real-world dataset. In today’s AI landscape, the cost and constraints of curating large-scale, high-quality datasets have become a primary bottleneck to progress. Thus, we will include the motivation of synthetic data generation from different aspects [19, 25], including: data scarcity, annotation cost reduction, privacy preservation, proprietary data protection, long-tail distributions, low-resource scenarios, etc.

Background. We will also include the background knowledge regarding synthetic data generation, from early rule-based augmentation or GAN-style generators that worked well in vision to advanced techniques utilizing Diffusion Models and Large Language Models. Also, we will provide an overview of the real-world applications of synthetic data generation and how it relates to the area of data mining. In this section, we hope to provide a quick glance at the topic to the audience.

3.2 Core Generative Models for Synthetic Data Generation

We will mainly cover 3 categories as the core generative models: Generative Adversarial Networks (GANs), Diffusion Models, and Large Language Models.

Generative Adversarial Networks. GANs [4] remain the “classics” of synthetic data generation: a generator learns to fool a discriminator that distinguishes real from fake, gradually shaping samples that follow the true data manifold. We will introduce how vanilla GANs work, some milestone GAN-style models, including Style-GAN [9], Drag-GAN [20], etc. We will introduce their pros and cons, and why they are not as popular as the 2 categories below.

Diffusion Models. Diffusion [6] treats generation as incremental denoising: data are gradually noised to a latent prior, then reconstructed step-by-step with a learnable reverse process. We will introduce how vanilla Diffusion Models work, some milestones, including DALL-E, Stable Diffusion [22], Sora, etc. We will compare their pros and cons with GAN-style models.

Large Language Models. Instruction-tuned LLMs have revolutionized text-centric synthesis: a single prompt can emit grammatically correct paragraphs. Different from the above 2 categories, this series of models focuses mainly on text data generation, either for texts as queries or images, videos as queries. We will introduce milestone models and methods for this section.

3.3 Synthetic Data in Practice

In this section, we will introduce some of the most recent and advanced frameworks for synthetic data generation. For text-based data, we will discuss systems such as MagPie [29], DataGen [7], and DyVal [35, 36]. For multimodal data (e.g., text-image or text-audio pairs), we will cover frameworks like Task-Me-Anything [33] and AutoBench-v [2].

We will explore how these frameworks are designed, the underlying generative techniques they employ, and how they address different challenges in data synthesis. Furthermore, we will analyze their respective strengths, such as scalability, controllability, and data diversity, as well as their limitations, including potential biases, domain generalization issues, and computational overhead.

3.4 Evaluation and Benchmarking

Evaluating synthetic data is a critical yet challenging task in machine learning and data science. Current approaches assess data fidelity, diversity, controllability, truthfulness, and downstream utility through a combination of quantitative metrics and task-specific performance on real-world benchmarks [7, 10, 18]. In practice, synthetic data is often evaluated by training models on generated datasets and then measuring their performance on downstream tasks, which serves as a proxy for real-world applicability. Despite these advances, robust and interpretable evaluation remains an open problem. In particular, existing methods struggle to comprehensively address issues such as data bias [31], ethical risks, and the generalization capabilities of synthetic data across different domains and applications.

3.5 Applications in Data Mining

Text Data. Synthetic text data enhances text mining tasks such as classification, relation extraction, and named entity recognition. Approaches mainly include: (1) generating or augmenting input text to enrich datasets [32], and (2) generating pseudo labels for unlabeled data to facilitate annotation [34], improving both data diversity and efficiency.

Tabular Data. Tabular data synthesis involves: (1) generative modeling with diffusion, flow-based, or GAN-based models [11], (2) conditional table generation guided by schema and control signals [14, 23], and (3) table extraction from raw text using LLMs [15]. Synthetic tables support privacy-preserving release, data augmentation, and robust learning.

Graph Data. Graph data synthesis advances molecule, protein, network analysis, and knowledge graph construction [12, 16]. Key approaches include: (1) structure-level generation of graph topologies [8], (2) node/edge-level augmentation [28], and (3) conditional generation from textual or structured input [30].

Sequential Data. Sequential data synthesis includes: (1) time series generation that captures complex temporal patterns [17], and (2) representation synthesis for sequential recommendation, augmenting user-item interactions [13]. These techniques balance class distributions, simulate rare events, and aid pretraining.

Visual & Multimodal Data. Visual and multimodal synthesis spans: (1) image generation with foundation diffusion models (e.g., Stable Diffusion, DALL-E), and (2) multimodal generation of aligned visual-language pairs. Synthetic data enables efficient creation of diverse, labeled datasets for improved training of vision and multimodal models.

3.6 Real-world Scenarios

In this section, we will discuss the utilization of synthetic data in various real-world data mining scenarios, including health, finance, and education. In the health domain, foundation models such as GPT-4 and hierarchical autoregressive transformers have been employed to generate synthetic clinical records and electronic health data, supporting tasks like named entity recognition and patient outcome prediction while preserving privacy [26]. In finance, generative models including Diffusion Models and GANs have been used to simulate realistic transaction data for fraud detection, address data imbalance, and facilitate data sharing among financial institutions under privacy constraints [21]. In the education sector, synthetic student performance records produced by GANs and LLMs have enabled accurate predictive modeling for student outcomes while mitigating data scarcity issues [3].

3.7 Hands-on Practice

In this section, we aim to provide a demo program as hands-on practice to show how to synthesize each of the types of synthetic data we mentioned in Section 3.5, including text [32], tabular [23], graph [12], sequential [17] and visual & multimodal [27] data.

3.8 Outlook

Pros & Cons. In this section, we outline both the pros and cons of the use of synthetic data in data mining application. The pros include: (1). enhancing data privacy by avoiding real personal records, (2). enabling large-scale data generation and (3). helping address data imbalances [1]. The cons involves: (1). failing to capture the nuances of real-world distributions, (2). learn spurious or unrealistic patterns, and (3). overfitting to the artificial distribution [5].

Challenges and Future Directions. In this section, we highlight several challenges and promising directions for future research in this area. Although model collapse [24] has been observed in generative models trained iteratively on synthetic data, its effects on the data distribution of data mining models remain underexplored and warrant further investigation. Moreover, there is still a lack of effective strategies for integrating generative model-based and

traditional data synthesis methods. Such integration could enable the generation of more trustworthy synthetic data across scenarios.

4 RELATED TUTORIALS

Synthetic Data in the Era of Large Language Models @ ACL 2025,
 Synthetic Tabular Data: methods, attacks and defenses @ KDD 2025
 Synthetic Healthcare Data Generation and Assessment: Challenges, Methods, and Impact on Machine Learning @ ICML 2021

While these tutorials each focus on a single modality or application, our session uniquely spans all major data types—text, tabular, graph, sequential, and multimodal—showcasing the latest generative models, end-to-end frameworks, and unified evaluation strategies tailored for diverse data mining tasks.

5 PRESENTER BIOGRAPHY

Dawei Li is a Ph.D. student in Computer Science at Arizona State University. Previously, He obtained his bachelor’s degree in Computer Science from Beijing Language and Cultural University and master’s degree in Data Science from the University of California, San Diego. His research focuses on techniques and risks from AI oversight. Dawei have published papers and served as reviewers in top NLP and Data Mining venues including ACL, EMNLP, NAACL, TKDD, PAKDD and SIGKDD Exploration.

Yue Huang is a Ph.D. student in Computer Science and Engineering at the University of Notre Dame. He earned his B.S. in Computer Science from Sichuan University. His research investigates the trustworthiness and social responsibility of foundation models. Yue has published extensively at premier venues including NeurIPS, ICLR, ICML, ACL, EMNLP, NAACL, CVPR, and IJCAI. His work has been highlighted by the U.S. Department of Homeland Security and recognized with the Microsoft Accelerating Foundation Models Research Award and the KAUST AI Rising Star Award (2025).

Ming Li is a Ph.D. student in Computer Science at the University of Maryland. Previously, He obtained his bachelor’s degree in Computer Science from Xi'an Jiaotong University and his master’s degree in Computer Science from Texas A&M University. His research focuses on post-training for foundation models and responsible and self-evolving AI. Ming has published papers and served as a reviewer in top NLP and Machine Learning venues, including ACL, EMNLP, ICLR, NAACL, and etc.

Tianyi Zhou is a tenure-track assistant professor of Computer Science at the University of Maryland, College Park (UMD). He received his Ph.D. from the University of Washington and worked as a research scientist at Google before joining UMD. His research interests are machine learning, natural language processing, and multi-modal generative AI. His team has published >130 papers in ML (NeurIPS, ICML, ICLR), NLP (ACL, EMNLP, NAACL), CV (CVPR, ICCV, ECCV), and journals such as IEEE TPAMI/TIP/TNNLS/TKDE, with >10000 citations. He is the recipient of the best student paper of ICDM 2013. He has been serving as an area chair of ICLR, NeurIPS, ACL, EMNLP, SIGKDD, AAAI, IJCAI, WACV, etc.

Xiangliang Zhang is a Leonard C. Bettex Collegiate Professor in the Department of Computer Science and Engineering, University of Notre Dame. She was an Associate Professor in Computer Science at the King Abdullah University of Science and Technology (KAUST), Saudi Arabia. She received her Ph.D. degree in computer

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Huan Liu is a Regent Professor in the School of Computing, and Augmented Intelligence, Arizona State University. He received his Ph.D. degree in Computer Science from the University of Southern California, in 1989. His research focuses on developing computational methods for data mining, machine learning, and social computing. Dr. Liu has been honored with numerous prestigious awards: ACM SIGKDD Innovation Award (2022) for his pioneering work in feature selection and social media mining, Fellow of ACM (2018), AAAI (2019), AAAS (2018), and IEEE (2012). He is Chief Editor of ACM TIST, Frontiers in Big Data and DMM, and has been actively involved on editorial boards and program committees for major conferences such as KDD, ICML, NeurIPS, AAAI, and IJCAI.

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