Do flow-matching models maintain higher feature dependency fidelity than VAEs when generating synthetic sample

Assignee Research

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Abstract

Deep generative models have made rapid progress in image, text, audio, and video generation, and are increasingly being applied to structured records. For tabular data, however, generative modeling remains difficult: a dataset may contain numerical and categorical attributes, missing values, sensitive fields, imbalanced categories, complex feature dependencies, and domain constraints. Earlier tabular data modeling methods based on GANs or VAEs have achieved useful results, but they can suffer from unstable training, mode collapse, weak modeling of multimodal distributions, and fragile handling

1 Introduction

This paper examines: Diffusion and Flow Matching Models for Tabular Data: A Survey. Research question: Do flow-matching models maintain higher feature dependency fidelity than VAEs when generating synthetic samples for low-frequency categories in structured data?.

2 Methodology

Systematic literature search across multiple databases yielded 12 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 4.7/10.

3 Results

12 papers retrieved. 19 claims extracted; 1 independently verified. Quality review score: 4.7/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
Formal differential privacy has begun to appear in tabular diffusion models.	×	0.06
Most tabular diffusion works rely on empirical privacy metrics such as distance-to-closest-record, attribute inference,	×	0.04
Recent memorization studies indicate that a small subset of records may dominate memorized generations.	×	0.02
Removing memorization-prone or rare records can change minority-group coverage.	×	0.01
Many diffusion and flow matching models operate as black-box generative systems.	✓	0.17
The anomaly detection method TCCM shows that feature-level residuals can support interpretability.	×	0.04
Explanation tools for synthesis and imputation are underdeveloped compared to anomaly detection methods.	×	0.06
Scaling, encoding, and inverse transformations can change how feature-level evidence is interpreted.	×	0.03
Healthcare models such as FlexGen-EHR and PatientFlow point toward multimodal and longitudinal tabular generation.	×	0.05
Most current benchmarks for tabular data generation remain single-table and static.	×	0.08
Several recent methods combine diffusion or flow matching with autoencoders, transformers, tree models, or feature-token	×	0.13
Diffusion SOS (2022) is a synthesis model for single, generic tables using SDEs.	×	0.03
STaSy (2023) is a synthesis model for single, generic tables using SDEs.	×	0.02
TabDDPM (2023) is a synthesis model for single, generic tables using DDPM+MLD.	×	0.02
CoDi (2023) is a synthesis model for single, generic tables using DDPM+MLD.	×	0.02
AutoDiff (2023) is a synthesis model for single, generic tables supporting any probability path.	×	0.04
MissDiff (2023) is a synthesis model for single, generic tables using SDEs.	×	0.02
Data augmentation for tabular data can be divided into data synthesis and over-sampling.	×	0.10
Over-sampling can be considered a special case of single table synthesis where only a part of the table is generated.	×	0.04

References

- http://arxiv.org/abs/2211.16889v1
- http://arxiv.org/abs/2303.04707v2
- http://arxiv.org/abs/2502.17119v2