Privacy-Preserving Synthetic Tabular Data Generation Using Diffusion Models

SEDS500 Graduation Project

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Abstract

Research Summary

This project investigates **diffusion models** as a privacy-preserving approach for generating synthetic tabular data.

Method: TabDDPM-style diffusion with hybrid Gaussian-Multinomial noise

Comparison: Against CTGAN (GAN-based) and SMOGN (interpolation-based)

Key Results:

- **87–98%** of baseline model performance with synthetic data alone
- Significantly outperforms CTGAN (35%) and SMOGN (fails completely)
- **Zero privacy leakage** (membership inference AUC = 0.51)

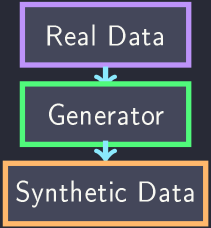
Conclusion: Diffusion models are superior for generating high-utility, privacy-preserving synthetic tabular data.

Motivation & Problem Definition

The Challenge:

- Organizations need to share data for ML collaboration
- Privacy regulations (GDPR, KVKK) restrict data sharing
- Traditional methods (GANs, interpolation) struggle with mixed data types

Solution: Synthetic Data



Research Question

Do diffusion models produce more realistic synthetic tabular data than traditional methods?

Evaluation Criteria:

1. **Utility**: ML performance on real data
2. **Privacy**: No information leakage

Proposed Solution

Implement TabDDPM-style diffusion for tabular data generation

Key innovations:

- Hybrid noise handling
- Gaussian for numerical features
- Multinomial for categorical features
- Log-space operations for stability
- KL divergence loss

Methods compared:

- **TabDDPM-style** (ours)
- CTGAN (GAN-based)
- SMOGN (interpolation)

Datasets:

- Production (5,370 samples)
- Ozel Rich (2,670 samples)

Related Research

Paper	Venue	Approach	Key Innovation
TabDDPM	ICML 2023	Diffusion	Hybrid Gaussian-Multinomial noise
CTGAN	NeurIPS 2019	GAN	Mode-specific normalization
STaSy	ICLR 2023	Score-based	Self-paced learning
TabSyn	ICLR 2024	Latent diffusion	Transformer VAE encoder

Why diffusion over GANs?

- GANs suffer from mode collapse and training instability
- Diffusion models have stable training dynamics
- Iterative refinement captures full data distribution

Our contribution: Implement and evaluate TabDDPM-style diffusion on real organizational datasets with privacy validation.

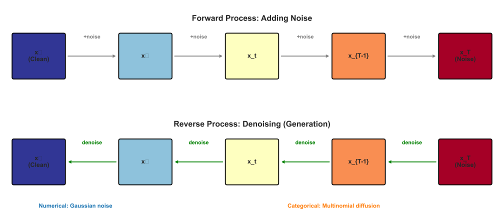
Solution: TabDDPM Diffusion Model

How Diffusion Works:

- **Forward**: Gradually add noise (T=1000 steps)
- **Reverse**: Learn to denoise step-by-step
- Neural network: noise $\rightarrow$ realistic data

TabDDPM Hybrid Approach:

- **Numerical**: Gaussian diffusion
- **Categorical**: Multinomial diffusion
- Process both simultaneously



Iterative denoising from random noise

Key Advantage

Stable training + captures full distribution (no mode collapse like GANs)

Datasets & Experimental Setup

Two real-world organizational datasets (Turkish fastener company):

Dataset	Domain	Samples	Features	Target
Production	Sales quotation	5,370	7 num + 35 cat	Quote amount
Ozel Rich	Custom mfg	2,670	2 num + 4 cat	Machine time

Evaluation scenarios:

1. **Replacement**: Train on synthetic only, test on real data
2. **Augmentation**: Train on real + synthetic, test on real data

Metrics: R^2 score (utility), MIA AUC (privacy)

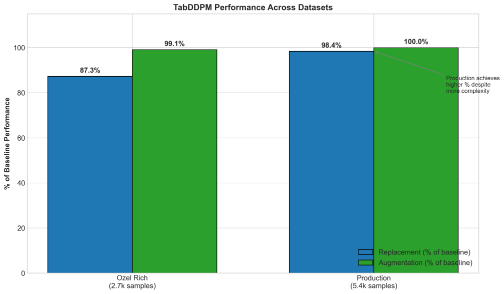
Results: Utility Comparison

Ozel Rich Dataset (Replacement scenario)

Method	R^2	%
Baseline	0.645	100%
SMOGN	-0.14	FAILED
CTGAN	0.229	35.5%
TabDDPM	**0.563**	**87.3%**

Production Dataset

Scenario	R^2	%
Replacement	0.979	**98.4%**
Augmentation	0.994	**100%**



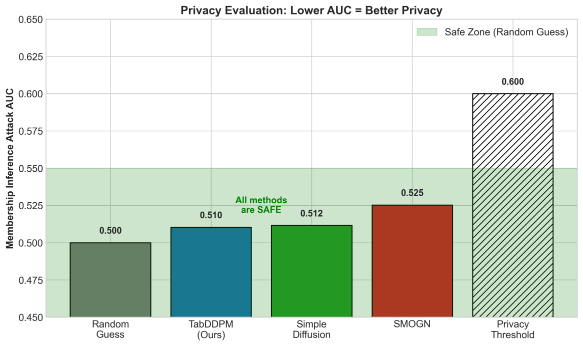
Key findings:

- TabDDPM: **87–98%** of baseline
- CTGAN: 35% | SMOGN: Failed
- Generalizes across datasets

Results: Privacy Evaluation

Membership Inference Attack: Can attacker identify training records?

Method	AUC	Status
Random	0.50	–
TabDDPM	**0.51**	SAFE
Simple Diff	0.51	SAFE
SMOGN	0.53	SAFE



AUC $\approx$ 0.5 = Random guessing = No privacy leakage

Key Result

TabDDPM: **Highest utility** (87–98%) + **Excellent privacy** (AUC = 0.51)

Conclusion & Future Work

Key Findings:

- TabDDPM: **87–98%** utility vs 35% (CTGAN)
- Privacy-safe: MIA AUC = 0.51 (random guessing)
- SMOGN fails on complex tabular data
- Generalizes across different datasets

Main Conclusion

Diffusion models are superior for privacy-preserving synthetic data

Limitations:

- 2 organizational datasets
- Basic privacy evaluation

Future Work:

- TabSyn (latent diffusion)
- Differential privacy
- Public benchmarks

Applications:

- Safe data sharing
- GDPR/KVKK compliance

Thank You

Questions?

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