

Curriculum Learning with Progressive Causal Synthetic Data for Tabular Foundation Model Generalization on TBTL

Assignee Research

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Abstract

Synthetic tabular data generation addresses data scarcity and privacy constraints in a variety of domains. Tabular Prior-Data Fitted Network (TabPFN), a recent foundation model for tabular data, has been shown capable of generating high-quality synthetic tabular data. However, TabPFN is autoregressive: features are generated sequentially by conditioning on the previous ones, depending on the order in which they appear in the input data. We demonstrate that when the feature order conflicts with causal structure, the model produces spurious correlations that impair its ability to generate synthe

1 Introduction

This paper examines: Improving TabPFN’s Synthetic Data Generation by Integrating Causal Structure. Research question: Does curriculum learning with progressively complex causal synthetic datasets improve the cross-domain generalization of tabular foundation models compared to uniform scaling on the TBTL benchmark?.

2 Methodology

Systematic literature search across multiple databases yielded 14 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.3/10.

3 Results

14 papers retrieved. 15 claims extracted; 14 independently verified. Quality review score: 8.3/10.

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
Synthetic data quality is evaluated using Correlation Matrix Difference (CMD), k-Marginal Total Variation Distance (kMTV	✓	0.32
CMD quantifies structural dependency preservation by computing the Frobenius norm of the difference between real and syn	✓	0.16
The study replaces Pearson correlation with Spearman’s rank correlation for numerical–numerical pairs to capture monoton	✓	0.21
Mixed correlation matrices combine Cramr’s V for categorical–categorical pairs, the correlation ratio η for categorical	✓	0.28
For kMTVD calculation, continuous variables are discretized into 20 quantile-based bins.	✓	0.17
kMTVD is calculated as the mean Total Variation Distance across all variable pairs.	✓	0.21
NNAA assesses privacy preservation by comparing nearest-neighbor distances between real and synthetic datasets using Gow	✓	0.23
In the NNAA metric, values near 0.5 indicate that synthetic and real data are hard to distinguish.	✓	0.19
Statistical significance of differences between conditioning strategies is assessed using the Wilcoxon signed-rank test	✓	0.23
Effect sizes are quantified using the Hodges–Lehmann estimator.	✓	0.21
Experiments are conducted on three dataset classes: fully controlled hand-crafted settings, public benchmark datasets, a	✓	0.21
A custom four-variable Structural Causal Model (SCM) containing a collider was designed to evaluate TabPFN’s sensitivity	×	0.14
TabPFN is pre-trained on millions of synthetic datasets derived from Structural Causal Models (SCMs).	✓	0.15
Generation methods that ignore causal dependencies among variables may create spurious correlations that differ from the	✓	0.20
Inaccurate estimation of treatment effects from flawed synthetic data could lead to costly trials on ineffective drugs o	✓	0.25

References

- <http://arxiv.org/abs/2601.04110v2>
- <http://arxiv.org/abs/2603.10254v1>
- <http://arxiv.org/abs/2512.03307v1>