CausalMixFT vs. GANs and Diffusion Models in Cross-Domain Tabular Few-Shot Learning

Assignee Research

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Abstract

This report synthesises findings from 14 peer-reviewed papers addressing the following research question: How does the CausalMixFT approach compare to other synthetic data augmentation methods (e.g., GANs, diffusion models) in cross-domain tabular few-shot learning benchmarks like TabFewShot. 10 claims were extracted from source literature; 1 was independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 4.5/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Causal Data Augmentation for Robust Fine-Tuning of Tabular Foundation Models. Research question: How does the CausalMixFT approach compare to other synthetic data augmentation methods (e.g., GANs, diffusion models) in cross-domain tabular few-shot learning benchmarks like TabFewShot?.

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 4.5/10.

3 Results

14 papers retrieved. 10 claims extracted; 1 independently verified. Quality review score: 4.5/10.

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
CausalMixFT achieves the highest median improvement of (+0.12$\pm$0.63) over the pre-trained model on 33 classification data	×	0.10
Default fine-tuning has a variability of $\pm$0.98, while CausalMixFT has a variability of $\pm$0.63, indicating greater instabi	×	0.08
CausalMixFT ranks first overall in average ranks across datasets, followed by the default fine-tuning baseline, with pur	×	0.07
Early stopping based on limited validation data leads to significant validation set overfitting depending on the fine-tu	✓	0.16
The normalization strategy used to compare performance across different data generators is based on the zero-shot perfor	×	0.04
CausalMixFT extends the fine-tuning framework by mixing real and causally grounded synthetic samples into the fine-tunin	×	0.12
SCM-Based Synthetic Augmentation (CausalMixFT) uses SCMs fitted to the target dataset to generate synthetic data that re	×	0.11
The PC and FCI algorithms are used to estimate the structural relations between features in the SCM framework.	×	0.04
DoWhy's SCM framework with additive noise models is used to sample and fit DAGs for generating synthetic samples.	×	0.05
Numerical features are modeled with regressors, and categorical features with classifiers in the SCM framework.	×	0.04

References

- http://arxiv.org/abs/2601.04110v2
- http://arxiv.org/abs/2504.20900v1
- http://arxiv.org/abs/2502.17119v2