

Scaling and Trade-offs in Fine-Tuning Tabular Foundation Models with CausalMixFT

Assignee Research

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Abstract

This report synthesises findings from 12 peer-reviewed papers addressing the following research question: How does fine-tuning tabular foundation models with CausalMixFT scale with increasing causal graph complexity (e.g., number of edges, latent confounders), and what is the trade-off between. 14 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.8/10. 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 fine-tuning tabular foundation models with CausalMixFT scale with increasing causal graph complexity (e.g., number of edges, latent confounders), and what is the trade-off between augmentation quality and computational efficiency when evaluated on SuperTab tasks?.

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 3.8/10.

3 Results

12 papers retrieved. 14 claims extracted; 0 independently verified. Quality review score: 3.8/10.

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	×	0.09
Default fine-tuning has a variability of ± 0.98 , while CausalMixFT has a variability of ± 0.63 , indicating greater stability	×	0.08
CausalMixFT ranks first overall in average ranks across datasets, followed by the default fine-tuning baseline.	×	0.07
Purely synthetic generators, including CTGAN, SCM, TabEBM, TableAugment, and Mixed-Model, show negative median improvement	×	0.08
The normalization strategy used to compare performance across different data generators is based on Gorishniy et al. [12]	×	0.05
The base model’s (Mitra’s) zero-shot performance is used as the performance baseline for normalization.	×	0.05
The normalized performance is computed as $\text{score}_{\text{normalized}} = \frac{\text{metric}_{\text{sign}}}{\text{score}_{\text{method}} / \text{score}_{\text{baseline}} - 1} \times 100\%$.	×	0.03
CausalMixFT extends the fine-tuning framework of Bhlér et al. [5] by mixing real and causally grounded synthetic samples	×	0.11
SCM-Based Synthetic Augmentation (CausalMixFT) uses SCMs fitted to the target dataset to generate synthetic data.	×	0.13
SCMs explicitly encode causal dependencies among features through a directed acyclic graph (DAG) and a set of structural	×	0.06
The PC and FCI algorithms are used to estimate the structural relations between the features.	×	0.04
DoWhy’s SCM framework with additive noise models is used to sample and fit DAGs.	×	0.03
Numerical features are modeled with regressors, and categorical features with classifiers in the SCM framework.	×	0.04
Synthetic samples are generated by sampling exogenous noise and propagating it through the fitted SCM.	×	0.04

References

- <http://arxiv.org/abs/2601.04110v2>
- <http://arxiv.org/abs/2512.03307v1>
- <http://arxiv.org/abs/2001.04197v4>