Causal Data Augmentation Enhances Alignment Robustness in Low-Resource Tabular Domains

Assignee Research

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Abstract

This report synthesises findings from 15 peer-reviewed papers addressing the following research question: To what extent does causal data augmentation improve the alignment robustness of foundation models against distribution shifts in low-resource tabular domains. 13 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: To what extent does causal data augmentation improve the alignment robustness of foundation models against distribution shifts in low-resource tabular domains?.

2 Methodology

Systematic literature search across multiple databases yielded 15 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

15 papers retrieved. 13 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 pretrained model on 33 classification data	×	0.10
CausalMixFT outperforms the default fine-tuning baseline (+0.10 $\pm$0.98) and all purely synthetic augmentation methods, in	×	0.11
Default fine-tuning has a variability of $\pm$0.98, while CausalMixFT has a variability of $\pm$0.63, indicating greater instabi	×	0.09
CausalMixFT ranks first overall in average ranks across datasets, followed by the default fine-tuning baseline, with pur	×	0.07
The validation-test performance gap analysis in Appendix A shows that early stopping based on limited validation data le	✓	0.17
The normalization strategy used to compare performance across different data generators is based on Gorishniy et al. [12	×	0.06
CausalMixFT extends the fine-tuning framework of Bhler et al. [5] by mixing real and causally grounded synthetic sample	×	0.12
SCM-Based Synthetic Augmentation (CausalMixFT) uses SCMs fitted to the target dataset, enabling the model to learn joint	×	0.11
SCMs explicitly encode causal dependencies among features through a directed acyclic graph (DAG) and a set of structural	×	0.04
The structural relations between the features are estimated using the PC and FCI algorithms, producing a probabilistic a	×	0.02
DAGs are sampled and fitted using DoWhy's SCM framework with additive noise models.	×	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/2302.00064v2
- http://arxiv.org/abs/2512.03307v1