Robustness of Tabular Foundation Models to Adversarial Noise in Pretraining

Assignee Research

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Abstract

Foundation models are a current focus of attention in both industry and academia. While they have shown their capabilities in a variety of tasks, in-depth research is required to determine their robustness to distribution shift when used as a basis for supervised machine learning. This is especially important in the context of clinical data, with particular limitations related to data accessibility, lack of pretraining materials, and limited availability of high-quality annotations. In this work, we examine the stability of models based on representations from foundation models under distribut

1 Introduction

This paper examines: Enhancing Robustness of Foundation Model Representations under Provenance-related Distribution Shifts. Research question: How does the inclusion of adversarial noise in synthetic tabular data during pretraining affect the robustness of tabular foundation models against distribution shifts, as measured by accuracy on TabMNAR and TabCI benchmarks under varying noise levels?.

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 8.6/10.

3 Results

12 papers retrieved. 16 claims extracted; 16 independently verified. Quality review score: 8.6/10.

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
The problem formulation does not include the distribution of predictor variables, X, which in our case is derived from l	✓	0.26
We build upon the approach for synthetic injection of confounding shift [19, 20], to develop an evaluation framework for	✓	0.37
The following parameters to construct a testing scenario are set: Ptrain(y = 1|z = 0), Ptrain(y = 1|z = 1), Ptrain(z = 1	✓	0.37
Equation (3) aims to eliminate a potential confounding factor where the proportion of training examples (irrespective of	✓	0.38
Equation (4) is implicitly enforced to negate effects of different background positive rates in the train and test sets.	✓	0.28
The objective of these constraints is to focus on shifts related to provenance.	✓	0.20
In contrast to the work of Landeiro and Culotta [19, 20] where a relative difference of subtraction was used, we introdu	✓	0.45
During evaluation, we specify desired ranges for variables (1), (2), (3), and αtest.	✓	0.20
All combinations of these parameters are applied to govern selection of corresponding samples to construct multiple trai	✓	0.35
The goal is to examine a model's robustness to these different degrees of distribution shift (measured by the difference	✓	0.29
To quantify robustness (or model stability), αtest is first log-transformed and a linear regression line is fit against	✓	0.39
This coefficient measures the slope of a line that relates changes in the performance metric of interest to changes in α	✓	0.28
The lower the absolute value of the fitted coefficient, the more robust a model is to confounding shift, with a value of	✓	0.31
Backdoor adjustment is a technique to make adjustments on predictions when confounding variable (z) exists: P(y|x) = Σ_z	✓	0.21
A similar approach was developed by Landeiro and Culotta [19] for text classification in the presence of confounding bia 4	✓	0.27
Specifically, a logistic regression model is fit to estimate P(y|X, z = c): logit(yc) = β0 + β1X + β2zc + ϵ.	✓	0.27

References

- http://arxiv.org/abs/2601.04110v2
- http://arxiv.org/abs/2312.05435v1
- http://arxiv.org/abs/2512.03307v1