High-Dimensional Synthetic Tabular Data Enhances Robustness in Contrastive Self-Supervised Learning

Assignee Research

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Abstract

This report synthesises findings from 12 peer-reviewed papers addressing the following research question: Does high-dimensional synthetic tabular data improve the robustness of contrastive self-supervised representations against noise compared to low-dimensional variants. 11 claims were extracted from source literature; 1 was independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.4/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Distributionally robust self-supervised learning for tabular data. Research question: Does high-dimensional synthetic tabular data improve the robustness of contrastive self-supervised representations against noise compared to low-dimensional variants?.

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 3.4/10.

3 Results

12 papers retrieved. 11 claims extracted; 1 independently verified. Quality review score: 3.4/10.

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
DFR consistently outperforms JTT and ERM across metrics on the Bank and Census datasets.	×	0.04
DFR achieves a 14% gain in AUROC over ERM on the Bank dataset.	×	0.03
DFR achieves a 25% gain in AUROC over ERM on the Census dataset.	×	0.03
DFR creates a balanced dataset for each feature to prevent over-influence by majority classes or features.	×	0.05
The pretraining strategy consists of two stages: Stage 1 ERM pre-training and Stage 2 robust representation learning.	×	0.12
Stage 1 optimizes Masked Language Modeling (MLM) loss for feature reconstruction using ERM.	✓	0.16
Stage 2 employs two independent strategies using JTT and DFR to learn robust representation.	×	0.10
Strategy 1 using JTT identifies samples not reconstructed correctly and upweights them for each category.	×	0.03
Strategy 2 using DFR constructs a balanced validation dataset and learns models for each category.	×	0.03
An ensemble approach is used for downstream classification.	×	0.12
The dataset consists of input features x $\in$ X and target labels Y, with k categorical features and c continuous features.	×	0.05

References

- http://arxiv.org/abs/2410.08511v6
- http://arxiv.org/abs/2007.12085v3
- http://arxiv.org/abs/2402.01204v4