What is the impact of integrating flow-matching oversampling on the robustness of classifiers against adversar

Assignee Research

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Abstract

Class imbalance is a common problem in supervised learning and impedes the predictive performance of classification models. Popular countermeasures include oversampling the minority class. Standard methods like SMOTE rely on finding nearest neighbours and linear interpolations which are problematic in case of high-dimensional, complex data distributions. Generative Adversarial Networks (GANs) have been proposed as an alternative method for generating artificial minority examples as they can model complex distributions. However, prior research on GAN-based oversampling does not incorporate rece

1 Introduction

This paper examines: Conditional Wasserstein GAN-based Oversampling of Tabular Data for Imbalanced Learning. Research question: What is the impact of integrating flow-matching oversampling on the robustness of classifiers against adversarial attacks in imbalanced tabular learning?.

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 3.7/10.

3 Results

12 papers retrieved. 9 claims extracted; 0 independently verified. Quality review score: 3.7/10.

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
Random oversampling can lead to problematic overfitting as identical samples appear multiple times in the training data.	×	0.05
SMOTE assumes that all columns are continuous.	×	0.02
SMOTE-Nominal Continuous (SMOTENC) is a variant of SMOTE for nominal and continuous data.	×	0.03
Borderline-SMOTE (B-SMOTE) concentrates on borderline minority class samples.	×	0.06
ADASYN selects minority class samples proportionally to the majority class cases in the k-nearest neighbours of both cla	×	0.08
Generative Adversarial Networks (GANs) are a framework for learning generative models through an adversarial process.	×	0.11
GANs have achieved impressive results, especially in the realm of images.	×	0.05
Vanilla GAN uses neural networks for both the generator (G) and the discriminator (D).	×	0.05
The generator's objective in a GAN is optimised if pg, the generator's distribution over x, is equal to the real distrib	×	0.03

References

- http://arxiv.org/abs/2008.09202v1
- http://arxiv.org/abs/2303.15127v1
- http://arxiv.org/abs/2307.02055v1