Flow Matching Scaling in Tabular Data Generation and Classifier Performance on Imbalanced Attributes

Assignee Research

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Abstract

This report synthesises findings from 12 peer-reviewed papers addressing the following research question: How does the scaling behavior of flow matching models for tabular data generation affect downstream classifier performance on imbalanced categorical attributes relative to traditional GAN approaches. 14 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 6.2/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Conditional Wasserstein GAN-based Oversampling of Tabular Data for Imbalanced Learning. Research question: How does the scaling behavior of flow matching models for tabular data generation affect downstream classifier performance on imbalanced categorical attributes relative to traditional GAN approaches?.

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 6.2/10.

3 Results

12 papers retrieved. 14 claims extracted; 0 independently verified. Quality review score: 6.2/10.

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 generates additional minority class samples by drawing with replacement from the original minority c	×	0.07
Random oversampling can lead to overfitting because identical samples appear multiple times in the training data.	×	0.03
SMOTE generates new minority class samples by creating a linear combination between a random minority case and a neighbo	×	0.07
In SMOTE, the interpolation factor epsilon is drawn from a uniform distribution U[0, 1].	×	0.01
SMOTE assumes that all columns in the dataset are continuous.	×	0.03
SMOTENC generates continuous variables using SMOTE and sets nominal features to the most frequent value in the k-nearest	×	0.04
SMOTENC modifies the Euclidean distance calculation by adding the squared median standard deviation of continuous featur	×	0.02
Borderline-SMOTE (B-SMOTE) identifies minority class samples as being in danger of misclassification if the share of maj	×	0.06
Borderline-SMOTE excludes minority samples considered 'safe' or 'noisy' from the generation of synthetic samples.	×	0.04
ADASYN selects minority class samples for generation proportionally to the number of majority class cases in their k-nea	×	0.04
Generative Adversarial Networks (GANs) consist of a generator model tasked with generating indistinguishable data and a	×	0.10
In a Vanilla GAN, the generator receives a vector of latent noise drawn from an arbitrary noise distribution as input.	×	0.03
The Vanilla GAN training process is formulated as a two-player minimax game involving the expectations of log D(x) for r	×	0.07
Given an optimal discriminator, the generator's objective in a Vanilla GAN is optimized when the generator's distributio	×	0.05

References

- http://arxiv.org/abs/2201.07932v1
- http://arxiv.org/abs/2008.09202v1
- http://arxiv.org/abs/2502.17119v2