What is the impact of flow-matching versus GAN-based augmentation on downstream classifier accuracy for imbala

Assignee Research

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Abstract

Supervised deep learning methods are enjoying enormous success in many practical applications of computer vision and have the potential to revolutionize robotics. However, the marked performance degradation to biases and imbalanced data questions the reliability of these methods. In this work we address these questions from the perspective of dataset imbalance resulting out of severe under-representation of annotated training data for certain classes and its effect on both deep classification and generation methods. We introduce a joint dataset repairment strategy by combining a neural network

1 Introduction

This paper examines: Mitigating Dataset Imbalance via Joint Generation and Classification. Research question: What is the impact of flow-matching versus GAN-based augmentation on downstream classifier accuracy for imbalanced tabular datasets?.

2 Methodology

Systematic literature search across multiple databases yielded 13 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

13 papers retrieved. 14 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
The proposed approach is evaluated on three publicly available datasets: CelebA, CUB-200-2011, and Horse2Zebra.	×	0.05
The performance of the classifier is measured in terms of the F1 score of the two classes.	×	0.05
The best performing classifier on the validation set is used for reporting the test-set performances.	×	0.02
Inception score may not be ideal for evaluating image-to-image translation tasks, especially in low data regimes.	×	0.04
Inception accuracy measures how well an inception-v3 model trained on real images can predict the true label of the gene	×	0.02
The evaluation procedure is repeated 5 times for each dataset, keeping the data fixed but using independent random initi	×	0.03
CelebA contains faces of over 10,000 celebrities, each with 20 images.	×	0.01
The proposed approach is evaluated on the CelebA dataset for a binary classifier predicting gender from face images.	×	0.06
For CelebA with 50 minority examples, the F1 score for the minority class is 0.1500 for the Vanilla model.	×	0.05
For CelebA with 500 minority examples, the F1 score for the minority class is 0.9160 for the Vanilla model.	×	0.05
For CUB-200-2011 with 12 minority examples, the F1 score for the minority class is 0.0240 for the Vanilla model.	×	0.04
For CUB-200-2011 with 125 minority examples, the F1 score for the minority class is 0.6160 for the Vanilla model.	×	0.04
For Horse2Zebra with 25 minority examples, the F1 score for the minority class is 0.0500 for the Vanilla model.	×	0.05
For Horse2Zebra with 100 minority examples, the F1 score for the minority class is 0.7680 for the Vanilla model.	×	0.05

References

- http://arxiv.org/abs/2201.07932v1
- http://arxiv.org/abs/2308.02966v1
- http://arxiv.org/abs/2008.05524v1