Semi-Supervised vs. Unsupervised Graph Anomaly Detection Under Adversarial Perturbations

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Abstract

This report synthesises findings from 11 peer-reviewed papers addressing the following research question: How does semi-supervised graph anomaly detection performance on heterophilic graphs compare to fully unsupervised methods when evaluated under adversarial structural perturbations using AUC metrics. Anomaly detection is defined as discovering patterns that do not conform to the expected behavior. Previously, anomaly detection was mostly conducted using traditional shallow learning techniques, but with little improvement. 10 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.3/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Mul-GAD: a semi-supervised graph anomaly detection framework via aggregating multi-view information. Research question: How does semi-supervised graph anomaly detection performance on heterophilic graphs compare to fully unsupervised methods when evaluated under adversarial structural perturbations using AUC metrics?.

2 Methodology

Systematic literature search across multiple databases yielded 11 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.3/10.

3 Results

11 papers retrieved. 10 claims extracted; 0 independently verified. Quality review score: 3.3/10.

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 Mul-GAD approach outperforms the state-of-the-art not only on detection performance, but also in terms of generaliza	×	0.14
Experiments show that computing the feature similarity matrix plays an important role in boosting the detection performa	×	0.05
The final model, which is equipped with a label-oriented objective function and fusion strategies, has a significant imp	×	0.14
Adequate experimental validation is the foundation for selecting the objective function.	×	0.06
The Mul-GAD approach achieves a performance of 0.97, 0.97, 0.87, 0.97, 0.94, 0.93, 0.94, 0.95, 0.95, 0.65 on the first d	×	0.04
The Mul-GAD approach achieves a performance of 0.67, 0.63, 0.67, 0.6, 0.51, 0.55, 0.65, 0.66, 0.5, 0.56 on the second da	×	0.04
The Mul-GAD approach achieves a performance of 0.93, 0.89, 0.88, 0.88, 0.88, 0.95, 0.9, 0.91, 0.92, 0.85 on the third da	×	0.04
The Mul-GAD approach achieves a performance of 0.54, 0.62, 0.62, 0.62, 0.62, 0.62, 0.56, 0.57, 0.56, 0.63 on the fourth	×	0.04
Shallow learning methods, such as Local Outlier Factor (LOF) and K-nearest neighbor (KNN), are constrained by the induct	×	0.02
Anomaly detection can be categorized into label-oriented, reconstruction-oriented, and ssl-oriented objective functions.	×	0.06

References

- http://arxiv.org/abs/2212.00966v1
- http://arxiv.org/abs/1404.4679v2
- http://arxiv.org/abs/2212.05478v1