Multi-View Aggregation Strategies and Anomaly Detection Performance in Cross-Domain Graphs

Assignee Research

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Abstract

This report synthesises findings from 7 peer-reviewed papers addressing the following research question: What is the impact of different multi-view aggregation strategies (e.g., attention-based vs. max-pooling) on the detection F1-scores across diverse cross-domain graph datasets, as benchmarked on. 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. 18 claims were extracted from source literature; 1 was independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 4.2/10. 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: What is the impact of different multi-view aggregation strategies (e.g., attention-based vs. max-pooling) on the detection F1-scores across diverse cross-domain graph datasets, as benchmarked on standard anomaly detection metrics?.

2 Methodology

Systematic literature search across multiple databases yielded 7 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 4.2/10.

3 Results

7 papers retrieved. 18 claims extracted; 1 independently verified. Quality review score: 4.2/10.

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
Mul-GAD optimizes at both view and feature levels.	×	0.08
Mul-GAD uses learnable parameters to determine the importance of each view.	×	0.05
Mul-GAD utilizes a feature similarity matrix to leverage complementary information while avoiding redundant information.	×	0.08
Computing the feature similarity matrix plays an important role in boosting detection performance.	×	0.04
The final Mul-GAD model, equipped with a label-oriented objective function and fusion strategies, shows significant impr	×	0.15
The authors claim to be the first to analyze the anomaly detection problem from the perspective of objective functions.	×	0.06
Label-oriented objective functions demonstrate more generalized performance compared to other types.	×	0.05
Mul-GAD provides two effective fusion strategies at the view and feature levels.	×	0.13
Both fusion strategies provided by Mul-GAD boost detection performance.	✓	0.15
Mul-GAD outperforms state-of-the-art methods in detection performance across the majority of datasets.	×	0.13
Mul-GAD outperforms state-of-the-art methods in terms of generalization across the majority of datasets.	×	0.10
Anomaly detection algorithms can be categorized into shallow learning and graph neural network methods.	×	0.12
Anomaly detection objective functions can be categorized as label-oriented, reconstruction-oriented, and ssl-oriented.	×	0.05
Shallow learning methods handle anomaly problems using spatial density, statistical distribution, and variants of classi	×	0.05
Spatial density methods are based on the hypothesis that there are fewer nodes or lower node density around anomalies.	×	0.03
Local Outlier Factor (LOF) computes the spatial density of each node, where lower density corresponds to a higher anomal	×	0.01
K-nearest neighbor (KNN) determines the class of a node based on the majority class of its k closest neighbors.	×	0.03
Shallow learning methods are constrained by inductive bias, making it difficult to detect abnormal nodes masquerading as	×	0.03

References

- http://arxiv.org/abs/2502.14293v2
- http://arxiv.org/abs/2212.05478v1
- http://arxiv.org/abs/1404.4679v2