Self-Supervised Contrastive Learning vs. Supervised Methods for Graph Anomaly Detection

Assignee Research

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Abstract

This report synthesises findings from 11 peer-reviewed papers addressing the following research question: How does the performance of self-supervised contrastive learning methods for graph anomaly detection compare to supervised methods in terms of inference efficiency on large-scale graphs with. Combining Graph neural networks (GNNs) with contrastive learning for anomaly detection has drawn rising attention recently. Existing graph contrastive anomaly detection (GCAD) methods have primarily focused on improving detection capability through graph augmentation and. 13 claims were extracted from source literature; 4 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 5.5/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Revisiting Graph Contrastive Learning for Anomaly Detection. Research question: How does the performance of self-supervised contrastive learning methods for graph anomaly detection compare to supervised methods in terms of inference efficiency on large-scale graphs with heterophilic properties?.

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 5.5/10.

3 Results

11 papers retrieved. 13 claims extracted; 4 independently verified. Quality review score: 5.5/10.

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 MAG framework unifies the classical GCAD algorithm.	×	0.08
The MAG model is evaluated on three citation networks: Cora, Citeseer, and Pubmed.	×	0.04
Anomalous nodes were generated by perturbing the graph structure and modifying the node features.	×	0.06
The injection algorithm for generating anomalous nodes follows the methods described in [6,13].	×	0.02
The MAG framework consists of two modules: graph augmentation and multi-GNN modules.	✓	0.27
The MAG framework unifies CoLA, ANEMONE, and GRADATE via contrast combinations.	×	0.06
The average AUC results for CoLA, ANEMONE, and GRADATE on Cora are 89.1%, 90.6%, and 90.1%, respectively.	×	0.01
The MAG framework improves the AUC results for CoLA, ANEMONE, and GRADATE on Cora to 90.3%, 91.1%, and 89.5%, respective	×	0.03
The AUC results for Radar, ANOMALOUS, DOMINANT, AnomalDAE, CoLA, ANEMONE, SL-GAD, GRADATE, L-MAG, and M-MAG on Cora, Cit	×	0.04
The MAG framework demonstrates that multi-GNN modules are the hidden contributors to performance improvements, not multi	✓	0.33
The L-MAG variant of the MAG framework outperforms state-of-the-art methods on Cora and Pubmed with low computational co	✓	0.19
The M-MAG variant of the MAG framework, equipped with multi-GNN modules, further improves detection performance.	✓	0.25
The combination of masked feature and removed edge in graph augmentation shows significant competitiveness.	×	0.05

References

- http://arxiv.org/abs/2305.02496v1
- http://arxiv.org/abs/2505.15103v2
- http://arxiv.org/abs/2212.05478v1