

# Contrastive Learning Integration in Mul-GAD for Robust Cross-Domain Graph Anomaly Detection

Assignee Research

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## Abstract

This report synthesises findings from 8 peer-reviewed papers addressing the following research question: To what extent does incorporating contrastive learning (e.g., via GraphCL) into the Mul-GAD framework improve robustness against adversarial attacks in cross-domain graph anomaly detection, as. 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. 15 claims were extracted from source literature; 3 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 4.9/10. 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: To what extent does incorporating contrastive learning (e.g., via GraphCL) into the Mul-GAD framework improve robustness against adversarial attacks in cross-domain graph anomaly detection, as measured by AUC-ROC and F1-score under noise injection?.

## 2 Methodology

Systematic literature search across multiple databases yielded 8 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 4.9/10.

### **3 Results**

8 papers retrieved. 15 claims extracted; 3 independently verified. Quality review score: 4.9/10.

### **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.	×	0.09
The MAG model consists of two modules: graph augmentation and multi-GNN modules.	✓	0.26
The datasets used are Cora, Citeseer, and Pubmed.	×	0.03
Anomalous nodes were generated by perturbing the graph structure and modifying the node features.	×	0.04
The injection algorithm follows the methods described in [6,13].	×	0.04
The baseline methods include Radar, ANOMALOUS, DOMINANT, AnomalyDAE, CoLA, ANEMONE, SL-GAD, and GRADATE.	×	0.03
The hyper-parameters were set the same for a fair comparison.	×	0.00
The MAG framework unifies CoLA, ANEMONE, and GRADATE via contrast combinations.	×	0.07
The MAG framework consists of normal node-subgraph, masked node-subgraph, node-node, and subgraph-subgraph contrast pair	×	0.04
The average AUC results for CoLA, ANEMONE, and GRADATE on Cora are 89.1%, 90.6%, and 90.1%, respectively.	×	0.01
The corresponding MAG combinations for CoLA, ANEMONE, and GRADATE on Cora are 90.3%, 91.1%, and 89.5%, respectively.	×	0.02
The AUC is used as the evaluation metric instead of accuracy, precision, and recall.	×	0.03
The L-MAG variant outperforms state-of-the-art methods on Cora and Pubmed with low computational cost.	✓	0.18
The M-MAG variant, equipped with multi-GNN modules, further improves detection performance.	✓	0.24
The combination of masked feature and removed edge shows significant competitiveness for graph augmentation.	×	0.06

## References

- <http://arxiv.org/abs/2305.02496v1>
- <http://arxiv.org/abs/2212.05478v1>
- <http://arxiv.org/abs/2103.00113v2>