Contrastive Learning Objectives Enhance Robustness in Hybrid Graph Neural Networks Under Adversarial Attacks

Assignee Research

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Abstract

This report synthesises findings from 14 peer-reviewed papers addressing the following research question: What is the impact of contrastive learning objectives on the robustness of hybrid graph neural networks against adversarial attacks in few-shot node classification tasks, evaluated on accuracy and. We present LaplaceGNN, a novel self-supervised graph learning framework that bypasses the need for negative sampling by leveraging spectral bootstrapping techniques. Our method integrates Laplacian-based signals into the learning process, allowing the model to effectively. 15 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.8/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Self-Supervised Graph Learning via Spectral Bootstrapping and Laplacian-Based Augmentations. Research question: What is the impact of contrastive learning objectives on the robustness of hybrid graph neural networks against adversarial attacks in few-shot node classification tasks, evaluated on accuracy and F1-score under adversarial perturbations on large-scale heterogeneous graphs?.

2 Methodology

Systematic literature search across multiple databases yielded 14 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 3.8/10.

3 Results

14 papers retrieved. 15 claims extracted; 0 independently verified. Quality review score: 3.8/10.

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 standard linear evaluation protocol for graphs involves training each graph encoder in a fully unsupervised manner t	×	0.06
GCN is used for node prediction tasks and GIN is used for graph prediction tasks as the teacher encoder gξ across all me	×	0.09
All experiments are repeated 10 times, and the mean and standard deviation of the evaluation metrics are reported.	×	0.03
For OGB datasets, the performance is evaluated with their original feature extraction and following the original trainin	×	0.03
For TU datasets, the standard protocols are followed, and the mean 10-fold cross-validation accuracy along with the stan	×	0.03
LaplaceGNN achieves 92.85 $\pm$ 0.74% accuracy on MUTAG, 80.52 $\pm$ 0.47% on PROTEINS, 77.12 $\pm$ 0.32% on IMDB-B, 52.44 $\pm$ 1.19% o	×	0.03
LaplaceGNN demonstrates consistent improvements over existing approaches across various graph types and tasks.	×	0.03
On WikiCS, LaplaceGNN establishes new state-of-the-art results with 82.34% accuracy, surpassing GRACE (80.14%) and BGRL	×	0.05
On the ogbn-arXiv dataset, LaplaceGNN achieves 74.87% test accuracy, outperforming both BGRL (71.64%) and supervised GCN	×	0.05
LaplaceGNN leverages spectral properties for robust feature learning and consists of three main components: a spectral a	×	0.10
The spectral augmentation module generates centrality-guided views to avoid tuning handcrafted transformations.	×	0.08
The adversarial online network ensures robust representations while the target network learns through knowledge distilla	×	0.04
The linear bootstrapping method eliminates the quadratic cost needed for negative sampling.	×	0.08
Laplacian augmentations and adversarial bootstrapped learning schemes are described in Algorithm 1 and Algorithm 2, resp	×	0.09
The centrality-based augmentation scheme proposes a principled method for perturbation based on centrality measures and	×	0.08

References

- http://arxiv.org/abs/2206.07869v1
- http://arxiv.org/abs/2506.20362v1
- http://arxiv.org/abs/2104.09369v1