Self-Supervised Contrastive Learning for Robust Graph Neural Networks Under High Attribute Missingness

Assignee Research

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Abstract

This report synthesises findings from 11 peer-reviewed papers addressing the following research question: To what extent does the self-supervised contrastive learning strategy in AmGCL improve robustness against high-percentage attribute missingness compared to standard graph imputation baselines. Graph Neural Networks (GNNs) conventionally operate under the assumption that node attributes are entirely observable. Their performance notably deteriorates when confronted with incomplete graphs due to the inherent message-passing mechanisms. 13 claims were extracted from source literature; 13 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 8.3/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Incomplete Graph Learning via Attribute-Structure Decoupled Variational Auto-Encoder. Research question: To what extent does the self-supervised contrastive learning strategy in AmGCL improve robustness against high-percentage attribute missingness compared to standard graph imputation baselines?.

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 8.3/10.

3 Results

11 papers retrieved. 13 claims extracted; 13 independently verified. Quality review score: 8.3/10.

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
Graph Neural Networks (GNNs) conventionally operate under the assumption that node attributes are entirely observable.	✓	0.28
The performance of GNNs notably deteriorates when confronted with incomplete graphs due to the inherent message-passing	✓	0.25
Current solutions either employ classic imputation techniques or adapt GNNs to tolerate missed attributes.	✓	0.27
The ability of current solutions to generalize is impeded especially when dealing with high rates of missing attributes.	✓	0.25
ASD-VAE harnesses the representations of the essential views on graphs, attributes and structures, into a common shared	✓	0.33
ASD-VAE ensures robust tolerance even at high missing rates.	✓	0.20
ASD-VAE parameterizes the shared latent space via a coupled-and-decoupled learning procedure.	✓	0.30
ASD-VAE separately encodes attributes and structures, generating representations for each view.	✓	0.29
A shared latent space is learned by maximizing the likelihood of the joint distribution of different view representation	✓	0.33
The shared latent space is decoupled into separate views, and the reconstruction loss of each view is calculated.	✓	0.32
The missing values of attributes are imputed from the learned latent space.	✓	0.27
The model offers enhanced resilience against skewed and biased distributions typified by missing information.	✓	0.26
The model brings benefits to downstream graph machine-learning tasks.	✓	0.21

References

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- https://doi.org/10.1109/tnnls.2021.3070843