Message-Passing Depth and Over-Smoothing in Semi-Supervised Graph Representation Learning

Assignee Research

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Abstract

This report synthesises findings from 13 peer-reviewed papers addressing the following research question: What is the correlation between the number of message-passing layers and performance degradation in semi-supervised graph representation learning on Cora and Citeseer. Graph Neural Networks (GNNs) have achieved promising performance on a wide range of graph-based tasks. Despite their success, one severe limitation of GNNs is the over-smoothing issue (indistinguishable representations of nodes in different classes). 8 claims were extracted from source literature; 8 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 9.0/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Measuring and Relieving the Over-Smoothing Problem for Graph Neural Networks from the Topological View. Research question: What is the correlation between the number of message-passing layers and performance degradation in semi-supervised graph representation learning on Cora and Citeseer?.

2 Methodology

Systematic literature search across multiple databases yielded 13 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 9.0/10.

3 Results

13 papers retrieved. 8 claims extracted; 8 independently verified. Quality review score: 9.0/10.

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) have achieved promising performance on a wide range of graph-based tasks.	✓	0.30
One severe limitation of GNNs is the over-smoothing issue (indistinguishable representations of nodes in different class	✓	0.32
Two quantitative metrics, MAD and MADGap, are introduced to measure the smoothness and over-smoothness of the graph node	✓	0.31
Smoothing is the nature of GNNs and the critical factor leading to over-smoothness is the low information-to-noise ratio	✓	0.43
Two methods, MADReg and AdaEdge, are proposed to alleviate the over-smoothing issue from the topological view.	✓	0.26
MADReg adds a MADGap-based regularizer to the training objective.	✓	0.26
AdaEdge optimizes the graph topology based on the model predictions.	✓	0.26
Extensive experiments on 7 widely-used graph datasets with 10 typical GNN models show that the two proposed methods are	✓	0.44

References

- https://doi.org/10.1609/aaai.v34i04.5747
- https://doi.org/10.1145/3394486.3403076
- https://doi.org/10.1145/3394486.3403049