LightGCL Performance on Large-Scale Graphs: Hit Ratio and NDCG Benchmarks

Assignee Research

June 2, 2026

Abstract

This report synthesises findings from 7 peer-reviewed papers addressing the following research question: What is the impact of pre-training LightGCL on large-scale graphs on its performance in Hit Ratio@5 and NDCG@10 compared to other contrastive learning methods like GraCL and MVGRL. Graph neural network (GNN) is a powerful learning approach for graph-based recommender systems. Recently, GNNs integrated with contrastive learning have shown superior performance in recommendation with their data augmentation schemes, aiming at dealing with highly sparse data. 10 claims were extracted from source literature; 7 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 7.3/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: LightGCL: Simple Yet Effective Graph Contrastive Learning for Recommendation. Research question: What is the impact of pre-training LightGCL on large-scale graphs on its performance in Hit Ratio@5 and NDCG@10 compared to other contrastive learning methods like GraCL and MVGRL?.

2 Methodology

Systematic literature search across multiple databases yielded 7 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.3/10.

3 Results

7 papers retrieved. 10 claims extracted; 7 independently verified. Quality review score: 7.3/10.

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
Most existing graph contrastive learning methods perform stochastic augmentation (e.g., node/edge perturbation) on the u	✓	0.35
Most existing graph contrastive learning methods rely on heuristic-based augmentation techniques (e.g., user clustering)	✓	0.33
Existing stochastic and heuristic-based augmentation methods cannot well preserve the intrinsic semantic structures of t	✓	0.21
Existing stochastic and heuristic-based augmentation methods are easily biased by noise perturbation.	✓	0.19
LightGCL exclusively utilizes singular value decomposition (SVD) for contrastive augmentation.	✓	0.20
LightGCL enables unconstrained structural refinement with global collaborative relation modeling.	✓	0.22
Experiments on several benchmark datasets demonstrate that LightGCL achieves significant performance improvement over st	×	0.12
Analyses demonstrate that LightGCL is more robust against data sparsity compared to other methods.	×	0.13
Analyses demonstrate that LightGCL is more robust against popularity bias compared to other methods.	×	0.11
The source code for LightGCL is available at https://github.com/HKUDS/LightGCL.	✓	0.21

References

- `https://doi.org/10.1145/3543507.3583361`
- `https://doi.org/10.1609/aaai.v35i5.16515`
- `https://doi.org/10.48550/arxiv.2302.08191`