Self-Supervised Contrastive Learning Enhances XSimGCL Robustness in Out-of-Domain Recommendations

Assignee Research

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Abstract

This report synthesises findings from 11 peer-reviewed papers addressing the following research question: What is the impact of incorporating self-supervised contrastive learning (e.g., SimCLR) on the recommendation robustness of XSimGCL when evaluated on out-of-domain datasets like Goodreads or Steam. Contrastive learning (CL) has recently been demonstrated critical in improving recommendation performance. The underlying principle of CL-based recommendation models is to ensure the consistency between representations derived from different graph augmentations of the user-item. 16 claims were extracted from source literature; 0 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 3.0/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: XSimGCL: Towards Extremely Simple Graph Contrastive Learning for Recommendation. Research question: What is the impact of incorporating self-supervised contrastive learning (e.g., SimCLR) on the recommendation robustness of XSimGCL when evaluated on out-of-domain datasets like Goodreads or Steam using normalized discounted cumulative gain (NDCG) and precision-recall curves?.

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 3.0/10.

3 Results

11 papers retrieved. 16 claims extracted; 0 independently verified. Quality review score: 3.0/10.

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
XSimGCL is sensitive to the edge dropout rates of graph augmentations, and even high dropout rates (e.g., 0.9) can still	×	0.07
The relationship between uniformity and performance is not linear. Pursuing excessive uniformity may compromise the abil	×	0.08
Uniformity can enhance performance.	×	0.04
There is a correlation between the convergence speed and the magnitude of the noise.	×	0.03
XSimGCL can attain a more uniform distribution of representations.	×	0.04
Cross-layer contrast through the lens of graph spectrum can enhance the efficacy of graph CL by harnessing the high-freq	×	0.05
The graph Laplacian, denoted by L = D - A, is a symmetric positive semi-definite matrix.	×	0.04
The graph's Fourier transform can be defined using the eigendecomposition of the Laplacian matrix.	×	0.01
Graph convolution between signal x and filter g in the spectral domain can be performed using the definition of the grap	×	0.02
Kipf et al. proposed to approximate graph convolution with the first-order Chebyshev polynomials.	×	0.05
Stacking K graph convolutional layers results in a low-pass filter where the high-frequency information is attenuated.	×	0.04
LightGCN is the backbone of the methods compared in the benchmark tables.	×	0.03
The performance metrics (Recall and NDCG) for LightGCN, SGL-ND, SGL-ED, SGL-RW, and SGL-WA are provided in Table (p3).	×	0.02
The performance metrics for different values of ϵ are provided in Table (p6).	×	0.04
The computational complexity for adjacency matrix, graph encoding, prediction, and contrast for LightGCN, SGL-ED, SimGCL	×	0.02
The dataset statistics for Yelp2018, Amazon-Kindle, Alibaba-iFashion, and Amazon-Electronics are provided in Table (p8).	×	0.01

References

- http://arxiv.org/abs/2211.05304v1
- http://arxiv.org/abs/2009.12007v1
- http://arxiv.org/abs/2209.02544v4