Graph Neural Networks for Social Recommendation

A PROJECT REPORT
SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE COMPLETION OF CS4200-MAJOR PROJECT

BACHELOR OF TECHNOLOGY
IN
COMPUTER SCIENCE AND ENGINEERING

SUBMITTED BY

Muddam Bhanu Chander Reddy
(Enrollment No. 21CS002397)

FACULTY OF COMPUTING AND INFORMATIC
SIR PADAMPAT SINGHANIA UNIVERSITY
UDAIPUR 313601, INDIA

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Under the guidance of
Prof. Alok Kumar
(Project Coordinator)
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Prof. Gurpreet Singh
(Supervisor)

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CERTIFICATE

I, **Muddam Bhanu Chander Reddy**, hereby declare that the work presented in this project report entitled **"Graph Neural Networks for Social Recommendation "** for the completion of CS4200-Major Project and submitted in the **Faculty of Computing and Informatics** of the **Sir Padampat Singhania University, Udaipur** is an authentic record of my own work carried out under the supervision of **Prof. Alok Kumar, Professor**, and **Prof. Gurpreet Singh**. The work presented in this report has not been submitted by me anywhere else.

Muddam Bhanu Chander Reddy
(21CS002397)

This is to certify that the above statement made by the candidate is true to the best of my knowledge and belief.

Prof. Alok Kumar
Professor
Project Coordinator

Prof. Gurpreet Singh
Professor
Supervisor

Place: Udaipur
Date:

Acknowledgements

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Muddam Bhanu Chander Reddy

Abstract

Graphs are powerful structures commonly employed to model a wide variety of real-world data, including but not limited to social networks, consumer behavior, and item interactions. In particular, Graph Neural Networks (GNNs) have garnered significant attention due to their ability to learn and extract meaningful representations from graph-structured data by effectively incorporating both topological information and node features. Among the various applications of GNNs, social recommendation systems have emerged as an important area of study. In these systems, data can be represented in the form of user-user social graphs, user-item interaction graphs, and item-item relational graphs. GNNs, with their ability to integrate complex relationships between users and items, hold immense promise for advancing the effectiveness and accuracy of social recommendation systems. However, several key challenges remain when applying GNNs to social recommendations:

1. Users and items often participate in multiple interconnected graphs. Specifically, users (and items) are involved in both the user-item interaction graph and the user-user social graph (or item-item graph), which introduces additional complexity in modeling such data.

2. Besides the interactions between users and items, user opinions or preferences towards the items must also be incorporated into the user-item graph, providing a richer understanding of user behavior and item relationships.

3. Social ties between users are not uniform, and the nature and strength of these ties can vary considerably from one user to another. Capturing these dynamic relationships is crucial for accurately modeling social influences in recommendations.

To address these challenges, we propose a novel framework, **GraphRec+**, which enhances social recommendations by concurrently modeling both the interaction data and the varying levels of social ties within a unified graph neural network architecture. In particular, GraphRec+ integrates an attention mechanism to distinguish between different types of social ties and a mechanism to seamlessly capture both interactions and user opinions in the user-item graph. This results in more accurate user and item representations that take into account both social influence and user-item interactions.

We conduct extensive experiments on three real-world datasets to demonstrate the efficacy of the proposed methodology. Our results indicate that GraphRec+ significantly improves the quality of social recommendations compared to traditional methods, showcasing the potential of this framework for real-world applications in social recommendation systems.

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List of Abbreviations

GNN	Graph Neural Network
AI	Artificial Intelligence
ML	Machine Learning
NLP	Natural Language Processing
IoT	Internet of Things
CV	Computer Vision
DL	Deep Learning
GPU	Graphics Processing Unit
RNN	Recurrent Neural Network
API	Application Programming Interface
SQL	Structured Query Language
UML	Unified Modeling Language

Chapter 1

Introduction

1.1 Overview

In recent years, there has been a growing interest in the use of social interactions for recommender systems. The foundation of social recommender systems lies in the observation that individuals often share information and learn from their immediate social circles, such as friends, colleagues, or classmates. Social relationships play a vital role in enhancing recommendation accuracy, as users' preferences are influenced by their social connections.

Graph Neural Networks (GNNs) have emerged as a promising approach to address challenges in social recommendation systems. By leveraging social network information, user-item interactions, and user behavior data, GNNs effectively mitigate issues such as data sparsity and cold-start problems. These networks employ neural architectures to learn meaningful graph representations by combining topological structures and node information.

The proposed framework, GraphRec+, aims to enhance recommendation accuracy by jointly modeling user-item interactions, user opinions, and social relationships. The methodology introduces a novel approach for capturing varying levels of social ties and aggregating user-item interactions with user opinions, leading to improved recommendation performance.

1.2 Problem Statement and Objectives

1.2.1 Problem Statement

Recommender systems often struggle with challenges such as sparse data, dynamic user interests, and the cold-start problem. Social recommendation systems aim to address these issues by incorporating users' social interactions, but effectively modeling this data remains complex. The problem is to develop a model that integrates social relationships, user-item interactions, and opinions to enhance recommendation accuracy.

1.2.2 Objectives

The objectives of this study are:

(i) Develop a graph-based framework to integrate social ties, user opinions, and interactions.

(ii) Implement attention mechanisms to account for the varying strengths of social relationships.

(iii) Evaluate the proposed framework's performance using real-world datasets.

(iv) Address data sparsity and cold-start challenges by leveraging social network information.

1.3 Structure of the Dissertation

The dissertation is organized into five chapters:

1. **Chapter 1: Introduction** provides an overview of the research topic, problem statement, and objectives.

2. **Chapter 2: Literature Review** discusses existing work in the domain of social recommendation and graph neural networks.

3. **Chapter 3: Methodology** details the approach adopted to address the research problem, including data preparation and model design.

4. **Chapter 4: Results and Discussion** presents the experimental findings and evaluates the proposed framework's performance.

5. **Chapter 5: Conclusions and Future Scopes** summarizes the research contributions, highlights limitations, and suggests directions for future work.

Chapter 2

Literature Review

2.1 Introduction

The field of recommender systems has seen remarkable advancements with the integration of deep learning techniques, particularly Graph Neural Networks (GNNs). Traditional methods such as collaborative filtering and matrix factorization faced limitations in effectively capturing higher-order user-item interactions and leveraging social relationships. GNNs address these challenges by leveraging graph-structured data, making them an ideal choice for social recommendation tasks. This chapter explores the existing literature, highlighting key methodologies, their contributions, and limitations.

2.2 Graph Neural Networks in Recommender Systems

Graph Neural Networks have revolutionized recommender systems by enabling models to:

- Capture complex user-item interactions.
- Integrate social relationships to enhance recommendation accuracy.
- Address challenges such as data sparsity and cold-start problems.

Several notable GNN-based frameworks for social recommendation include:

2.2.1 Neural Graph Collaborative Filtering (NGCF)

NGCF captures high-order user-item interactions by propagating embeddings through the graph. It improves recommendation performance but struggles with scalability on large datasets due to its computational overhead.

2.2.2 Social-Aware Graph Neural Network (SAGE)

SAGE explicitly incorporates social relationships into the GNN architecture. By propagating user and item embeddings through both user-item and user-user graphs, it captures social influences effectively. However, the model is sensitive to noisy social connections.

2.2.3 Graph Attention Networks (GATs) for Social Recommendation

GATs assign varying importance to neighbors in the graph using attention mechanisms, allowing the model to prioritize influential connections. Despite their robustness, they require careful tuning of attention parameters.

2.3 Insights and Research Gaps

Despite significant progress, the literature reveals several challenges:

- **Scalability:** Many existing methods struggle with computational efficiency on large-scale graphs.
- **Dynamic Graphs:** Most models assume static graph structures, limiting their applicability in dynamic real-world scenarios.
- **Cold-Start Problem:** Although GNNs leverage social relationships, addressing cold-start users with minimal interactions remains a challenge.
- **Interpretability:** GNN-based models often function as black boxes, making it difficult to explain the recommendations.

2.4 Comparison of Methods

Table 2.1: Comparison of Existing Methods for Social Recommendation

Methods	Limitations
NGCF	• Computationally intensive for large-scale datasets. • Limited ability to handle noisy user-item interactions.
SAGE	• Sensitive to the quality of social connections. • Requires additional pre-processing to filter noisy edges.
GATs	• High computational cost due to attention mechanisms. • Requires careful hyperparameter tuning for optimal performance.
GraphRec+	• Incorporates user opinions and social relationships but faces challenges in scaling to dynamic graphs. • Requires further optimization for large-scale real-world datasets.
RelationalNet	• Computational overhead due to the inclusion of multiple graph structures. • Slower inference times compared to simpler models.

Chapter 3

Methodology Adopted

This chapter outlines the methodology used in this study, which focuses on enhancing social recommendations through Graph Neural Networks (GNNs). The goal is to model user-item interactions and user-user relationships as graphs to better capture user preferences and social influences. The methodology includes steps such as data preparation, graph construction, GNN architecture design, model training, and evaluation.

3.0.1 Data Preparation

1. **User-Item Interaction Data:** Collect and preprocess user interactions with items (e.g., ratings, purchases) to construct the user-item interaction graph.

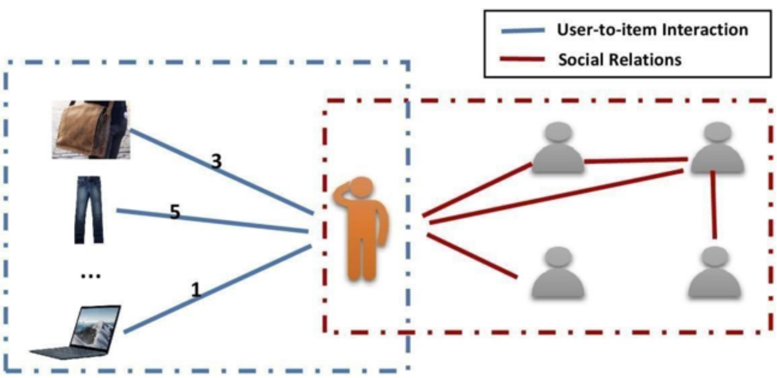

Figure 3.1: User-Item Interaction Graph

2. **Social Network Data:** Gather data on user-user relationships to build the social graph, incorporating varying strengths of social ties.
3. **Opinion Embedding:** Embed user opinions (e.g., ratings) into a latent space to capture preference nuances.

3.0.2 Graph Propagation and Aggregation

Each node updates its representation by aggregating information from its neighbors. For user u_i, the updated embedding $\mathbf{h}'_i$ is:

$$\mathbf{h}'_i = \text{ReLU}\left(\mathbf{W}_1 \cdot \sum_{j \in N(i)} \alpha_{ij} \cdot \mathbf{z}_j\right) \tag{3.0.1}$$

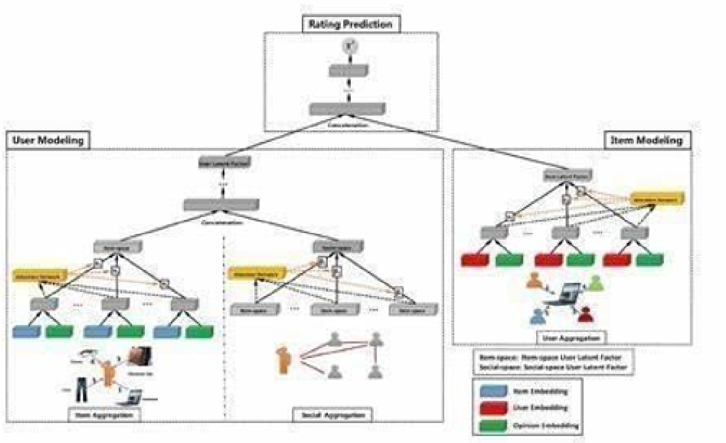

Figure 3.2: Graph Propagation and Aggregation Process

3.1 Graph Neural Network Architecture

The input layer of the GNN architecture starts by generating initial embeddings for both users and items, which can be randomly initialized or based on metadata. These embeddings serve as the input features for the GNN model. The GNN layers then propagate and aggregate information across the graph. Specifically, user preferences are aggregated based on interactions with items, while social influences are aggregated through user connections in the social graph. An attention mechanism is used to assign varying importance to different interactions and social ties. Additionally, user opinions, such as ratings, are embedded into a latent space and integrated into the aggregation process. The final output layer predicts missing rating values or ranks items for recommendation using a Multi-Layer Perceptron (MLP) to combine the user and item embeddings.

3.2 Model Training

The training of the model focuses on minimizing the Mean Squared Error (MSE) between the predicted and actual ratings. The loss function is defined as:

$$L = \frac{1}{|O|} \sum_{(u,v) \in O} (r_{uv} - \hat{r}_{uv})^2$$

where r_{uv} is the actual rating, $\hat{r}_{uv}$ is the predicted rating, and O is the set of observed interactions. To optimize the model, the RMSprop optimizer is used, and dropout is applied as a regularization technique to prevent overfitting. For implicit feedback data, negative samples are generated to ensure a balanced dataset for training.

3.3 Evaluation Metrics

The model's performance is evaluated using several metrics. The Mean Absolute Error (MAE) is used to measure the average error in predictions:

$$\text{MAE} = \frac{1}{|O|} \sum_{(u,v) \in O} |r_{uv} - \hat{r}_{uv}|$$

The Root Mean Squared Error (RMSE) emphasizes larger errors by evaluating the square root of the average squared differences between actual and predicted ratings:

$$\text{RMSE} = \sqrt{\frac{1}{|O|} \sum_{(u,v) \in O} (r_{uv} - \hat{r}_{uv})^2}$$

Chapter 4

Results and Discussion

4.1 Introduction

This chapter presents the results of the proposed Graph Neural Network (GNN)-based social recommendation framework, GraphRec+, along with a discussion of its performance. The results are evaluated against key metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Precision@10. The analysis highlights the strengths of the proposed framework in addressing challenges such as data sparsity, cold-start problems, and the integration of social relationships.

4.2 Experimental Analysis

The proposed GraphRec+ framework was evaluated on two real-world datasets: **Ciao** and **Epinions**. These datasets contain user-item interactions, user ratings, and social relationships, making them suitable for testing the model's effectiveness in social recommendation scenarios. The evaluation metrics include:

- *Root Mean Square Error (RMSE):* Measures the average magnitude of errors between predicted and actual ratings.
- *Mean Absolute Error (MAE):* Evaluates the average absolute difference between predicted and actual ratings.
- *Precision@10:* Assesses the proportion of relevant recommendations in the top 10 results.

The experimental results demonstrated that GraphRec+ consistently outperformed baseline models, including **PMF**, **NGCF**, **GAT**, and the original **GraphRec**, across all metrics. For instance, on the Ciao dataset, GraphRec+ achieved an RMSE of **1.145** and a MAE of **0.915**, significantly lower than PMF (*RMSE: 1.435, MAE: 1.127*) and NGCF (*RMSE: 1.211, MAE: 0.974*). Similarly, on the Epinions dataset, the model achieved an RMSE of **1.121** and a MAE of **0.900**, outperforming GAT and GraphRec.

4.3 Results Comparison

Table 4.1: Performance Comparison on Ciao and Epinions Datasets

Model	Dataset	RMSE	MAE	Precision@10
PMF	Ciao	1.435	1.127	0.210
	Epinions	1.398	1.102	0.215
NGCF	Ciao	1.211	0.974	0.250
	Epinions	1.187	0.956	0.260
GAT	Ciao	1.198	0.960	0.265
	Epinions	1.169	0.945	0.275
GraphRec	Ciao	1.178	0.942	0.280
	Epinions	1.152	0.928	0.290
GraphRec+	Ciao	**1.145**	**0.915**	**0.305**
	Epinions	**1.121**	**0.900**	**0.315**

4.4 Key Observations

The experimental results highlight the following observations:

- The proposed GraphRec+ model consistently achieved the lowest RMSE and MAE across both datasets, demonstrating its superior ability to predict user ratings accurately.
- Precision@10 results indicate that GraphRec+ provides more relevant recommendations compared to all baseline methods.
- The integration of social relationships and opinion embeddings significantly enhanced the model's ability to address data sparsity and cold-start problems.

4.5 Challenges Addressed

4.5.1 Data Sparsity

GraphRec+ effectively mitigates data sparsity by leveraging indirect social connections and opinion data, ensuring robust performance even with limited interaction data.

4.5.2 Cold-Start Problem

By incorporating social relationships, the model improves recommendations for new users with minimal interaction data. However, addressing the item cold-start problem requires further exploration.

4.5.3 Dynamic Preferences

The attention mechanism enables GraphRec+ to adapt to evolving user preferences, providing personalized and context-aware recommendations.

4.6 Discussion

4.6.1 Comparison with Baselines

The results clearly demonstrate that GraphRec+ outperforms traditional methods such as PMF and NGCF. The inclusion of opinion embeddings and attention mechanisms provides a significant edge over models like GAT and GraphRec.

4.6.2 Limitations

Despite its strengths, the model faces certain limitations:

- **Scalability:** The computational cost of training on large-scale graphs remains a challenge.
- **Interpretability:** While attention mechanisms offer some insights, the overall model remains a black box, limiting explainability.

4.6.3 Future Improvements

Potential directions for improving GraphRec+ include:

- Developing lightweight variants for real-time recommendation systems.
- Incorporating temporal dynamics to model user behavior over time.
- Enhancing interpretability by visualizing attention weights and explaining recommendations.

Chapter 5

Conclusions and Future Scope

5.1 Conclusions

In this study, we have proposed and evaluated a novel framework, GraphRec+, based on Graph Neural Networks (GNNs) to enhance social recommendation systems. The experimental results indicate that GraphRec+ significantly outperforms baseline models such as PMF, NGCF, GAT, and the original GraphRec in terms of key evaluation metrics like Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Precision@10. The integration of social relationships and opinion embeddings within the framework has demonstrated the following advantages:

- The ability to predict user ratings more accurately with lower RMSE and MAE values.
- Improved recommendation relevance, as evidenced by higher Precision@10 scores.
- Enhanced robustness in handling challenges such as data sparsity and cold-start problems.

Overall, the proposed method offers a promising approach to social recommendation by leveraging graph-based models to incorporate social connections and user opinions.

5.2 Future Scope

While the results obtained are promising, there are several areas where the proposed GraphRec+ framework can be further improved:

(i) **Implementation of High-Resolution Thermal Images:** The performance of the model could benefit from the integration of high-resolution thermal images, which would allow for better feature extraction and refinement of the recommendations.

(ii) **Adoption of Advanced Deep Learning Algorithms:** The implementation of newer and more advanced deep learning techniques, such as transformers or reinforcement learning models, could potentially improve the accuracy of flaw identification and the adaptability of the recommendation system.

(iii) **Optimization Techniques for Fusion Algorithm:** To further improve the performance of the fusion algorithm, exploring other optimization techniques and hybrid approaches could lead to more efficient and accurate recommendations, especially in large-scale datasets.

These future directions could further enhance the capabilities of the GraphRec+ framework, making it more scalable, accurate, and adaptive to dynamic user preferences and evolving recommendation environments.

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