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A Rating-Enhanced Graph Neural Network Recommendation Systems

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Abstract: In recent years, Graph Neural Networks (GNNs) have increasingly become a research hotspot. To further explore the application prospects of GNNs in the recommendation field, this paper conducts an in-depth study on the utilization of rating information. A rating-enhanced Graph Neural Network recommendation model is proposed. This model improves upon existing approaches by first obtaining the embedding of ratings through automatic feature engineering. Then, it utilizes a cross-attention coefficient to effectively integrate the rating embedding vectors with the embedding vectors of the two nodes, thereby obtaining the coefficients for graph spatial convolution. Experimental results show that the coefficients obtained by this model are positively correlated with the ratings, and the recommendation accuracy of graph convolution is significantly improved.

Keywords: Graph Neural Networks, Recommendation Systems, Rating Enhancement, Cross-Attention Coefficient

1. Introduction

Recommendation systems, as a data mining technology, have been widely applied in fields such as e-commerce, social networks, and online education. Traditional recommendation algorithms often rely on techniques such as matrix factorization and collaborative filtering[1]. However, as the complexity and scale of data increase, traditional methods often face issues like low computational efficiency and insufficient accuracy[2]. In recent years, Graph Neural Networks (GNNs) have become an important research direction in recommendation systems due to their advantages in handling complex graph-structured data[3].

This study proposes a rating-enhanced Graph Neural Network (GNN) recommendation method, which aims to combine the structural learning capability of GNNs with rating information to improve recommendation performance[4]. Specifically, we design a GNN model based on rating enhancement, which includes user and item modules as well as prediction and training modules. The model concatenates the latent factors of users and items using a multi-layer perceptron (MLP) and uses this information for rating prediction and model training[5].

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2. Method

This study proposes a rating-enhanced graph neural network (GNN) recommendation method, aiming to integrate the structural learning capability of GNNs with rating information to enhance recommendation performance[6]. Specifically, we design a rating-enhanced GNN model comprising a user module, an item module, and a prediction and training module. The model concatenates latent factors of users and items through a multilayer perceptron (MLP), utilizing this information for rating prediction and model training[7]. The architecture of the proposed GNNRM-SE (Graph Neural Network Recommendation Model with Score Enhancement) is illustrated in Figure 1.

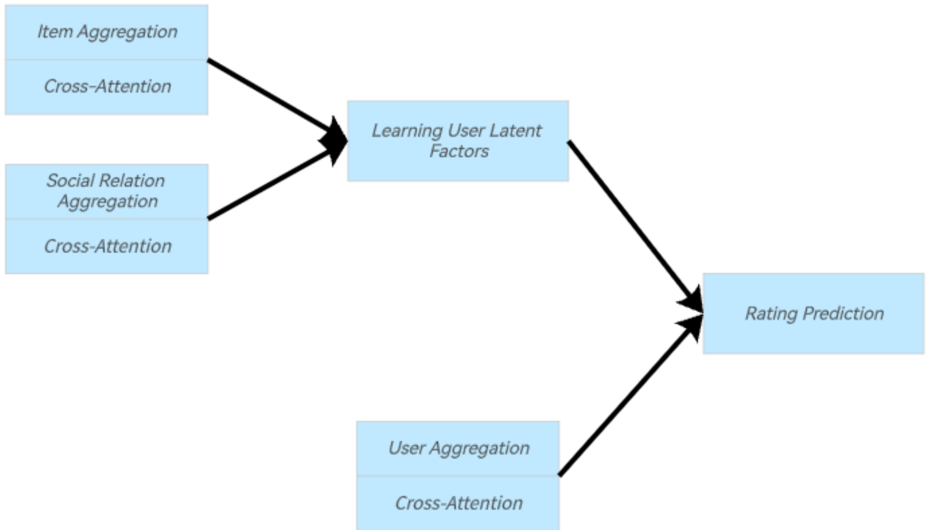

Figure 1: GNNRM-SE Overall architecture.

2.1. User Latent Factor Learning in Item Space

The user latent factors in the item space, $\mathbf{h}_i^I$, are learned from all items a user p_i has interacted with and their corresponding ratings, as follows:

$$\mathbf{h}_i^I = \sigma\left(\mathbf{W} \cdot Aggre_{items}\left(\{\mathbf{x}_{ia}, \forall a \in C(i)\}\right) + \mathbf{b}\right) \tag{1}$$

Here, $\mathbf{h}_i^I$ denotes the user's latent factor in item space, $C(i)$ represents all items interacted by user p_i or the neighbors of user p_i in the user-item interaction graph, and x_{ia} is a representation vector[8].

2.2. Rating Activation

A rating-activated interaction representation is constructed by concatenating item embedding vector g_a and rating embedding vector e_r, and then processing them through a multilayer perceptron (MLP), denoted as MLP_v[9] [9].This MLP fuses the item and rating information:

$$\mathbf{x}_{ia} = MLP_v([g_a \oplus e_r]) \tag{2}$$

An overview of the cross-attention coefficient acquisition algorithm is illustrated in Figure 2.

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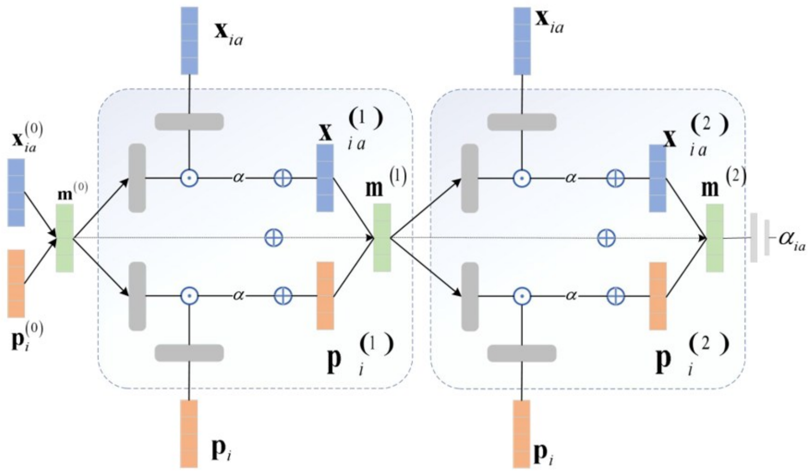

Figure 2: Overview of cross attention coefficient acquisition algorithm.

2.3. Representation Vectors

Representation vectors are computed by combining the rating-activated interaction representation with user features, maintaining memory vectors from previous layers[10]. The memory vector at layer kk is:

$$\mathrm{m}^{(\mathrm{k})} = \mathrm{m}^{(\mathrm{k}-1)} + \mathrm{x}_{\mathrm{ia}}^{(\mathrm{k})} \odot \mathrm{p}_{\mathrm{i}}^{(\mathrm{k})} \tag{3}$$

The calculation of the rating-activated representation vector is:

$$\boldsymbol{h}_{\boldsymbol{x}}^{(k)} = tanh\left(\boldsymbol{W}_{\boldsymbol{x}}^{(k)} \boldsymbol{x}_{ia}\right) \odot tanh\left(\boldsymbol{W}_{\boldsymbol{x},\boldsymbol{m}}^{(k)} \boldsymbol{m}_{\boldsymbol{x}}^{(k-1)}\right) \tag{4}$$

$$\alpha_{\boldsymbol{x},n}^{(k)} = soft\ max\left(\boldsymbol{W}_{\boldsymbol{x},\boldsymbol{h}}^{(k)}\ \boldsymbol{h}_{\boldsymbol{x}}^{(k)}\right) \tag{5}$$

$$\boldsymbol{x}_{ia}^{(k)} = tanh\left(\alpha_{\boldsymbol{x},n}^{(k)} \boldsymbol{x}_{ia}\right) \tag{6}$$

Similarly, the user feature representation vector calculation is:

$$\boldsymbol{h}_{p}^{(k)} = tanh\left(\boldsymbol{W}_{p}^{(k)} \boldsymbol{p}_{i}\right) \odot tanh\left(\boldsymbol{W}_{p,\boldsymbol{m}}^{(k)} \boldsymbol{m}_{p}^{(k-1)}\right) \tag{7}$$

$$\alpha_{p}^{(k)} = soft\ max\left(\boldsymbol{W}_{p,\boldsymbol{h}}^{(k)}\ \boldsymbol{h}_{p}^{(k)}\right) \tag{8}$$

$$\boldsymbol{p}_{i}^{(k)} = \alpha_{p}^{(k)} \boldsymbol{p}_{i} \tag{9}$$

2.4. Attention Mechanism

An initial attention coefficient α_{ia}^{*} is obtained through an MLP based on the final memory vector $\boldsymbol{m}^{(k)}$:

$$\alpha_{ia}^{*} = MLP\left(\boldsymbol{m}^{(k)}\right) \tag{10}$$

Then, the actual attention coefficient is computed using:

$$\alpha_{ia} = \frac{exp(\alpha_{ia}^{*})}{\sum_{a \in C(i)} exp\,(\alpha_{ia}^{*})} \tag{11}$$

By aggregating neighbor user latent factors in the item space $\mathrm{h}_{\mathrm{o}}^{\mathrm{I}}$, we obtain the social-space latent factor $\mathbf{h}_i^S$ of user p_i:

$$\mathbf{h}_i^S = \sigma\left(\mathbf{W} \cdot Aggre_{neighbors}(\{\mathbf{h}_i^I, \forall o \in N(i)\}) + \mathbf{b}\right) \tag{12}$$

The closeness between users βio\beta_{io} modulates this aggregation process:

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$$\boldsymbol{h}_i^S = \sigma\left(\boldsymbol{W}\cdot\left\{\sum_{o\in N(i)}\beta_{io}\,\boldsymbol{h}_o^I\right\}+\boldsymbol{b}\right) \tag{13}$$

where β_{io} measures the closeness between users.

Finally, the item-space and social-space latent factors h_i^I and $\mathbf{h}_i^S$ are concatenated and input into a standard multilayer perceptron to obtain the final user latent factor h_i:

$$\boldsymbol{h}_1 = \left[\boldsymbol{h}_i^I \oplus \boldsymbol{h}_i^S\right] \tag{14}$$

$$\boldsymbol{h}_2 = \sigma(\boldsymbol{W}_2 \cdot \boldsymbol{c}_1 + \boldsymbol{b}_2) \tag{15}$$

$$\cdots\cdots$$

$$\boldsymbol{h}_i = \sigma(\boldsymbol{W}_l \cdot \boldsymbol{c}_{l-1} + \boldsymbol{b}_l) \tag{16}$$

where ll indexes neural network layers, and $\boldsymbol{W}_l$, $\boldsymbol{b}_l$ represent weights and biases for the lth layer.

2.5. Training Loss

The training loss is defined as:

$$Loss = \frac{1}{2|\boldsymbol{O}|}\sum_{i,j\in\boldsymbol{O}}\left(r_{ij}^{'} - r_{ij}\right)^2 \tag{18}$$

Here, $|\boldsymbol{O}|$ denotes the number of observed ratings, r_{ij} is the actual rating user p_i gave to item g_j, and $r_{ij}^{'}$ is the predicted rating.

3. Experimental Results

To ensure optimal model performance, the embedding dimension is set to 16, with a learning rate of 0.05 and a default three-layer hidden network structure. Each experiment is conducted ten times, and the average results are reported to enhance the reliability of performance evaluation. To objectively assess the recommendation effectiveness of the proposed GNNRM-SE model, a comparative analysis is conducted against the following three baseline recommendation models:

SocialMF[11]: This model incorporates trust information into the recommendation system and propagates trust signals within a matrix factorization framework to enhance prediction accuracy.

DeepSoR[12]: This approach employs a deep neural network to learn user representations from social relationships and integrates these representations into probabilistic matrix factorization for rating prediction.

GraphRec[13]: This model is designed to fully exploit user-item interactions and user-user relationships within the graph neural network recommendation framework. It also considers the varying strengths of edges in the graph and jointly utilizes these factors to improve recommendation accuracy.

Table 1: This caption has one line so it is centered

Dataset	metric	Model			
		SocailMF	DeepSoR	GraphRec	GNNRM-SE
Ciao	MAE	0.9003	0.7881	0.7720	0.760
	RMSE	1.0522	10.4487	1.0303	1.0224
Epinions	MAE	0.8798	0.8621	0.8301	0.8101
	RMSE	1.1376	1.1253	1.0938	1.0826

4. Results Analysis

The experimental results presented in Table 1 demonstrate the superior performance of the proposed GNNRM-SE model compared to the baseline methods (SocialMF, DeepSoR, and GraphRec) across both the Ciao and Epinions datasets. On the Ciao dataset, GNNRM-SE achieves the lowest MAE (0.760) and RMSE (1.0224), outperforming the strongest baseline, GraphRec, by 1.56% in MAE and 0.77% in RMSE. Similarly, on the Epinions dataset, GNNRM-SE attains the best MAE (0.8101) and RMSE (1.0826), surpassing GraphRec by 2.41% and 1.02%, respectively. These improvements highlight the effectiveness of integrating multi-faceted interaction relationships (user-item, item-user, and user-user) and leveraging cross-attention mechanisms to capture nuanced rating-based signals.

Notably, SocialMF exhibits the weakest performance due to its reliance on matrix factorization with limited capacity to model complex graph-structured interactions. While DeepSoR improves upon SocialMF by incorporating deep neural networks, it still underperforms compared to graph-based approaches (GraphRec and GNNRM-SE), emphasizing the importance of explicitly modeling edge strengths and hierarchical aggregation in recommendation systems. The proposed model's ability to jointly optimize user-item interactions, social relationships, and rating-enhanced attention coefficients contributes to its robustness across diverse evaluation metrics. The consistency in performance gains over ten independent trials further validates the reliability of the reported results.

5. Discussion

In the study of leveraging user rating information in graph neural network recommendation models, the proposed model distinguishes itself by directly incorporating rating values as inputs, unlike models such as GCMC. The model generates embedding vectors that are concatenated with feature vectors of either users or items, which are then fed into a shallow multi-layer perceptron. The output embeddings, along with the feature vectors of items or users, are subsequently input into a cross-attention coefficient acquisition algorithm designed to thoroughly integrate information from both sources. This process yields attention coefficients for domain convolution, which have been empirically shown to effectively reflect the ordered information inherent in rating magnitudes. Furthermore, the model aggregates interaction information between users and items from both user-centric and item-centric perspectives, as well as user social relationship information from a user-centric viewpoint, all while integrating rating information through cross-attention coefficients. This multi-level, multi-faceted approach comprehensively considers valuable reference information within the recommendation scenario, resulting in more accurate and well-founded recommendation outcomes.

6. Conclusion

In the context of rating-enhanced graph neural network recommendation models, although the proposed model effectively captures interactions between users and items, items and users, as well as among users themselves, and is capable of modeling the strength of these interactions, many real-world recommendation scenarios often involve additional auxiliary information, such as user and item attributes. In the current model, the feature information of users or items is represented by low-dimensional vectors generated through neural network mappings of user or item identifiers, which fails to incorporate actual attribute information. Exploring the integration of user or item feature information into the neural network computation presents a promising and intriguing research direction. By incorporating explicit attributes such as user demographics, behavioral preferences, or item categories and descriptions, the model's representational capacity could be further enhanced, potentially leading to more accurate and interpretable recommendations. This direction not only holds

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theoretical significance but also offers practical benefits for improving the performance and personalization of recommendation systems.

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