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Personalized Point-of-Interest Recommendation Using Improved Graph Convolutional Network in Location-Based Social Network

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Abstract: Data sparsity limits the performance of point-of-interest (POI) recommendation models, and the existing works ignore the higher-order collaborative influence of users and POIs and lack in-depth mining of user social influence, resulting in unsatisfactory recommendation results. To address the above issues, this paper proposes a personalized POI recommendation using an improved graph convolutional network (PPR_IGCN) model, which integrates collaborative influence and social influence into POI recommendations. On the one hand, a user-POI interaction graph, a POI-POI graph, and a user–user graph are constructed based on check-in data and social data in a location-based social network (LBSN). The improved graph convolutional network (GCN) is used to mine the higher-order collaborative influence of users and POIs in the three types of relationship graphs and to deeply extract the potential features of users and POIs. On the other hand, the social influence of the user's higher-order social friends and community neighbors on the user is obtained according to the user's higher-order social embedding vector learned in the user–user graph. Finally, the captured user and POI's higher-order collaborative influence and social influence are used to predict user preferences. The experimental results on Foursquare and Yelp datasets indicate that the proposed model PPR_IGCN outperforms other models in terms of precision, recall, and normalized discounted cumulative gain (NDCG), which proves the effectiveness of the model.

Keywords: POI recommendation; location social network; data sparsity; graph convolutional network; social influence

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1. Introduction

With the development of smart devices with GPS satellite positioning functions and mobile internet, location-based services have received widespread attention in social networks [1–5]. A large number of location-based social network (LBSN) service websites and software, such as Gowalla, Foursquare, Yelp, Twitter, Dianping, etc., appear in people's social lives. Users can check in on LBSNs through a series of activities, such as recording, location sharing, and interacting with friends. Point-of-interest (POI) recommendation is one of the important services of LBSNs, which not only facilitates users discovering locations of interest and reduces decision-making time but also helps merchants know user preferences more comprehensively, find target groups more accurately, and provide personalized services [6,7]. Due to the important role played by POI recommendations in real life, it has gradually become a current research hotspot [8–11].

Initially, POI recommendations adopt the collaborative filtering (CF) method for recommendations. Matrix factorization (MF) is the most commonly used method to learn the potential embedding vectors of users and POIs and calculate users' preferences for POI by modeling the two vectors in the form of the inner product. However, the MF method makes it difficult to capture collaborative information in user-POI interaction data. In this case, people began to use a series of methods, such as neural networks and graph models, to solve them. Someone used the graph neural network (GNN) to learn embedding vectors in graph data. GNN updates the current node embedding vector by aggregating neighbor node information, which can integrate node information, edge information, and topology structure in the graph to better learn the embedding vector [12]. T. N. Kipf et al. [13] derived a simplified graph convolutional network (GCN) operation model based on approximate techniques, which is considered the "pioneering work" in the field of GNN. Recently, graph neural network collaborative filtering recommendations [14,15] have become an effective recommendation method, which uses GCN to encode user–item historical interaction information into the representation embedded space, thus improving the recommendation effect [16].

With the explosive growth of the number of users and locations, POI recommendation faces three challenges. Firstly, data sparsity reduces the accuracy of traditional POI recommendation models. Secondly, the massive amounts of data in real life require models to have higher data-processing capabilities. While ensuring the recommendation's performance, both model efficiency and scalability need to be considered [17]. Finally, current POI recommendation methods are unable to effectively capture complex collaborative information in users' social relationships and user-POI interactions, which limits the performance of POI recommendations [18].

In response to the problems of data sparsity, low model efficiency, and poor recommendation performance in the current POI recommendation task, this paper proposes a personalized POI recommendation using an improved graph convolutional (PPR_IGCN) model. The main contributions are as follows:

- Apply the improved GCN to POI recommendation, construct a user-POI interaction graph, a POI-POI graph, and a user–user graph based on user history check-in data, deeply mine collaborative information in three types of relationships, and learn user and POI higher-order collaborative embedding vectors to improve recommendation performance;
- Based on the users' higher-order social embedding vector learned in the user–user graph, the higher-order social friend influence of the user and social friends and the community neighbor influence of the user and close neighbors are captured to alleviate data sparsity;
- Conduct experiments on real datasets to evaluate the performance of the proposed model, PPR_IGCN. The experimental results show that the model outperforms other existing models, which verifies the effectiveness of the proposed model.

The rest of this paper is organized as follows: Section 2 introduces the related work on POI recommendations and GCN. Section 3 provides a detailed introduction to the proposed model, PPR_IGCN. Section 4 conducts a series of experiments on two real datasets, introduces the experimental setup, and analyzes the experimental results. Section 5 summarizes the work of this paper.

2. Related Work

This section introduces the related work of POI recommendations and GCN-based recommendations.

2.1. POI Recommendation

POI recommendation is an important task in the recommendation field, which can help users find new locations of interest. Gao et al. [19] considered the characteristics of user check-in behavior changing over time. They used the MF model to model the check-in behavior at different time states and learned users' time check-in preferences for location recommendations. Liu et al. [20] jointly learned users' geographic and interest preferences through a Poisson factorization model. Aiming at data sparsity and preference dynamics, Wang et al. [21] used knowledge graph embedding technology to encode time, geographic, and semantic information and built a joint MF framework on the user-POI graph to use side information to enhance the dynamic preference prediction of users.

Xu et al. [22] proposed a POI recommendation framework that integrates the influence of users' social and personal interests and check-in order. They used the convolutional filter and multilayer perceptron model to mine the sequential influence between user check-in POIs and used the metric learning method to model users' social relationships. Zhu et al. [23] proposed a graph embedding representation model that integrates social and geographic influences. The user embedding vector is obtained by combining user embedding with social graph embedding, and the POI embedding vector is obtained by combining POI embedding with geographic graph embedding. Under the neural network framework, the potential connections between users and POIs are explored to obtain user preferences. Cao et al. [24] used the Bayesian personalized sorting method to integrate social relationships and geographic information and combined the BPR framework with POI clustering information to form the POI recommendation list. Lian et al. [25] used the two-dimensional kernel density estimation method to simulate the phenomenon of spatial clustering. Based on the weighted MF, the user active region vector and POI influence region vector are fused into the user and POI implicit spaces to improve the recommendation effect.

2.2. Recommendation Based on GCN

GNN can be used to handle various types of graph structures and has a wide range of applications in the fields of knowledge graphs and recommendation systems. GCN is a category of GNN and has strong feature extraction and learning abilities. GCN applies the convolutional neural network used for image processing to deal with the problem of graph structure and obtains node feature information in space by continuously optimizing convolution parameters. The basic equations of GCN are as follows:

$$\mathbf{h}_i^{(l+1)} = \sigma\left(\sum_{j \in N_i} \frac{1}{C_{ij}} \mathbf{h}_j^{(l)} \mathbf{w}^{(l)}\right) \tag{1}$$

$$\frac{1}{C_{ij}} = \hat{\mathbf{D}}^{-\frac{1}{2}} \hat{\mathbf{A}} \hat{\mathbf{D}}^{-\frac{1}{2}} \tag{2}$$

$$\hat{\mathbf{A}} = \mathbf{A} + \mathbf{I} \tag{3}$$

where $\sigma(\cdot)$ is the activation function for nonlinear transformation, N_i is the neighbor set of node i, C_{ij} is the normalization factor, $\mathbf{A}$ is the adjacency matrix of node i, $\hat{\mathbf{D}}$ is the corresponding degree matrix of $\hat{\mathbf{A}}$, $\mathbf{h}_i^{(l+1)}$ is the embedding vector of node i in layer $l+1$, the embedding vector of the node i and all the neighbors of node i in layer l are represented by $\mathbf{h}_j^{(l)}$, and $\mathbf{w}^{(l)}$ is the weight of layer l.

The GCN model is mainly divided into the embedding layer, embedding propagation layers, and prediction layer. Firstly, the data are input into the embedding layer, the initialized embedding vector representation is obtained, and then the embedding vectors are input into the embedding propagation layers. Secondly, during the message-passing process of the embedding propagation layer, the embedding vectors are updated through message construction and message aggregation operations. Finally, based on the updated embedding vectors, the prediction results are made in the prediction layer. The framework graph is shown in Figure 1.

Wang et al. [26] emphasized the importance of collaborative signals in the CF method and proposed the GNN-based recommendation framework NGCF. In the NGCF framework, collaborative signals are explicitly encoded in the form of higher-order connectivity through embedding propagation to obtain the user–item interaction embedding vector. Wu et al. [27] pointed out the importance of spatial and temporal factors in POI recommendations and proposed a GARG model that combines attention mechanisms and GCN to improve the recommendation's performance. He et al. [28] found that the two most common feature transformations and nonlinear activation designs of GCN in NGCF have little effect on the performance improvement of CF, so they proposed a LightGCN model that only contains the most basic components of GCN. Chang et al. [29] utilized GGLR to capture highly nonlinear geographic influences in POIs. The potential representations of input and output geographic influences are obtained based on a graph autoencoder, and the trained geographical potential representations are used to estimate users' preferences in the GNN-based POI recommendation model (GPR); thus, the accuracy of POI recommendations is improved. Li et al. [30] obtained the social impact set of users on Markov nets through the belief propagation algorithm, calculated the similarity and familiarity of social users in the set, and linearly integrated the social impact and geographical location impact for location recommendations. Zhong et al. [31] proposed the hybrid graph convolution networks for the POI recommendation framework, built a spatial graph based on the geographical distance between POI pairs, and used GCN to represent the higher-order connectivity in POIs, which alleviated the sparse check-in problem. Ying et al. [32] first proposed the PinSage algorithm by applying GCN to recommendation systems. This algorithm combines efficient random walks with graph convolution to generate node embeddings containing graph structure and node feature information.

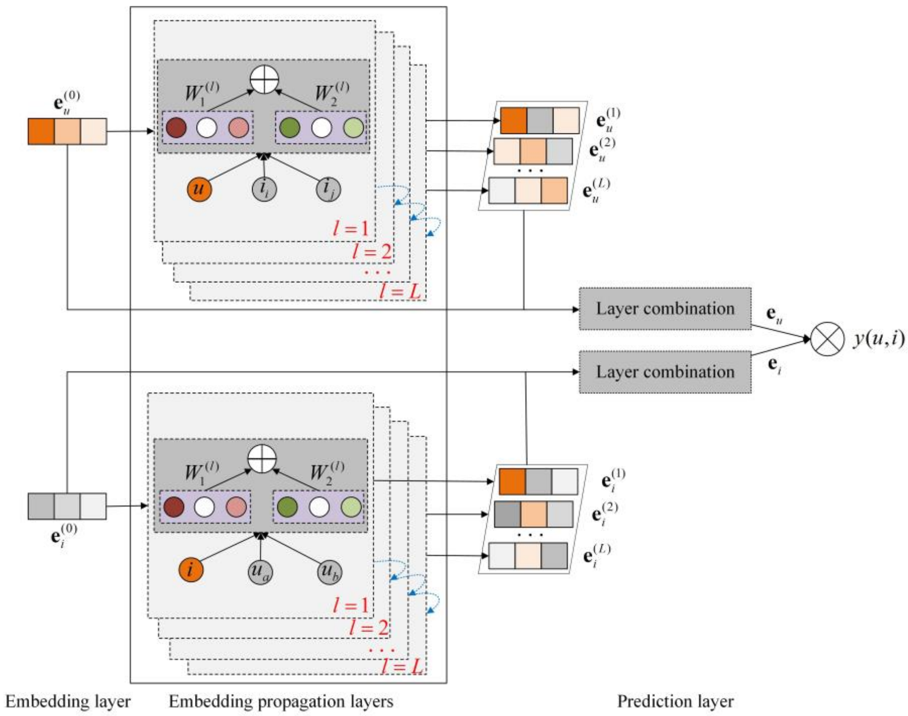


Figure 1. GCN model framework graph.

3. Proposed Model

3.1. Preliminaries

Define the user set $U = \left\{u_1, u_2, \ldots, u_{|U|}\right\}$ and POI set $P = \left\{p_1, p_2, \ldots, p_{|P|}\right\}$, where $|U|$ denotes the total number of users and $|P|$ denotes the total number of POIs. According to the user and POI interaction records, the user-POI interaction matrix $\mathbf{R}$ can be obtained. If a user has visited the POI, the element value of $\mathbf{R}$ is 1, otherwise, it is 0. The potential embedding vectors of user u and POI p are represented by d-dimension m_u and m_p, respectively. The check-in behavior is denoted by the three tuple $< u, p, c >$, which represents that user u has checked in c times on POI p. The user check-in behavior can be transformed into the user-POI interaction frequency matrix $\mathbf{R}_c$. When user u has not visited POI p, the value of element R_{up} is the number of visits in $\mathbf{R}_c$. The goal of this paper is to discover the top K previously unvisited locations that users are most interested in a given user check-in information.

3.2. PPR_IGCN Model

The PPR_IGCN model includes the following two parts: collaborative influence and social influence. The collaborative influence uses the improved GCN to mine higher-order collaborative information in the user check-in data, which reaches the limited convergence state of the embedding propagation layer through the loss function, in order to learn the impact of the three types of relationships represented by a user-POI interaction graph, a POI-POI graph, and a user–user graph on users' preferences and obtain the collaborative embedding vector between user and POI. Based on the users' social information and characteristics, social influence combines friend-based collaborative filtering with improved GCN to mine the influence of higher-order social friends and community neighbors on users' preferences to alleviate data sparsity. The overall framework of the model is shown in Figure 2.

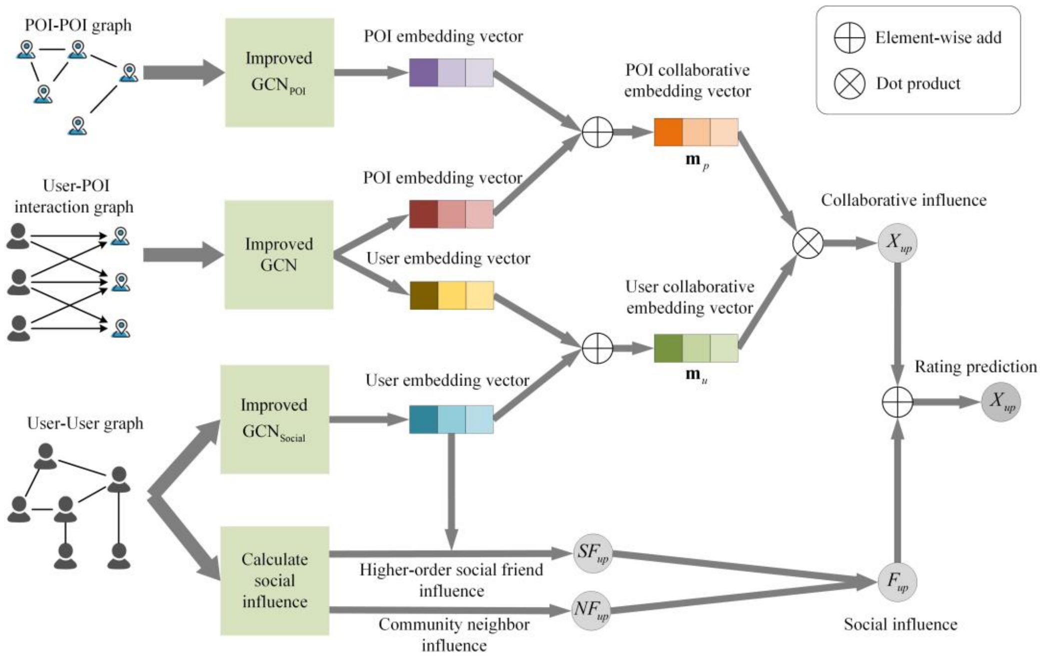


Figure 2. PPR_IGCN model framework graph.

3.3. The Learning Mode of Multi-Dimensional Collaborative Influence

Based on the three types of relationships represented by a user-POI interaction graph, a POI-POI graph, and a user–user graph, this section proposes a learning mode of multi-dimensional collaborative influence.

3.3.1. Learning the Collaborative Influence of the User-POI Interaction Graph

User-POI check-in information can be expressed as a user-POI interaction graph, as shown in Figure 3a, which can be converted into a higher-order neighbor node graph, as shown in Figure 3b. Since the neighbors of the node u_i carry collaborative information, they can affect the preference of node u_i. Therefore, GCN is used to mine the higher-order neighbor information of node u_i to enrich the characteristic information of node u_i, which can alleviate the sparsity of the interaction data. In the embedding layer, the d-dimensional initial embedding vectors of user and POI are defined, which are shown in Equations (4) and (5).

$$\mathbf{M}_U^{(0)} = [\mathbf{m}_{u_1}^{(0)}, \ldots, \mathbf{m}_{u_{|U|}}^{(0)}]^{\mathrm{T}} \tag{4}$$

$$\mathbf{M}_P^{(0)} = [\mathbf{m}_{p_1}^{(0)}, \ldots, \mathbf{m}_{p_{|P|}}^{(0)}]^{\mathrm{T}} \tag{5}$$

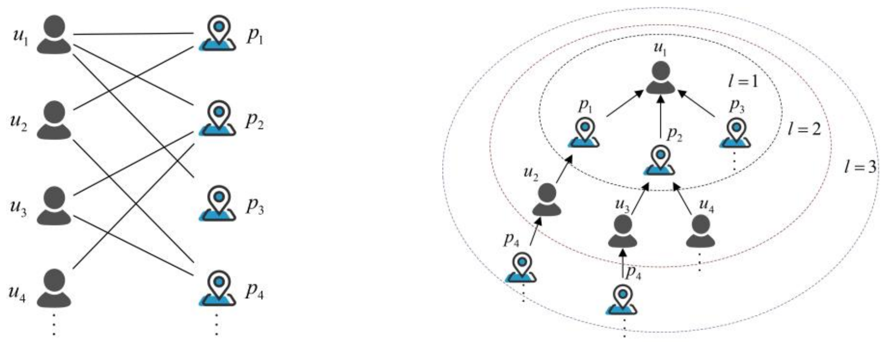


Figure 3. First-order connectivity versus higher-order connectivity. (**a**) User-POI interaction graph; (**b**) Higher-order neighbor graph for u_1.

The standard GCN model mentioned in Section 2.2 uses the nonlinear activation function and multiple feature transformation matrices in the embedding propagation layer to update the node embedding vector. However, when GCN is applied to the recommendation field, the nodes in the user-POI interaction graph do not have rich semantic information, and only the data of user ID and POI ID are put into the model for training. Therefore, the above two operations are not conducive to learning node embedding vectors and will increase the training difficulty. So, the GCN model can be simplified, i.e., the first-order neighbor's collaborative information is obtained through message aggregation of an embedding propagation layer, and multiple embedding propagation layers are stacked to obtain the higher-order neighbor's collaborative information to update the node embedding vector. After removing the nonlinear activation function and feature transformation matrices, the message-passing process is abstracted, considering the self-connection operation of the nodes, as shown in Equations (6) and (7).

$$\mathbf{m}_u^{(l+1)} = \frac{1}{|N_u|+1}\mathbf{m}_u^{(l)} + \sum_{q \in N_u} \frac{1}{\sqrt{|N_u|+1}\sqrt{|N_q|+1}}\mathbf{m}_q^{(l)} \tag{6}$$

$$\mathbf{m}_p^{(l+1)} = \frac{1}{|N_p|+1}\mathbf{m}_p^{(l)} + \sum_{v \in N_p} \frac{1}{\sqrt{|N_v|+1}\sqrt{|N_p|+1}}\mathbf{m}_v^{(l)} \tag{7}$$

where u and v represent users, p and q represent POIs, $\mathbf{m}_u^{(l+1)}$ and $\mathbf{m}_p^{(l+1)}$ represent the embedding vectors of user u and POI p in the embedding propagation layer $l+1$, respectively, N_u, N_p, N_v, and N_q represent the neighbor sets of the nodes u, p, v, and q, and $|N_u|$, $|N_p|$, $|N_v|$, and $|N_q|$ represent the neighbor numbers of the nodes u, p, v, q.

Generally speaking, deeper collaborative information can be learned by stacking more embedding propagation layers, but too many embedding propagation layers will cause an over-smoothing problem, i.e., each node will tend to form an exactly identical embedding vector, resulting in a decrease in model performance [26]. Therefore, this paper further improves the GCN model, and the specific process is as follows:

According to Equation (1), the limit of message passing can be obtained when the number of embedding propagation layers tends to infinity, as shown in Equation (8).

$$\lim_{l\to\infty}\left(\frac{1}{C_{ij}}\right)^{l}=\frac{\sqrt{|N_i|+1}\sqrt{|N_j|+1}}{2a+b} \tag{8}$$

where a and b are the total number of nodes and edges in the graph, respectively.

Due to the existence of the limit, the superposition of multiple embedding propagation layers can be skipped and directly enable the user and POI embedding vectors to reach the convergence state of infinite layer message propagation, as shown below.

$$\mathbf{m}_u=\lim_{l\to\infty}\mathbf{m}_u^{(l+1)}=\lim_{l\to\infty}\mathbf{m}_u^{(l)} \tag{9}$$

$$\mathbf{m}_p=\lim_{l\to\infty}\mathbf{m}_p^{(l+1)}=\lim_{l\to\infty}\mathbf{m}_p^{(l)} \tag{10}$$

Equations (9) and (10) align the end user embedding vector that aggregates higher-order neighbor collaboration information with the embedding vectors of layer l and layer $l+1$. Therefore, Equation (6) can be rewritten as Equation (11).

$$\mathbf{m}_u=\frac{1}{|N_u|+1}\mathbf{m}_u+\sum_{p\in N_u}\frac{1}{\sqrt{|N_u|+1}\sqrt{|N_p|+1}}\mathbf{m}_p \tag{11}$$

By further simplifying Equation (11), the convergence state of the GCN embedding propagation layer can be obtained, as shown below.

$$\mathbf{m}_u=\sum_{p\in N_u}w_{up}\mathbf{m}_p \tag{12}$$

$$w_{up}=\frac{1}{|N_u|}\sqrt{\frac{|N_u|+1}{|N_p|+1}} \tag{13}$$

Next, convergence is reached by making the values on both sides of Equation (12) closer, i.e., the higher the similarity on both sides of the equation, the closer to the convergence state. Specifically, after normalizing the embedding vector, the cosine similarity between the two is maximized, and Equation (14) is obtained.

$$\max\sum_{p\in N_u}w_{up}{\mathbf{m}_u}^{\mathrm{T}}\mathbf{m}_p \tag{14}$$

To facilitate optimization and avoid over-smoothing, the sigmoid activation function and negative log-likelihood estimation are introduced, random negative sampling [33] is added to the training process, and, finally, the constraint function L_{up} is obtained.

$$L_{up}=-\sum_{(u,p)\in D^+}w_{up}\log(\sigma({\mathbf{m}_u}^{\mathrm{T}}\mathbf{m}_p))-\sum_{(u,q)\in D^-}w_{uq}\log(\sigma(-{\mathbf{m}_u}^{\mathrm{T}}\mathbf{m}_q)) \tag{15}$$

$$D=\left\{(u,p,q)\middle|(u,p)\in D^+,(u,q)\in D^-\right\} \tag{16}$$

where D is the set of all user-POI pairs in the training set, D^+ represents the set of positive sample pairs, and D^- represents the set of negative sample pairs. The constraint function can make the model approximate to reach the effect of infinite superimposed embedding propagation layers, thereby mining the infinite higher-order neighbor collaboration information in the user-POI interaction graph.

3.3.2. Learning the Collaborative Influence of the POI-POI Graph

To make the learned user preferences more accurate, the weighted adjacency matrix **E** of the POI-POI graph is constructed using the user-POI interaction matrix **R**, as shown in Equation (17).

$$\mathbf{E} = \mathbf{R}^{\mathrm{T}}\mathbf{R} \tag{17}$$

Model the POI-POI graph based on the convergence state of the known GCN embedding propagation layer to capture the impact of different relationships on users' preferences. The constraint function of learning the POI-POI graph is similar to Equation (15). The weighted adjacency matrix **E** of the POI-POI graph is relatively dense. To avoid introducing noise or unreliable information during the optimization process, only effective information pairs are selected for training. In addition, the user-POI positive sample pairs are used to learn the POI-POI relationship during training, which not only ensures the unity of the training conditions but also reduces the training difficulty. Thus, the constraint function L_{pq} for mining POI-POI relationships is obtained, as shown in Equation (18).

$$L_{pq} = -\sum_{(u,p)\in D^+}\sum_{q\in N(p)} w_{pq}\log(\sigma(\mathbf{m}_p{}^{\mathrm{T}}\mathbf{m}_q)) \tag{18}$$

where w_{pq} represents the constraint coefficient. When the embedding propagation layer of GCN reaches the convergence state, the value of w_{pq} can be calculated according to Equation (19). $N(p)$ represents the set of the top n locations selected that are most similar to POI p, i.e., the top n POIs with the highest w_{pq} value are selected for training.

$$w_{pq} = \frac{\mathbf{E}_{pq}}{c_p}\sqrt{\frac{c_p+1}{c_q+1}} \tag{19}$$

where c_p and c_q represent the degrees of POI p and POI q, respectively.

3.3.3. Learning the Collaborative Influence of the User–User Graph

Based on the idea described in Section 3.3.2, learn the user higher-order social embedding vector in the user–user social graph, as shown in Equations (20) and (21).

$$L_{uv} = -\sum_{(u,p)\in D^+}\sum_{v\in N(u)} w_{uv}\log(\sigma(\mathbf{m}_u{}^{\mathrm{T}}\mathbf{m}_v)) \tag{20}$$

$$w_{uv} = \frac{G_{uv}}{c_u}\sqrt{\frac{c_u+1}{c_v+1}} \tag{21}$$

where G_{uv} is one of the elements in the user–user graph, constructed according to the information of the user and direct social friends, c_u and c_v represent the degrees of user u and user v, respectively, and $N(u)$ represents the set of the top n friends selected that are most similar to user u.

3.4. Learning Social Influence

In real life, friends attend the cinema to watch movies, eat in restaurants, check in at scenic spots, etc., as well as friends will recommend favorite locations to each other, and friends of friends will also affect users' interest preferences. Under the circumstances, the user's behavior is susceptible to the influence of social relations to a certain extent, and this paper refers to it as higher-order social friend influence. In addition to the higher-order social friend influence, neighbors also recommend their favorite locations to each other, and users who are geographically close to the user also affect the user's behavior, which forms the community neighbor influence.

Next, use friend-based collaborative filtering and improved GCN technology to mine users' social influence. According to the user social embedding vector learned in Section 3.3.3, the user's higher-order social friend influence SF_{up} is obtained.

$$SF_{up} = \frac{\sum_{v \in SF_u} S_{uv} \cdot R_{vp}}{\sum_{v \in SF_u} S_{uv}} \tag{22}$$

$$S_{uv} = w \cdot \exp(-\frac{\|\mathbf{m}_u - \mathbf{m}_v\|^2}{\sigma^2}) + (1-w) \cdot \frac{|N_u \cap N_v|}{|N_u \cup N_v|} \tag{23}$$

where SF_u represents the set of direct friends of user u, S_{uv} represents the similarity between user u and friend v, and R_{vp} represents the check-in frequency of friend v at POI p. w is the weight coefficient, σ is the scale parameter, and N_u and N_v represent the check-in sets of user u and friend v respectively.

The definition of community neighbor influence NF_{up} is similar to Equation (22). The community neighbor set selects the top n neighbors closest to the user. The similarity calculation between the user and the community neighbors is shown in Equation (24).

$$N_{uv} = \frac{|N_u \cap N_v|}{|N_u \cup N_v|} \tag{24}$$

In summary, the user's social influence F_{up} is obtained, as shown below.

$$F_{up} = \eta_1 SF_{up} + \eta_2 NF_{up} \tag{25}$$

$$\eta_1 = \frac{1}{1 + e^{-(\mathbf{z}_1{}^{\mathrm{T}}\mathbf{f}_1)}} \tag{26}$$

where η_1 and η_2 are the correlation weight coefficients of the two social influences, which have the same form. Taking η_1 as an example, $\mathbf{f}_1$ represents the user feature vector, and $\mathbf{z}_1$ is the weight vector of $\mathbf{f}_1$.

3.5. Model Prediction and Optimization

Based on learning the user-POI interaction graph, POI-POI graph, and user–user graph, the higher-order collaborative embedding vectors of the user and POI are obtained. The collaborative influence X_{up} is obtained in the form of dot product of the higher-order collaborative embedding vectors of the user and POI.

$$X_{up} = \mathbf{m}_u{}^{\mathrm{T}}\mathbf{m}_p \tag{27}$$

Combine collaborative influence and social influence to obtain the final user preference prediction rating Y_{up}.

$$Y_{up} = \alpha X_{up} + \beta F_{up} \tag{28}$$

where α and β are the weight coefficients to control the two influences.

To increase the generalization ability and stability of the model, the Bayesian personalized ranking (BPR) loss function is used to optimize the model, as shown in Equation (29).

$$L_{BPR} = -\sum_{(u,p) \in D^+} \log(\sigma(Y_{up})) - \sum_{(u,q) \in D^-} \log(\sigma(-Y_{uq})) \tag{29}$$

where the positive and negative sample pairs used by the BPR loss function are consistent with L_{up}.

According to the above idea, the objective function L of the PPR_IGCN model training is obtained, as shown in Equation (30).

$$L = L_{BPR} + w_1 L_{up} + w_2 L_{pq} + w_3 L_{uv} + \lambda\|\Theta\| \tag{30}$$

where w_1, w_2, and w_3 are hyperparameters that control the importance of user-POI relations, POI-POI relations, and user–user relations. λ is the L2 regularization parameter, which is used to prevent overfitting. Θ is a trainable parameter.

4. Experiments

4.1. Datasets

In this section, two real-world datasets, Foursquare [34] and Yelp [35], are used to test the algorithm's performance. The datasets include users' ID, POI ID, check-in timestamp, POI latitude and longitude, social relationships between users, etc. Preprocess the data in advance to remove users with less than ten check-in POIs and POIs with less than ten visitors. The specific dataset information is shown in Table 1. It can be seen that the data are very sparse. In addition, the dataset is divided based on check-in time, with 70% being the training set, 20% being the testing set, and the remaining 10% being the validation set.

Table 1. Statistics of the experimental datasets.

Dataset	Number of Users	Number of POIs	Number of Check-Ins	Number of Social Links	Density
Foursquare	30,887	18,995	860,888	265,533	0.14%
Yelp	2551	13,474	124,933	32,512	0.29%

4.2. Evaluation Metrics

This paper uses three common evaluation metrics: precision rate Precision@K, recall rate Recall@K, and normalized discounted cumulative gain NDCG@K. Specifically, as shown in Equations (31)–(33).

$$Precision@K = \frac{1}{|U|}\sum_{u}^{|U|}\frac{|R_u \cap \mathrm{T}_u|}{K} \tag{31}$$

$$Recall@K = \frac{1}{|U|}\sum_{u}^{|U|}\frac{|R_u \cap \mathrm{T}_u|}{|R_u|} \tag{32}$$

$$NDCG@K = \frac{1}{|U|}\sum_{u}^{|U|}\frac{|R_u \cap G_u|}{|R_u|} \tag{33}$$

$|U|$ denotes the number of users, K denotes the number of POI recommended to each user, $K \in \{10, 20\}$, R_u denotes the set of locations that users actually visit in the test set, T_u denotes the K POI recommended to the user, and G_u denotes the level of K POI recommended to the user.

4.3. Parameter Settings

After tuning the parameters through cross-validation, set the batch size to 2048, the negative sampling rate to 300, the learning rate $lr = 10^{-3}$, the regularization coefficient $\lambda = 10^{-4}$, the weight coefficient $w = 0.5$, $\alpha = 1.1$, $\beta = 1$, and the hyperparameter $w_1 = 1$, $w_2 = 0.01$, and $w_3 = 0.01$. The Adam [36] algorithm is used to optimize the model parameters. The weight coefficients η_1 and η_2 of the higher-order social friend influence and community neighbor influence can be learned in the training model. Next, the value of dimension d of the user and POI embedding vectors and the value of the number n of the most similar locations/friends/neighbors are discussed. The experimental parameters are described and shown in Table 2.

Table 2. Parameters of the experiment.

Parameter	Meaning	Value
lr	Learning rate	10^{-3}
d	The dimension of user and POI embedding vectors	192
w	Calculate the weight coefficient of similarity between the users and friends	0.5
α, β	Coefficients that control the weight of collaborative and social influence when computing user preferences	1.1, 1
n	The number of the most similar locations/friends/neighbors	10
w_1, w_2, w_3	Hyperparameters that control the importance of user-POI relation, POI-POI relation, and user–user relation	1, 0.01, 0.01
λ	L2 regularization parameter	10^{-4}

(1) Determination of user and POI embedding vector dimension d

Figure 4 shows the impact of different d values on the PPR_IGCN model on the Foursquare and Yelp datasets. When $d < 192$, the evaluation metric shows a gradual upward trend as d increases. When $d = 192$, the recommendation performance reaches its best. When $d > 192$, the recommendation performance deteriorates. The main reason is that smaller d cannot capture potential features in the data well, which will lead to information loss. A larger d may introduce too much noise and redundant information, leading to the overfitting of the model. So set the user and POI embedding vector dimensions to $d = 192$.

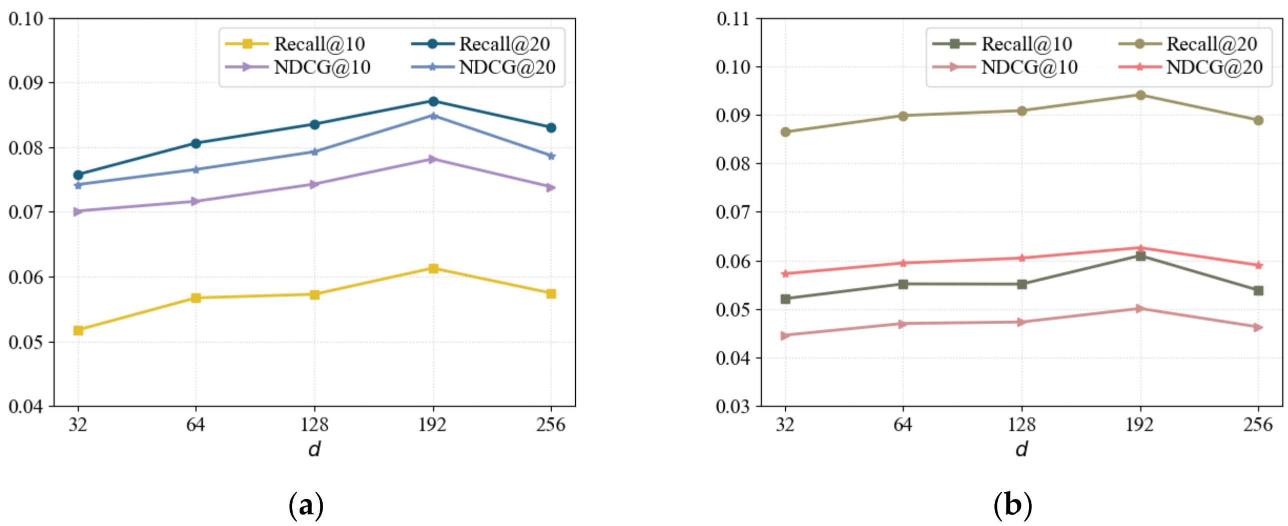


Figure 4. The impact of d on performance. (**a**) Foursquare; (**b**) Yelp.

(2) Determination of the number n of the most similar locations/friends/neighbors

Figure 5 shows that as the n value increases, the evaluation metrics display a trend of rising first and then falling. When n is 5, the performance is poor due to insufficient utilization of POI-POI and user–user relationships, ignoring a part of useful interaction influences, making it difficult to capture real user preferences. When n is too large, some less similar relationships may be introduced in the learning process, making the accuracy of the recommendation decrease. Therefore, set n to 10.

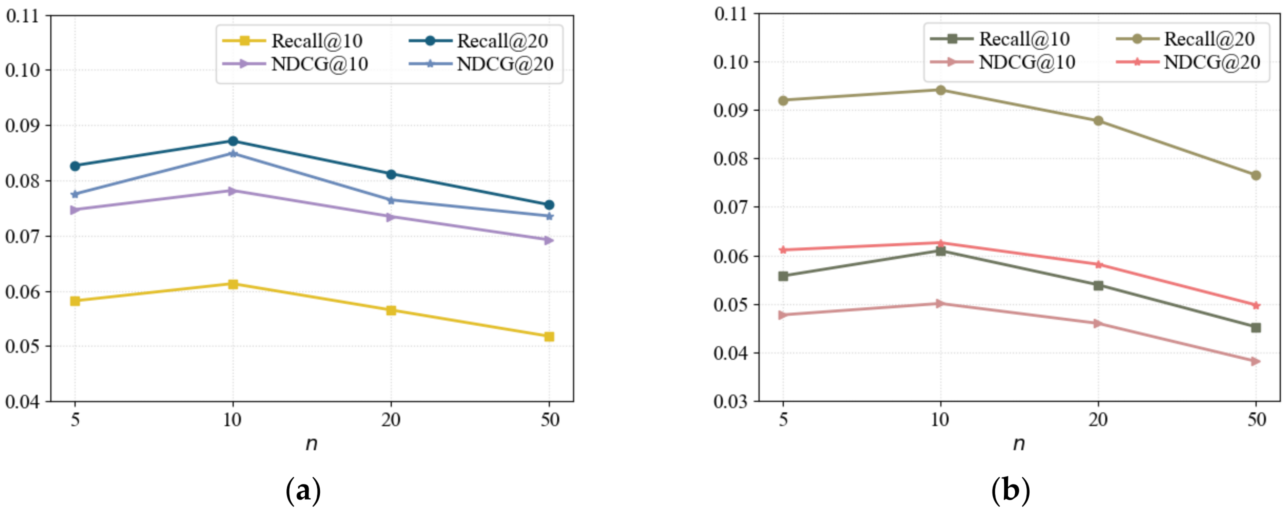


Figure 5. The impact of n on performance. (**a**) Foursquare; (**b**) Yelp.

4.4. Compared Experiment

To verify the effectiveness of the method proposed in this paper, the following methods are selected for comparison:

(1) LightGCN [28]: This model removes unnecessary feature transformation and nonlinear activation in traditional GCNs, simplifying the design of neighborhood aggregation in GCN;

(2) FGRec [34]: A fine-grained POI recommendation framework is proposed; a group friend model is designed to capture social influence; a joint Poisson factor model is used to learn category influence; and the personalized Gaussian kernel model is used to capture geographic information influence;

(3) LGLMF [37]: A method for implementing POI recommendations by integrating the local geographic model into the logistic MF algorithm;

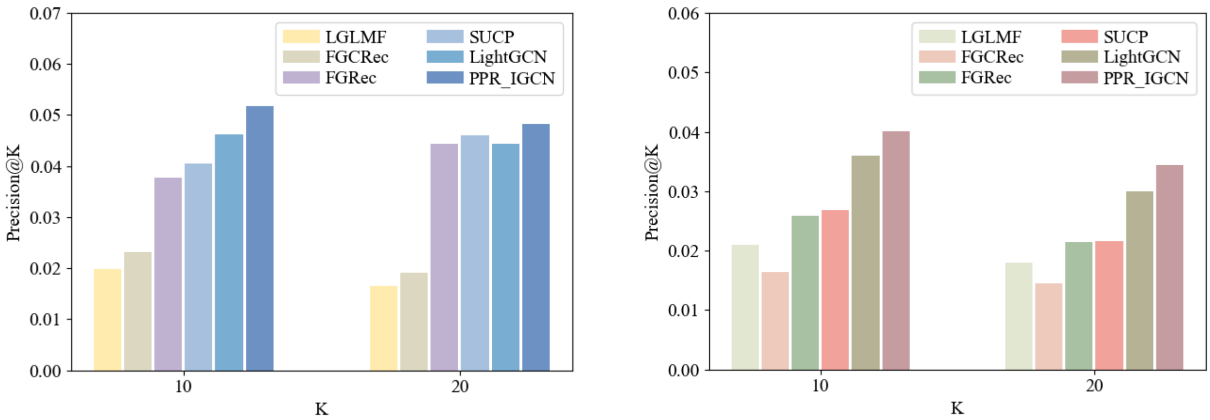
(4) FGCRec [38]: A unified probability distribution model based on four key geographic features that captures geographic influence from the perspectives of users and locations and explores the contribution of check-in frequency;

(5) SUCP [39]: A social user activity center POI recommendation system, which jointly models the user activity center and social relationships based on CF.

4.5. Performance Comparison and Analysis

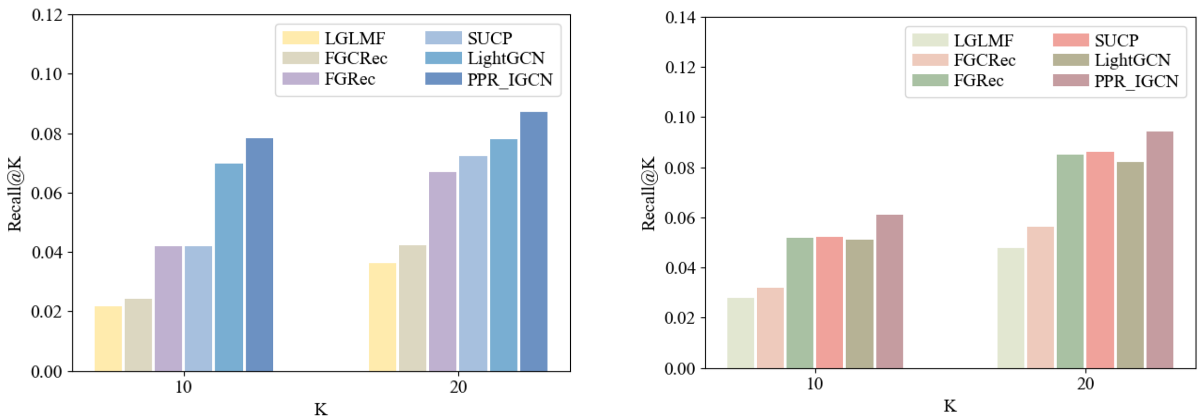
This section compares the proposed PPR_IGCN model with the five models in Section 4.4 on the Foursquare and Yelp datasets through the three evaluation metrics described in Section 4.2. Figures 6–8 show that PPR_IGCN performs better than the other five models, proving the positive impact of introducing POI-POI relations and user–user relations into the improved GCN on recommendation performance.

The results show that the recommendation effects of LGLMF and FGCRec are inferior to other models because these models only consider geography influence and do not consider rich context influence. FGRec introduces the inherent influence of social, category, and geographic information on users into the model, which can more accurately capture users' preferences. Similarly, SUCP takes into account the influence of social, geographical, and temporal information, and the performance of the model is also improved. Taking the Foursquare dataset, for example, the Recall@20 of FGRec and SUCP have increased by 83.7% and 98.8%, respectively, compared with LGLMF, indicating that rich context information and multiple relationships can significantly affect model performance. However, the recommendation effect of PPR_IGCN is better than SUCP. Taking the Yelp dataset, for example, the Recall@10 of PPR_IGCN is 16.9% higher than SUCP. These show that mining higher-order collaborative information in the user–user relationship graph while considering the influence of multiple social relationships on users is more conducive to learning social influence.



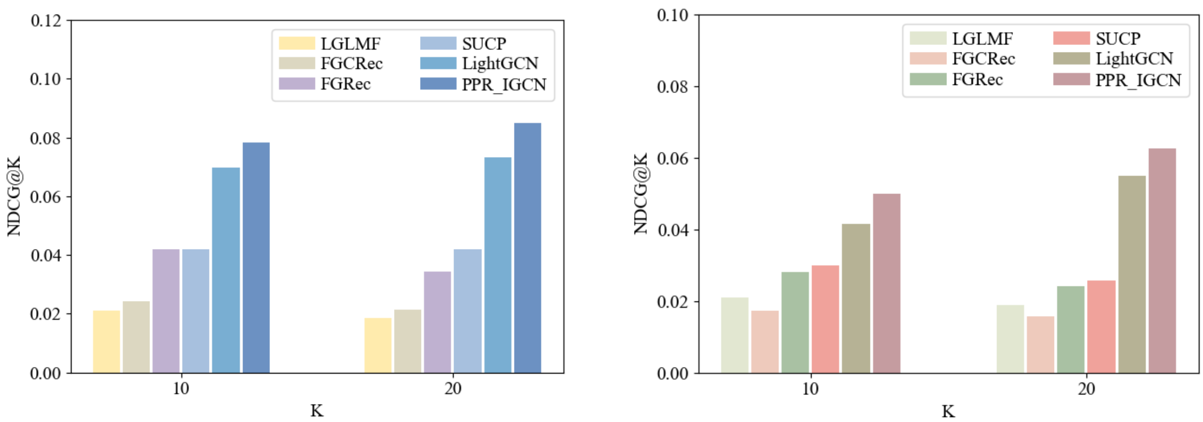
(**a**) (**b**)

Figure 6. Precision@K comparison on Foursquare and Yelp datasets. (**a**) Foursquare; (**b**) Yelp.



(**a**) (**b**)

Figure 7. Recall@K comparison on Foursquare and Yelp datasets. (**a**) Foursquare; (**b**) Yelp.



(**a**) (**b**)

Figure 8. NDCG@K comparison on Foursquare and Yelp datasets. (**a**) Foursquare; (**b**) Yelp.

LightGCN shows better performance than SUCP, which indicates that traditional methods, such as MF based on CF, cannot learn the deep influence of user-POI interaction information, which reflects the important role of using GCN to mine higher-order collaborative information in graphs. In addition, during the training process of the Yelp dataset, LightGCN needs more than 300 epochs to achieve the best results, but PPR_IGCN only needs more than 30 epochs. The main reason is that the message passing and multiple stacked embedding propagation layers in GCN are omitted, which fully reflects the advantages of learning the improved GCN on large graphs. For the Foursquare and Yelp datasets, PPR_IGCN compared with LightGCN, Precision@10 increased by 12.1% and 11.3%, respectively, Recall@10 increased by 15.8% and 19.6%, respectively, and NDCG@10 increased by 12.2% and 20%, respectively. The reason is that PPR_IGCN not only takes into account the higher-order collaborative information in the user-POI interaction graph but also captures the collaborative influence and social influence in the POI-POI graph and user-POI graph. As a result, model performance is improved, providing users with more accurate recommendations.

4.6. Ablation Study

To evaluate the impact of POI-POI relations and user–user relations on the model, this section compares the experimental results of two variants of PPR_IGCN, which are PPR_IGCN-I and PPR_IGCN-II, respectively. PPR_IGCN-I only learns from the user-POI relationship graph, i.e., w_2 and w_3 of Equation (30) are set to 0, respectively. PPR_IGCN-II learns from the user-POI relationship graph and POI-POI relationship graph, i.e., w_3 of Equation (30) is set to 0.

Figures 9 and 10 show that the model performance is improving continuously with the increase in learning relationships. The experimental results of PPR_IGCN-II and PPR_IGCN-I verify the effectiveness of learning POI-POI relations. The experimental results of PPR_IGCN-II and PPR_IGCN show the positive effect of social influence on POI recommendations. In the process of learning social influence, mining the higher-order collaborative influence between the user and friends and comprehensively considering the user's higher-order social friends and community neighbors in the model can alleviate the data sparsity, thus improving POI recommendation performance.

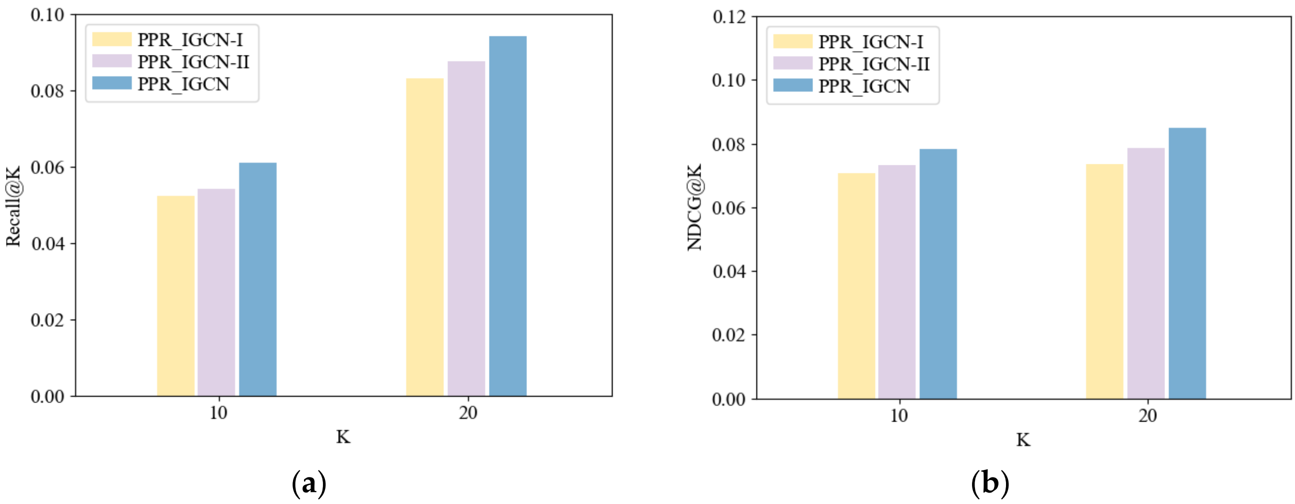


Figure 9. (**a**) Recall@K and (**b**) NDCG@K comparison on Foursquare.

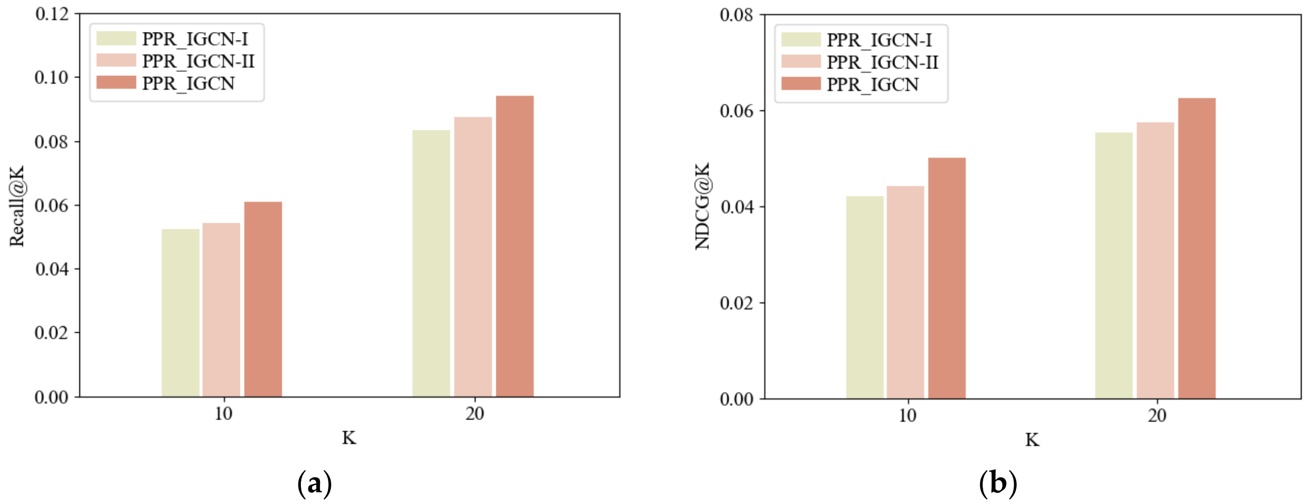


Figure 10. (**a**) Recall@K and (**b**) NDCG@K comparison on Yelp.

5. Conclusions

This paper proposes a personalized POI recommendation using an improved GCN model. This model comprehensively considers the higher-order collaborative influence of users and POIs and the social influence between users, which alleviates the problems of data sparsity and poor recommendation performance. The message-passing process in GCN is simplified, i.e., the constraint loss is directly used to reach the convergence state of infinite layer embedding propagation. The improved GCN is used to deeply mine the collaborative influence of the user-POI interaction graph, POI-POI graph, and user–user graph to learn the higher-order collaborative embedding vectors of the user and POI. The model also captures the social influence of higher-order social friends and community neighbors on the user. The experimental results prove that the recommendation effect of the PPR_IGCN model is superior to other models. In addition to the three types of relationships and social factors considered in this paper, factors such as POI category and time can also have an impact on users' preferences. In future work, more context information will be effectively integrated into the model to further improve POI recommendation performance.

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