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Multi-Graph Convolutional Network for Fine-Grained and Personalized POI Recommendation

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Abstract: With the advent of the era of rapid information expansion, the massive data backlog that exists on the Internet has led to a serious information overload problem, which makes recommendation systems a crucial part of human life. In particular, the Point-Of-Interest (POI) recommendation system has been applied to many real-life scenarios, such as life services and autonomous driving. Specifically, the goal of POI recommendation is to recommend locations that match their personalized preferences to users. In existing POI recommendation methods, people tend to pay more attention to the impact of temporal and spatial factors of POI on users, which will alleviate the problems of data sparsity and cold start in POI recommendation. However, this tends to ignore the differences among individual users, and considering only temporal and spatial attributes does not support fine-grained POI recommendations. To solve this problem, we propose a new *Fine-grained POI Recommendation With Multi-Graph Convolutional Network* (FP-MGCN). This model focuses on the content representation of POIs, captures users' personalized preferences using semantic information from user comments, and learns fine-grained representations of users and POIs through the relationships between content–content, content–POI, and POI–user. FP-MGCN employs multiple embedded propagation layers and adopts information propagation mechanisms to model the higher-order connections of different POI-related relations for enhanced representation. Fine-grained POI is finally recommended to users through the three types of propagation we designed: content–content information propagation, content–POI information propagation, and POI–user information propagation. We have conducted detailed experiments on two datasets, and the results show that FP-MGCN has advanced performance and can alleviate the data sparsity problem in POI recommendation tasks.

Keywords: POI recommendation; Multi-Graph Convolutional Network; information propagation; high-order connections; POI-related relation

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1. Introduction

With the widespread use of smart terminals and the development of location technology, Location-Based Social Networks (LBSNs) are widely used in people's lives, such as Yelp and Dianping. Users use these platforms to share their location information with their project experiences of interest, which we call Points-Of-Interest (POI). In recent years, POI recommendation has received increasing attention from scholars because of the serious information overload problem caused by the drastic user growth and data accumulation, which makes it increasingly difficult for users to find items of interest from a large amount of service information.

Compared to traditional recommendation problems, POI recommendations present a more serious challenge: (1) Complex decision-making process. POI recommendations not only have richer contextual information, but also the selection of POI preferences is constrained by a variety of factors. These rich contexts make POI recommendations more complex than traditional recommendations. (2) The problem of data sparsity, heterogeneity. The density of POI datasets is usually lower than traditional recommendation datasets, such as books, movies, etc. [1], usually, only binary implicit feedback is available. (3) Dynamic personalization of user preferences. User preferences for POIs and content also change as more historical data on different factors are accumulated. For example, a trip to Las Vegas may be of interest to a casino, but that does not mean that gambling is a preferred need for this user [2]. The user record graph in different POI scenes is shown in Figure 1. Through observation, it can be found that obtaining a comprehensive expression of fine-grained POI is essential to capture the user's personalized preferences.

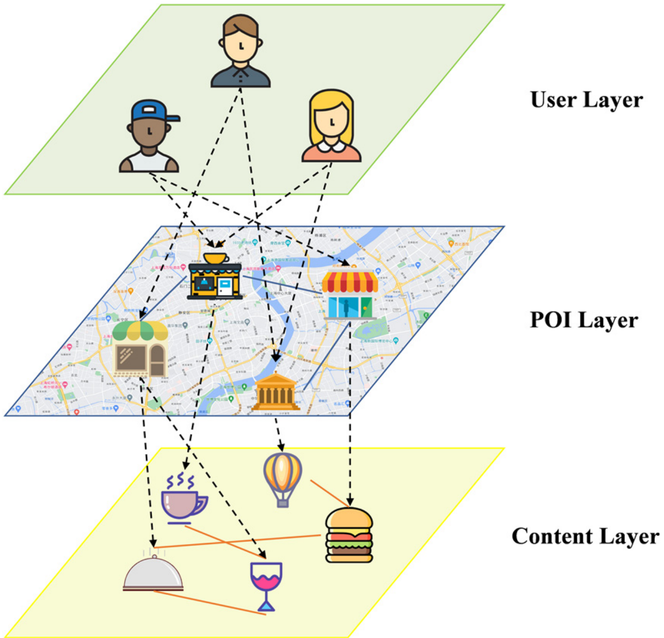


Figure 1. User record graph of POI recommendation scenarios. It contains three layers: user layer, POI layer and content layer, and the icons of each layer represent different nodes.

Existing POI recommendation methods can be divided into four categories according to method distinctions: Collaborative Filtering recommendation (CF) [3,4], Content-Based recommendation (CB) [5,6], social relationship-based recommendation [7,8], and network structure-based recommendation [9,10]. Existing methods tend to concentrate on using spatio-temporal context for POI recommendations, which focus more on temporal information, geographic information, and user social relationships in social networks, and use shallow interaction information such as clicks or check-ins as the basis for recommendations. However, these methods would ignore the user's perception, while the lack of semantic association information would lead to coarse-grained POIs and user representations, resulting in one-sided personalized recommendations.

Graph Convolutional Network (GCN) is a model of representation learning from non-Euclidean structures proposed in recent years and achieved a good recommendation effect [11]. The use of graph structure to express POI can reflect the rich relationships and content in POI data, making the POI embedding more comprehensive. Additional information can be obtained by aggregating neighbor node features for the purpose of alleviating data sparsity. By stacking multiple convolutional aggregation operations, the target node obtains higher-order semantic information and also transmits feature information to the far end of the graph; however, convolutional computation on graphs with a large number of complex relational connections can also present a number of challenges: (1) Ignored POI content information. The POI is treated as an atomic item, and the difference in POI content is ignored. For example, a restaurant can have both dinner and afternoon tea, and its preference for different users creates a difference. (2) Not targeted for the purpose of aggregating neighborhood characteristics. This can lead to many features that do not have personalized preference content being aggregated, thus limiting the recommendation performance.

In order to solve the above problems and challenges, this paper proposes a Fine-grained POI Recommendation With Multi-Graph Convolutional Network (FP-MGCN). Firstly, the rich interactions between entities (users, POIs, and content) are represented as graph-structured data, which contains interaction and semantic information extracted from check-in information, comment information, etc. Secondly, FP-MGCN extracts useful structural and feature information from between nodes and uses multiple graph convolution layers for information propagation in the graph, thus exploring high-order connectivity information in the graph for the purpose of enhanced representation learning. At the same time, the use of targeted aggregated distribution can dig deeper into the semantic association information in content–content, content–POI, and POI–user. Then, by designing three information propagation methods (content–content, content–POI, and POI–user information propagation) to capture users' personalized requirements and potential preference information to make fine-grained POI recommendations. Finally, we have conducted detailed experiments on two real datasets, and the results demonstrate that our method is state-of-the-art. The main contributions of this work we summarize as follows:

- To the best of our knowledge, this is the first attempt to study POI recommendations using multi-view graphs. We emphasize the importance of user reviews and experiences of content in POI recommendations and integrate the features of content into POI expressions for fine-grained POI recommendations.
- We propose a new POI recommendation model Fine-grained POI Recommendation With Multi-Graph Convolutional Network (FP-MGCN). It learns a comprehensive representation of users and Fine-grained POIs by using content–content, content–POI, and POI–user relationship graphs.
- We conducted extensive experiments using two real-world datasets and the results demonstrated the advancement and effectiveness of FP-MGCN.

2. Related Work

In this section, we introduce the work related to POI recommendation and graph-based recommendation.

2.1. POI Recommendation

The goal of the POI recommendation task is to recommend POI items to users that meet their requirements. From the perspective of modeling POI information, the emphasis perspective of popular POI recommendation methods can be classified into the following four categories: Spatio-temporal-based methods, geographical information-based methods, social information-based methods, and semantic information methods. In the spatio-temporal-based method, Dai et al. [12] exploit the ordered nature of temporal and spatial information in the check-in information to capture the user's preference at a specific time. Shi et al. [13] combined CF and Bayes methods into a unified framework for discovering information about users' periodic and proximity preferences for POIs. In the geographical information-based method, Liu et al. [14] used the geographical characteristics of different POIs with geographic sensitivity information to explore the association information between users and unvisited POIs for recommendation. In the social information-based method, Davtalab et al. [7] designed the method of integrating POI rating with a user's social network in the matrix factorization process for POI recommendation for different groups of users. He et al. [15] proposed a method to discover users' POI preferences using social relationships as edge information, mainly using linear graph convolutional collaborative filtering. In semantic information methods, Zhang et al. [16] used semantic information of geography to jointly train the contextual information with graphical models of user–poi and user–user interactions for POI recommendation. Tang et al. [17] constructed a semantic spatial graph containing geographic and category influences, used semantic information as one of the aggregated contents of POI node features, took geographic influences into account, and achieved good recommendation results.

2.2. Graph-Based Recommendation

In recent years, graph-based recommendation has become the hot topic of research in academia and industry. Graph data are a kind of non-Euclidean data that can better characterize different structures and relationships. Graph neural networks (GNNs), as one of the important techniques for extracting features of objects represented by graph data, have achieved good results in several application scenarios, e.g., user social networks [18], user sequential behavior graphs [19], etc. At the same time, the message passing algorithm [20,21] has been extensively studied to provide new ideas for graph-based recommendation, so that feature messages from neighboring nodes can be passed to the target node to obtain higher quality representation. Wang et al. [22] proposed Neural Graph Collaborative Filtering (NGCF), which stacks multiple layers of interaction information for embedding propagation to exploit the higher-order connected representation of user–item. However, due to the complexity of the model, training consumes a lot of time and computing power. Berg et al. [23] proposed a graph-based self-encoder framework Graph Convolutional Matrix Completion (GC-MC), with a bilinear decoder to reconstruct rating connections. Nevertheless, this approach is not applicable to large web-scale scenarios for the time being. Zheng et al. [24] combined a graph-based model and factorization machines model, which solved the problem of data sparsity to some extent, but it ignored the higher-order interaction information of user–item. Yu et al. [25] proposed ContextWRank, a method that uses meta-paths to model semantic association information and check-in information of POIs to explore the interest connection between users and their friends and POIs. He et al. [26] proposed LightGCN, which is a simplified and enhanced GCN that uses the neighbor aggregation component of GCN in collaborative filtering and obtains better results; however, LightGCN only propagates linearly over the user–item interaction graph, ignoring the item–item related properties.

The research on the above-related work reveals that researchers have paid more attention to the influence of spatio-temporal information, geographic information, and social relationships on users' personalized preferences in their studies on POI recommendation tasks; however, with the development of the LBSNs platform and the increase in data, the expression of user interaction for POI can no longer be atomic, and the content of specific interaction can be mined through the semantic information of user evaluation of POI, the association information on the content level can enrich the expression of POI characteristics, and finally, the fine-grained POI recommendation to the user.

3. Task Formulation

We set the fine-grained POI recommendation task as follows. Denote $\mathcal{G}$ a heterogeneous graph that contains three nodes: user, POI, and content. The internal connectivity of the heterogeneous graph $\mathcal{G}$ consists of three subgraphs, as follows: (1) User–POI bipartite graph, mainly for coding historical user–POI interaction information. (2) POI–content bipartite graph, which contains rich semantic information in user evaluation and represents the relationship between POI and content. (3) Content graph, which encodes the rich relationships between contents. Specifically,

- **User–POI bipartite graph.** It contains the user–POI interaction information, which is expressed as follows:
$$\mathcal{G}_1 = \{(u, x_{ui}, i) \mid u \in \mathcal{U}, i \in \mathcal{I}\} \tag{1}$$
where x_{ui} is an identifier indicating whether user u has interacted with POI i (e.g., comment or check-in). $\mathcal{U}$ and $\mathcal{I}$ denote the set of users and the set of POIs, respectively. If interaction has occurred, then $x_{ui} = 1$, otherwise $x_{ui} = 0$.
- **POI–content bipartite graph.** It connects POI information with content information and contains the content of items present in the POI, which is represented as follows:
$$\mathcal{G}_2 = \{(i, y_i^c, c) \mid i \in \mathcal{I}, c \in C\} \tag{2}$$

where c denotes the content information in the content set C and y_i^c is the multi-hot encoding (an encoding method to encode multiple attributes into one feature) of POI i. when $y_i^c = 1$ indicates the presence of content c in this POI, otherwise $y_i^c = 0$.

- **Content Graph.** It shows the rich relationships between contents, containing attribute associations and descriptive contents in semantic information. Formally,

$$\mathcal{G}_3 = \{(c, a, c^*) c \in C, a \in \mathcal{A}, c^* \in C\} \tag{3}$$

where $\mathcal{A}$ denotes the set of contents and $a \in \mathcal{A}$ is a certain content. The specific properties are described in detail below.

Our task is to learn the interaction function $\hat{y}_{ui} = \} (\mathcal{G}, \Theta)$ from the heterogeneous graph $\mathcal{G}$, which is used to predict the probability of the user's choice of POI. Where Θ denotes the model parameters of the function $\}$. We have specified the following for the recommended tasks:

Input: The heterogeneous graph $\mathcal{G}$ specifically contains three bipartite subgraphs: User–POI bipartite graph $\mathcal{G}_1$, POI–content bipartite graph $\mathcal{G}_2$, and Content Graph $\mathcal{G}_3$.

Output: The prediction function $\hat{y}_{ui} = \} (\mathcal{G}, \Theta)$ is used to predict the probability of user interaction with the POI.

4. Methodology

In this section, we detail the proposed fine-grained POI recommendation model FP-MGCN. As shown in Figure 2, FP-MGCN specifically consists of three components: the embedding layer, the information propagation layer, and the prediction layer.

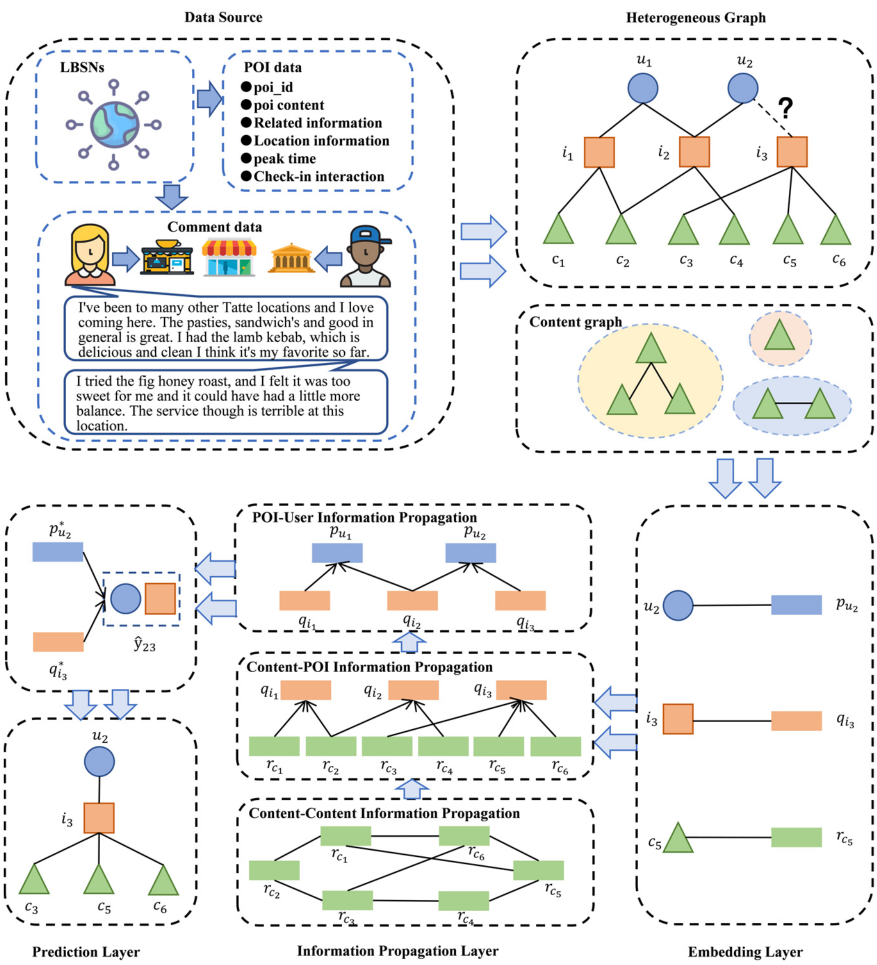


Figure 2. The framework of FP-MGCN model.

The FP-MGCN model first parametrizes different types of nodes into vector representations by different embedding methods. Then the embeddings from the neighbors of the nodes are recursively propagated on the content graph, POI–content graph, and user–POI graph, respectively, to update their representations in order to obtain the fine-grained node representations. Finally, the final representations of users and POIs are aggregated at the prediction layer, and the predicted match scores (i.e., probability of interaction) are output. We introduce the specific components separately in the section below.

4.1. Embedding Layer

User and POI Embedding. Since embedding-based methods are excellent in capturing the synergistic information between user and POI, and achieve good results in POI recommendations. We choose the more popular [27,28] method for embedding, and the embedding p_u and q_i for user u and POI i as follows, respectively:

$$p_u = Pe_u, q_i = Qe_i \tag{4}$$

where e_u and e_i are one-hot vectors. $P \in \mathbb{R}^{S\times|\mathcal{U}|}$ and $Q \in \mathbb{R}^{S\times|\mathcal{I}|}$ are the parameters of the embedding, $|\mathcal{U}|$ and $|\mathcal{I}|$ denote the number of users and POIs, and S represents the size of the embedding.

Content Embedding. Content is the item information contained in each POI, and users visit the POI to interact with the corresponding item, so content information is critical to users' preferences for the selection of POIs. In real life, the content of the POI plays a decisive role in the POI node; for example, users tend to choose a restaurant for a particular dish they want to enjoy; therefore, we need to project POI content, users, and POIs into the same vector space. We define each content c to correspond to an embedding vector r_c, so that we can obtain the content information of POI i to represent a set of embedding vectors r_c as R_c, as follows:

$$R_c = \{r_c \mid z_i^c = 1\} \tag{5}$$

4.2. Information Propagation

In our proposed FP-MGCN model, three main information propagations are used: content–content propagation, content–POI propagation, and POI–user propagation. Next, we describe them separately.

4.2.1. Content–Content Propagation

Since the content information of POI has the same attributes and association information, we exploit its internal connection by building the content graph. In real life, user choice often only responds to the interaction for a POI, but the preference for a POI depends on the service content of the POI, and the response to different content also affects the user's preference. For example, users like the food of a restaurant, but do not like the noisy environment of the restaurant; therefore, the propagation of content information is crucial for users' high-quality service recommendation. Specifically, we consider four types of nodes and relationships of content: items, scenes, services, and locations.

POI items. We connect the same consumption content of users in POI; the main reason for users' choice of POI is the consumption items in POI, which have an extremely important influence on users' interest preference—this is the most content in the review information. For example: the user for the restaurant consumption of the main evaluation of the dish information.

POI scenario. The scenario situation is also an important factor for users' POI selection. We connect POI points that have the same scenario content. Specifically, we take into account: environment, occasion (gathering, dating, etc.), consumption level, and other content.

POI services. By analyzing the semantic information of most reviews, we can find that the service information of POI is also as popular in the reviews, and focusing on the service information of POI can capture the fine-grained preference choices of users. For example, if a user has a high rating of the POI's dishes but hates its slow serving speed, we can recommend a POI with higher service quality for this user by aggregating the service attribute features.

POI Location. This content is the basic information for POI recommendation, and POIs with the same area location are connected and aggregated in the POI content as features with a certain weight.

In content aggregation, we mainly consider connecting content information with the same attributes to obtain a fine-grained representation of POI nodes. The content information is related through attributes to more clearly characterize the content node, so content propagation needs to process each attribute in content $\mathcal{A}$ separately, with the following equation:

$$m^{a}_{c\leftarrow c^{*}} = \frac{1}{|\mathcal{N}^{a}_{c}|} \sum_{c\prime \in \mathcal{N}^{+}_{||}} W_1 r^{l-1}_{c*} \tag{6}$$

where $m^{a}_{c\leftarrow c^{*}}$ denotes the messages delivered to target node c by neighboring content nodes connected to attribute a. $\mathcal{N}^{a}_{c}$ denotes the neighborhood content nodes in target content node c connected due to attribute a. l denotes the number of iterative layers of propagation, and W_1 denotes the weight matrix. Since there are four relationships in content graph, we consider two different aggregation approaches as follows:

$$sum : r^{l}_{c} \sum_{a\in\mathcal{A}} m^{a}_{c\leftarrow c'} \tag{7}$$

$$\text{concate} : r^{l}_{c} = CON\left(\left\{m^{a}_{c\leftarrow c'} \mid a \in \mathcal{A}\right\}\right) \tag{8}$$

We aggregate its output by stacking L-layer graph convolutions to ensure the modeling of higher-order connectivity information, and finally obtain a comprehensive representation of the content x^{*}_{k}, with the following equation:

$$r^{*}_{c} = CON(\{r^{l}_{c} \mid c \in [0, L]\}) \tag{9}$$

4.2.2. Content–POI Propagation

A POI contains multiple items of content information, such as a western restaurant for both afternoon tea and dinner. In the real recommendation scenario, we need to capture the real preferences of users. Considering the variability of different content information for POI description, we enhance the POI representation by using the rating information of content reviews.

Content Strategic Information Construction. For POI, we improve its representation using the content information connected by the POI–content bipartite graph $\mathcal{G}_2$. In particular, the information received by POI q_i from content neighbor nodes is expressed as follows:

$$m_{r\rightarrow q} = \frac{1}{|\mathcal{N}_q|} \sum_{r\in\mathcal{N}_q} r^{*} \tag{10}$$

within $m_{r\rightarrow q}$ is the information from the content neighbor nodes. $\frac{1}{|\mathcal{N}_q|}$ is the normalization term and $\mathcal{N}_q$ denotes the content neighbor nodes of the target node.

POI Strategic Information Aggregation. To obtain the fine-grained comprehensive representation of POI, we need to aggregate information from neighborhood nodes and self-expression information. Specifically, the formula is expressed as follows:

$$q^{*}_{i} = F\left(q_i, m_{r\rightarrow q}\right) \tag{11}$$

within q^{*}_{i} denotes an improved representation of POI, incorporating its own features and feature information from content neighbor nodes. For the selection of aggregation methods, we use advanced aggregation means to solve the aggregation between heterogeneous information.

The GCN aggregation [29] sums the two representations and performs nonlinear processing as follows:

$$F_{gcn}(q_i, m_{r\to q}) = LeakyReLU(W_2(q_i + m_{r\to q})) \tag{12}$$

within W_2 is the parameter to be learned.

The bi-interaction aggregation [30,31] considers the heterogeneous nature of the information $m_{r\to q}$ from content neighbors and the node POI embedding information q_i, and uses sum and element-wise for the operation, as follows:

$$F_{bi}(q_i, m_{r\to q}) = LeakyReLU(W_3(q_i + m_{r\to q}) + LeakyReLU(W_4(q_i \odot m_{r\to q})) \tag{13}$$

within *LeakyReLU* is a commonly used nonlinear activation function and W_3, W_4 are the parameters to be learned.

4.2.3. POI–User Propagation

It is proposed in [32] that user–POI collaboration signals help capture users' personalized preferences for POIs; therefore, we construct $\mathcal{G}_1$ by collecting users' historical interaction information and check-in information to enrich the user representation. Capture users' potential preferences by aggregating information about the characteristics of neighboring nodes in interactions. The information $m_{q\to p}$ of user u from the set $\mathcal{N}_p$ of POI neighbors in the graph is:

$$m_{q\to p} = \frac{1}{|\mathcal{N}_p|} \sum_{q\in\mathcal{N}_p} q_i^* \tag{14}$$

within $\frac{1}{|\mathcal{N}_p|}$ denotes the normalized term.

Similar to the POI strategic information aggregation, the user node representation p_u^* updated by the aggregation operation is:

$$p_u^* = F(p_u, m_{q\to p}) \tag{15}$$

where p_u^* receives the effect of its own embedding and the propagation of information from the POI node, respectively. $F(\cdot)$ denotes the aggregation function, which is implemented in the same way as above, with the formula:

$$F_{gcn}(p_u, m_{q\to p}) = LeakyReLU(W_5(p_u + m_{q\to p})) \tag{16}$$

$$F_{bi}(p_u, m_{q\to p}) = LeakyReLU(W_6(p_u + m_{q\to p})) + LeakyReLU(W_7(p_u \odot m_{q\to p})) \tag{17}$$

within W_5, W_6 and W_7 are the parameters to be learned.

4.3. Prediction Layer and Optimization

Up to now, we have obtained the fine-grained representation of the user and POI. To predict the likelihood of user–POI interactions, we use the inner product to perform the computation, as most recommendation models do, in the following form,

$$\hat{y}_{ui} = p_u^{*T} q_i^* \tag{18}$$

We use a two-by-two learning approach to optimize the model parameters [33]. We distinguish observed interactions from unobserved interactions by assigning 1 and 0, respectively, in the following form,

$$T_{\mathcal{S}} = \{(u, i, j) \mid y_{ui} = 1 \wedge y_{uj} = 0\} \tag{19}$$

where $T_{\mathcal{S}}$ is the training set and the triplet (u, i, j) in which user u has interacted with POI i but never with POI j.

For the selection of the loss function, we used the recommended popular Bayesian Personalized Ranking (BPR) loss [34] to optimize the model parameters F, with the following equation,

$$\mathcal{L} = \sum_{(u,i,j)\in\mathcal{D}_{\mathcal{S}}} -ln\sigma\left(\hat{y}_{ui} - \hat{y}_{uj}\right) + \lambda\| \ F \ \|^2 \tag{20}$$

within λ is the regularization term and σ is the sigmoid function. The parameter set F contains the matrix and biases that can be learned in the model, and the optimal parameters that are obtained by training samples in the model training.

4.4. Time Complexity Analysis

For the FP-MGCN model, the time cost comes from two main components: the embedding representation complexity and the message passing complexity. The computational complexity for node embedding is denoted as $\mathrm{O}\left(K_m s^2\right)$, where K_m denotes the number of all entities. Message passing has the computational complexity of $\mathrm{O}(K_n^l s^2)$, where K_n^l is the number of entities at the l-th level. Thus, the total training complexity of FP-MGCN is $\mathrm{O}\left(K_m s^2\right) + \mathrm{O}(K_n^l s^2)$. For several popular graph-based computational model complexities, we set the number of layers to l and the number of samples to K. The computational complexity is $\mathrm{O}(K^l s^2)$ for KGCN [35], $\mathrm{O}\left(lKs^2\right)$ for RippleNet [36], and $\mathrm{O}\left(l|\mathcal{G}|s^2\right)$ for KGAT [30] with no sampling strategy. In comparison, our proposed FP-MGCN model has the same level of computational complexity.

Meanwhile, we also compare the computation time of various graph-based models. The time cost of RippleNet, KGCN, KGAT, and FP-MGCN is 360 s, 260 s, 580 s, and 350 s, respectively. It can be concluded from the observation that our model does not trade off computational accuracy at the cost of huge time.

5. Experiments

We conducted detailed experiments on two real datasets to answer the questions as follows.

RQ1: How advanced is FP-MGCN compared to other POI-recommended methods?

RQ2: How effective are the components of the FP-MGCN model for the results?

RQ3: What is the variability of performance on the model for user groups with different sparsity levels?

5.1. Datasets

We evaluate the proposed model on two real-world datasets:

- Dianping (www.dianping.com): The Dianping dataset includes user information, POI, comment information, sign-in information, label information, etc. (accessed on 30 June 2022), from October 2017 to October 2019 within Nanjing.
- Yelp (https://www.yelp.com/dataset/challenge): The Yelp dataset is a very popular benchmark dataset in POI recommendations(accessed on 30 June 2022). The version we are using is from the Yelp Challenge. The Yelp data set contains user, POI, comment data, location information, and other data. This experiment used data updated before February 2020.

The final valid data are shown in detail in Table 1. To filter the noisy data, in the Dianping dataset, we selected the POI and users with more than 5 interactions to ensure that the data are not too sparse. In the Yelp dataset, we filtered the POI with at least 10 visits and users with at least 10 interactions. In our experiments, we selected the first 60% as the training set, the middle 20% as the validate set, and the last 20% as the ground truth for the test. We ignored the relational information of the user nodes in our experiments and the two datasets used are independent of each other.

Table 1. The statistics of datasets.

Dataset	#Users	#POIs	#Check-Ins	Density
Dianping	17,649	12,872	362,680	0.1627%
Yelp	30,595	18,496	783,291	0.1902%

5.2. Baselines

We have compared the following baseline methods to prove the effectiveness of FP-MGCN and test its performance.

- BPR [33]: A representative collaborative filtering method that uses Bayesian Personalized Ranking (BPR) loss optimization matrix decomposition to recommend POIs by implicit feedback.
- FM [37]: Factorization Machine (FM) is a matrix decomposition-based recommendation algorithm that recommends items through higher-order feature crossover.
- Matapath2vec [38]: This is a meta-path recommendation method based on heterogeneous networks. The random walk is applied to solve the recommendation problem for the characteristics of heterogeneous networks.
- GC-MC [23]: A GCN-based recommendation method to update node embeddings by using GCN encoders.
- KGAT [30]: Graph modeling using a neural network framework and attention mechanisms is one of the more advanced approaches in Graph-based methods.

5.3. Experiments Setup

Evaluation Metrics. For POI recommendation, we use Top-k recommendation, i.e., we rank the POIs that are not visited by users and recommend the k POIs with the highest scores as entries to users. To verify the sophistication of the model, we choose two evaluation metrics, recall and NDCG, to evaluate the model. For these two metrics, we take the average of all users as the report.

Parameter Settings. We chose TensorFlow(version:1.1.12, creator:google brain, location:San Francisco Bay Area, California) as the experimental platform for both our model and the implementation of the baseline method. We set the embedding dimension of all models to 64 in order to ensure fairness in comparison with the baseline methods. We use a grid search for hyper-parameters: the learning rate lr in the range [0.0001, 0.0005, 0.001, 0.005, 0.01, 0.05], The learning range of the regularization parameter is $[1e^{-6}, 1e^{-5}, 1e^{-4}, 1e^{-3}, 1e^{-2}, 1e^{-1}]$. For the graph-based methods, we set the number of connected layers to 3 and the size of each layer to be fixed at 64. For Matapath2vec, we manually define its meta-path as user–poi–content–user. The rest of the above hyperparameters are the same as the original paper description values or the default values in the original code.

5.4. Performance Comparison (RQ1)

We conducted comparison experiments in two real data sets and the experimental results are shown in Table 2. Based on the experimental results, we have the following observations:

- Our proposed FP-MGCN is ahead of the baseline methods on both datasets. The results show that the fine-grained POI representation can be obtained by the method of multiple embedding propagation layers and information propagation mechanism, and the recommendation results are more personalized by including user semantic information and POI content information.
- Compared to KGAT, one of the more advanced graph-based methods, our model performance holds some advantages. This shows the importance of the relationship between the contents of POI. It has the recommended quality improvement in the same level of computational complexity.
- Compared to the GCN-based recommended method GC-MC, the results reflect the advantage of our setting multiple propagation mechanisms. We followed the original

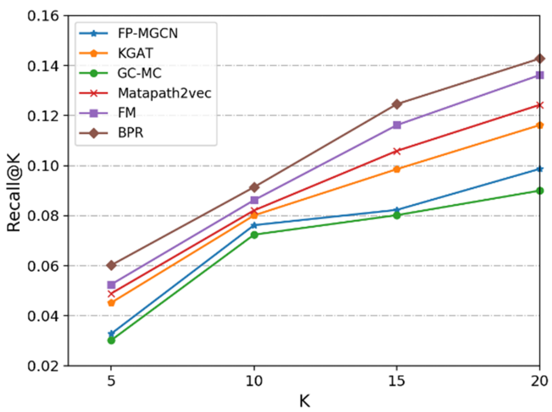
setting and used only one convolutional layer, so GC-MC can only aggregate the information of first-order neighbors.

- Matapath2vec performs poorly compared to other baselines due to the difficulty of manually defining optimal meta-paths in graph structures with complex content.
- In the comparison of all baseline methods, KGAT performs the best, which illustrates the advantage of graph structure for complex relationship and content characterization. BPR performs the worst, indicating that simply conducting inner product between embeddings is difficult to characterize complex relationships.
- Compared to the same content metric on both datasets, the Dianping dataset has better results than Yelp. This is because the semantic information extracted from the review information in the Dianping dataset is of higher quality than Yelp, and the cut is more densely associated with the content.

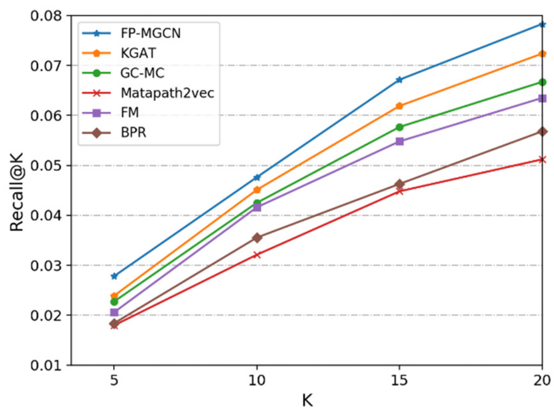
Table 2. Performance of approaches on Dianping and Yelp.

Methods	Dianping		Yelp	
	Recall@10	**NDCG@10**	**Recall@10**	**NDCG@10**
BPR	0.0762	0.0513	0.0355	0.0445
FM	0.0801	0.0635	0.0416	0.0463
Matapath2vec	0.0724	0.0472	0.0321	0.0362
GC-MC	0.0821	0.0658	0.0425	0.0472
KGAT	0.0862	0.0688	0.0451	0.0485
FP-MGCN	0.0914	0.0711	0.0476	0.0518

The specific top-k recipe recommendation results are shown in Figures 3 and 4, and we can observe that FP-MGCN has leading results, which can prove the advancement and reliability of FP-MGCN.



(**a**)

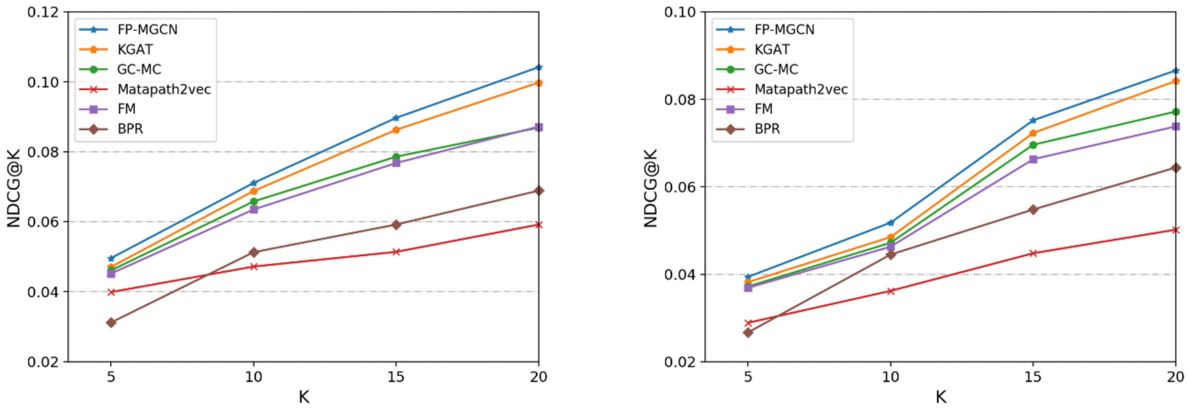


(**b**)

Figure 3. The results of Recall@K on two datasets. (**a**) Recall@K on Dianping; (**b**) Recall@K on Yelp.

5.5. Study of FP-MGCN (RQ2)

To further explore the embedding propagation framework of FP-MGCN, we analyze its impact from different perspectives. The effects of depth and different aggregators on each part are explored separately.



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

Figure 4. The results of NDCG@K on two datasets. (**a**) NDCG@K on Dianping; (**b**) NDCG@K on Yelp.

5.5.1. Effect of Model Depth

We explore the best performance by varying the stacking of layers in the FP-MGCN model. The exploration for depth reflects the effect of the number of different aggregation iterations on the model performance. Specifically, we vary the number of propagation layers L in [1–5], and the results are shown in Table 3; through analysis, we can conclude that:

- Increasing the model depth can significantly improve the performance of FP-MGCN. We observe that the performance of FP-MGCN-2 and FP-MGCN-3 is significantly higher than that of FP-MGCN-1. Benefiting from second and third-order connectivity, FP-MGCN achieves optimal performance by efficiently modeling the higher-order relationships between content, POI, and user nodes.
- Continuing to increase the model depth, we can find that the performance of FP-MGCN-4 and FP-MGCN-5 decreases significantly. This indicates that an excessive number of aggregation iterations of the model can lead to overfitting phenomena and noise can interfere more with the recommendation performance.

Table 3. The effect of different embedding propagation layers on the model.

	Dianping		Yelp	
	Recall@10	**NDCG@10**	**Recall@10**	**NDCG@10**
FP-MGCN-1	0.0865	0.0672	0.0455	0.0506
FP-MGCN-2	0.0906	**0.0716**	0.0468	0.0512
FP-MGCN-3	**0.0914**	0.0711	**0.0476**	**0.0518**
FP-MGCN-4	0.0887	0.0698	0.0462	0.0508
FP-MGCN-5	0.0796	0.0655	0.0443	0.0498

5.5.2. Effect of Aggregators in Content Graph

We explore the impact on performance by applying different aggregators to the content graph. We applied two different aggregators to FP-MGCN, and the results are shown in Table 4; through analysis, we can conclude that:

- The comparison shows that the performance of FP-MGCN-SUM is better than that of FP-MGCN-CON. The reason for this is that summation can superimpose feature relations better than connection.
- By jointly analyzing Tables 2 and 4, we can conclude that even with the FP-MGCN-CON scheme, we still outperform the other baseline methods and the results show the effectiveness and robustness of the FP-MGCN model in content graph modeling.

Table 4. The impact of different aggregators on the model.

	Dianping		Yelp	
	Recall@10	**NDCG@10**	**Recall@10**	**NDCG@10**
FP-MGCN-CON	0.0899	0.0701	0.0464	0.0502
FP-MGCN-SUM	**0.0914**	**0.0711**	**0.0476**	**0.0518**

5.5.3. Effect of Aggregators for Representations

To research the effect of using different aggregators on characterization and performance, we performed experiments on two variants of FP-MGCN (which can be found in Section 4.2.2), and the results are shown in Table 5. We can observe that FP-MGCN-BI outperforms FP-MGCN-GCN in terms of performance, which is due to the fact that FP-MGCN-BI simulates the similarity between self and neighbor representations by adding additional feature interactions, which ultimately improves the learning of representations. The results demonstrate the rationality and effectiveness of the dual-interaction aggregator in solving the heterogeneity of the two graphs.

Table 5. Effect of aggregators for representations.

	Dianping		Yelp	
	Recall@10	**NDCG@10**	**Recall@10**	**NDCG@10**
FP-MGCN-GCN	0.0882	0.0667	0.0449	0.0477
FP-MGCN-BI	**0.0914**	**0.0711**	**0.0476**	**0.0518**

5.6. User Group Experiment (RQ3)

To investigate whether FP-MGCN can alleviate the sparsity problem of POI data and the robustness of the recommended entries, we experimented with the model by dividing the user group into groups with different sparsity levels. To verify its advanced performance, we conducted experiments on the Dianping dataset and added the best-performing KGAT from the baseline method for comparison. The results are shown in Figure 5. It is worth noting that we set the interaction size to be the same in different groups. Through the figure, we can analyze that:

- The experimental performance of our proposed FP-MGCN outperforms the optimal baseline method KGAT for all user groups, which indicates that FP-MGCN can mitigate the POI data sparsity problem. The reason for this is that FP-MGCN defines the content graph and utilizes its connectivity information.
- We can find that dense user groups can improve the performance of both models, which indicates that enriching the information of user–POI interactions can better capture users' personalized preferences.

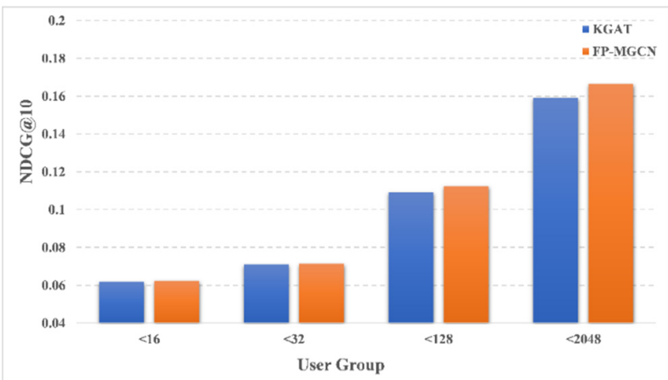


Figure 5. The performance of the model in different sparsity distributions of user groups.

6. Conclusions and Future Work

In this paper, we believe that the existence of complex connections between content–content, content–POI, and POI–user in POI recommendation is important for the precision and personalization of recommendations. Based on this, we propose the Fine-grained POI Recommendation With Multi-Graph Convolutional Network (FP-MGCN), which uses multiple embedding layers and information propagation mechanisms to model higher-order connections to obtain fine-grained user and POI representations, and finally, for personalized recommendations. Finally, we conducted extensive experiments on two real-world datasets, and the results proved the rationality and effectiveness of FP-MGCN for modeling POI heterogeneous graph structure data. In addition, we also conduct experiments on each component of the FP-MGCN model, and the experiments prove the rationality and necessity of the component to the model. We think it makes sense to explore the fine-grained POI embedding representation and to match the recommendations to users' personalized preferences. With the development of social network technology, helping users to select the appropriate POI from the huge amount of information by capturing their more detailed service preference needs is indispensable for people to pursue higher quality service content.

In our future work, we will explore the following three targets: (1) Exploring POI recommendations for real-time scenarios, e.g., a user who previously favored high-calorie restaurants and recently wants to lose weight. (2) Diversification of recommendations, the current focus of this work is on the precision and personalization of recommendations, which may lead to a lack of diversity in the recommended results, such as: health habits, etc. (3) Try more advanced information aggregation and propagation methods.

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Data Availability Statement: The Yelp, Dianping dataset used in this study is publicly accessible, and the Yelp dataset is available at: https://www.yelp.com/dataset/challenge, accessed on 30 June 2022. The Dianping dataset (Nanjing) is available at: www.dianping.com, accessed on 30 June 2022.

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