Point of Interest Recommendation Based on Graph Convolutional Neural Network

Fubo Zhai¹, Baozhu Li¹*

¹School of Information Science and Engineering, University of Jinan, Shandong Province, 250022, China
²School of Information Science and Engineering, University of Jinan, Shandong Province, 250022, China
³*Corresponding author’s e-mail: ise_libz@ujn.edu.cn

Abstract. The rapid development of the mobile Internet makes location-based social networks (LBSNs) play an increasingly important role in practical applications. Among them, point of interest (POI) recommendation is a research hotspot in the current context. As a kind of graph data, social network can naturally express the data structure in real life. In view of the current POIs recommendation research ignoring the diversity of graph data, we proposed a POI recommendation based graph convolutional neural network (PBGCN) model, which used the check-in information, popularity characteristics of interest points, and users’ social behaviors to recommend interest points through graph convolutional neural networks (GCN). Compared with other latest recommendation methods, our model has improved accuracy. This proves the feasibility of GCN in point of interest recommendation.

1. Introduction

In recent years, with the vigorous development of mobile Internet and the popularity of wireless communication devices, location-based social networks (LBSNs) such as Foursquare, Brightkite, Yelp, have been widely used in human society. In LBSNs, users can share their locations via check-in of points of interest (POIs) and share their experiences in real life[1]. Figure.1 illustrates a typical check-in example in LBSNs.

Fig1. A typical check-in example of a user in LBSNs

Unlike online social networks, in addition to the social relationship between users, LBSNs also
include the relationship between geographic locations, and the sign-in relationship between users and locations. By mining these rich relationships in LBSNs, it is possible to effectively recommend points of interest and enhance user experience. Cheng et al. [2] used a multi-center Gaussian distribution to model the distance distribution between POIs, and combined with social relationships for POI recommendation. Zhang et al. [3] used kernel density estimation to simulate the distance distribution between any two POIs in order to avoid errors caused by the uniform distribution of all users, and constructed a geographic factor influence model.

Recently, recurrent neural networks (RNNs) [4,5] such as Long and Short-term Memory [6] have been successfully applied to the next point of interest recommendation. However, RNNs cannot well capture the sequence information that users sign in. With the introduction of the Attention Mechanism [7], Huang et al. [8] proposed an attention-based spatiotemporal LSTM network to capture contextual information to improve recommendation accuracy.

However, the data object of the above research is Euclidean spatial data, which ignores the diversity of graph data, leading to poor recommendation results. To this end, Thomas N. Kipf et al. [9] used graph convolutional neural networks (GCN) to deal with semi-supervised classification problems and achieved good results. Our work is motivated by this, we proposed to use GCN to solve the problem of point of interest recommendation, so as to improve the accuracy of recommendation. We also have defined the concept of location familiarity by mining user check-in information, combined with the popularity characteristics of interest points. The specific contributions are as follows:

- According to the characteristics of the popularity of points of interest, the time is divided into four time slots.
- Define the concept of familiarity. We believe that the user's sign-in to a certain POI is related to the user's familiarity with this point. In other words, if the user does not know or does not understand this point, the possibility of checking in is very low.
- We embed the above information into the graph convolutional neural network, and model the social network through the user's check-in record to recommend the next possible point of interest for the target user.

2. Materials and Methods

2.1 Problem Statement

Let \( U = \{u_1, u_2, ..., u_M\} \) be a set of users and \( L = \{l_1, l_2, ..., l_N\} \) be a set of locations, where \( M \) and \( N \) are the total number of users and locations, respectively. In this work, we intend to recommend the next POI that users are most likely to visit next.

2.2 Feature Extraction

2.2.1 POI Popularity Analysis

POI popularity is generally considered to be a priori preference of users for POI. Figure 2 shows that the number of check-ins for each POI is different in a day. Statistics show that the higher POI popularity, the more frequently they are visited. For example, people usually walk in the park in the morning and eat in the restaurant at noon, so the park and restaurant are more likely to be visited in the morning and noon respectively. According to the popularity of each point of interest, we divide a day into four different time slots, i.e., 6:00-11:00, 11:00-16:00, 16:00-21:00 and the remaining time is the fourth time slot.

2.2.2 POI Familiarity

In this part, we present the familiarity of POI. We assume that the possibility of user \( u \) visiting a certain POI \( l \) is positively correlated with the user’s familiarity with \( l \). POI familiarity is calculated by the following equation (1):
\[ \text{fam} = \frac{C_{li}}{\sum_{i=1}^{n} C_{li}} \cdot \frac{C_{lu}}{\sum_{u=1}^{m} C_{lu}} \]  

(1)

where \( C_{li} \) represents the number that location \( l_i \) has been visited, and \( C_{lu} \) represents the number that user \( u \) checked in the location \( l_i \).

### 2.3 Model Building

We use undirected graphs \( G = (V,E) \) to build PBGCN model, where \( V \) represents users, and \( \forall v_j \in V, j = 1,2,...,M \). For \( \forall v_j = \langle l_i, t_k, \text{fam} \rangle \), it means that user \( u_j \) visited location \( l_i \) in the \( k \)-th time period. If both users \( u_1 \) and \( u_2 \) have signed in at least one point of interest, connect the two users. According to the Symmetric normalized Laplacian,

\[ L = I_n - D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \]  

(2)

where \( I_n \) is identity matrix, \( A \) is adjacency matrix and \( D \) is degree matrix, the convolution formula is obtained:

\[ g_{\Theta} \ast x = U g_{\Theta} U^T x \]  

(3)

where \( x \) represents the feature vector, \( g_{\Theta} \) is the convolution kernel and \( U \) is the eigenvector matrix of the Laplacian matrix. We introduced a degree matrix to solve the problem of not considering the self-transmission of the node information. But for each forward propagation, the matrix product must be calculated, which might cause the calculation cost of this formula is too large. To circumvent this problem, \( g_{\Theta} \) can be well-approximated by a truncated expansion in terms of Chebyshev polynomials \( T_k(x) \) up to Kth order:

\[ g_{\Theta}(\Lambda) \approx \sum_{k=0}^{K} \theta_k T_k(\tilde{\Lambda}) \]  

(4)

with a rescaled \( \tilde{\Lambda} = \frac{2}{\Lambda_{\max}} \Lambda - I_N \), \( \Lambda_{\max} \) denotes the largest eigenvalue of \( L \). Based on the convolution kernel, we got a new convolution formula:

\[ g_{\Theta} \ast x = \sum_{k=0}^{K} \theta_k T_k(\tilde{L})x \]  

(5)
where $\theta \in R^K$ is the vector of Chebyshev coefficient, $\tilde{L} = 2L / \lambda_{\text{max}} - I_N$. We supposed $\lambda_{\text{max}} \approx 2$, $K = 1$, and finally get the PBGCN propagation formula:

$$ Z = f(x, A) = \text{soft} \max( \tilde{A}\sigma(\tilde{A}x^{(0)})w^{(1)}) $$

where $A$ is the adjacency matrix, $w$ is the parameter matrix and $\tilde{A} = A + I_N$. At last, we use the cross entropy loss function to train the PBGCN model.

### 3. Results & Discussion

#### 3.1 Data Processing

We evaluate our model on public Bright kite check-in datasets, which contains a total of 4,747,287 check-in records. Each record contains user ID, POI ID, GPS and timestamp. For the dataset, we removed users who have checked in fewer than 2,100 POIs, and then removed POIs which fewer than 3,000 users checked in. After pre-processing, the dataset contains 224,918 check-in records. In following experiments, we take the first 75% check-ins as the training set, the latter 25% as the test set.

#### 3.2 Comparative Results

In this paper, we use accuracy to evaluate the performance of different methods. The accuracy is plotted in Figure 3. The accuracy of our proposed PBGCN model reached 0.1698. When epoch=10, the result change tends to be flat.

![Figure 3. Performance of Methods Utilizing Spatial Influence](image)

Compared with other latest recommendation methods (see Table 1), our model has improved accuracy.

| Methods   | PMF   | RNN   | LSTM  | ST-LSTM | PBGCN |
|-----------|-------|-------|-------|----------|-------|
| Accuracy  | 0.0167| 0.0460| 0.0538| 0.0920   | 0.1698|

### 4. Conclusions

In this paper, we proposed a new POI recommendation model based on graph convolutional neural network (PBGCN). By mining the user's historical check-in records, location popularity, and proposing location familiarity features, we use GCN for modeling to recommend the next POI for the target user. The experiments demonstrate that our model outperformed the state-of-the-art methods on real-world datasets. This proves the feasibility of GCN in POI recommendation and provides a new solution to the problem of POI recommendation. In future work, we would incorporate more information into the model.
to further improve the performance. Besides, we plan to extend the proposed method to investigate further the next new POI recommendation problem.

References
[1] Li N, Chen G. (2009) Analysis of a Location-Based Social Network. In: International Conference on Computational Science & Engineering. IEEE.

[2] CHENG C, YANG H, KING I. (2012) Fused matrix factorization with geographical and social influence in Location-based social networks. In: Proceedings of the 26th AAAI Conference on Artificial Intelligence. Toronto, Canada, 2012

[3] ZHANG J D, CHOWC Y, LI Y H. (2013) iGSLR: Personalizedgeo-social location recommendation: a kernel density estimation approach. In: Proceedings of the 21st ACM SIGSPATIAL International Conference on Advances in Geographical Information Systems, New York. pp. 334-343

[4] Chen M, Li W Z, Qian L, et al. (2020) Next POI Recommendation Based on Location Interest Mining with Recurrent Neural Networks. Journal of Computer Science and Technology, J.35(3):603-616.

[5] Wang M F, Lu Y S, Huang J L . (2019) SPENT: A Successive POI Recommendation Method Using Similarity-Based POI Embedding and Recurrent Neural Network with Temporal Influence. In 2019 IEEE International Conference on Big Data and Smart Computing (BigComp).

[6] Hochreiter S, Schmidhuber J.(1997) Long short-term memory. Neural computation, J.9(8): 1735-1780.

[7] A.Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin. (2017) Attention is All You Need. Neural Information Processing Systems 2017(NIPS ’17), pp. 6000-6010

[8] Huang L, Ma Y, Wang S, et al. An Attention-based Spatiotemporal LSTM Network for Next POI Recommendation[J]. IEEE Transactions on Services Computing, PP(99):1-1.

[9] Kipf T N, Welling M. (2016) Semi-Supervised Classification with Graph Convolutional Networks[J]. https://arxiv.org/abs/1609.02907