Category-Aware Successive Poi Recommendation Via Graph Embedding from H-Node2Vec Deep Model

Jin Hu[1,a], Jinghua Zhu [1,b] and Heran Xi[1,c,*]

[1]School of Computer Sicence and Technology, Heilongjiang University Harbin, China
a. 2191489@s.hlju.edu.cn, b. zhujinghua@hlju.edu.cn, c. 2003071@hlju.edu.cn
**Heran Xi*

Keywords: lbsn, poi, recommendation, category-aware.

Abstract: As considerable amounts of POI check-in data have been accumulated,successive point-of-interest (POI) recommendation is increasingly popular. Due to the scarcity of check-in data, how to accurately capture user preferences and poor interpretation in the temporal model are two major problems faced by traditional recommender systems.To this end, we propose a new category-aware social-geographic deep model.Our model consists of a pre-training module, an encoder module and a filter module,designed to learn the POI embedded representation incorporating social relations and geographical influences, and serves as the initial values for two LSTM based encoders.The two encoders are designed to capture user preferences in the POI category and user preferences for the POI at the current moment.The filter module is used to filter the candidate POIs through the category of POIs.Finally, we sort the candidate set by considering three specific dependencies: user-poi, user-poi category, and current preferences of POI users.Experiments were conducted on two large real datasets.Experimental results show that our CATDM is superior to existing models.

1. Introduction

With the growing popularity of location-based social networks (LBSNs), a large number of users share their check-in and their experiences when visiting different POI points.The large amount of data available provides a variety of research opportunities for POI recommendations [1,2,3].Relevant studies believe that modeling sequential check-in information is crucial for POI recommendation [6,2].Recent studies have shown that pre-trained POI embedding is effective in improving recommendation performance [6,7] . This approach aims to learn the representation of the POI based on a large number of check-in data and to use pre-trained embedding as the initial value of the potential representation of the POI in the traditional recommendation model [3,8].With Large-scale network embedding has become an effective method to solve complex network structure.The application of network embedding method to LSBN-based POI recommendation system can help the system capture the correlation characteristics based on society and geography, so as to improve the recommendation quality and enhance the interpretability of the model.

This paper aims to investigate the influence of POI category information and graph embedding on the performance of POI recommendation model.We propose a category-aware graph embedding representation deep model (Category-aware poi recommendation with social-geographic graph embedding deep model).CASGD

In the pre-training process, we use Node2VEC algorithm to obtain POI pseudo sequences combining social relations and geographic information through random walk.Then put the sequence as input into the skip-gram model for training and learn the embedded representation of POI.This method not only considers the second-order approximation of POI[5], but also extends the approximation range.Therefore, POI embeddings with similar user populations are more relevant.

In order to capture the user's interests and preferences in POI categories and POI, we set up two LSTM based encoders;In the first encoder, we get top-K POI categories that the user is most interested in after filtering.More specifically, the maincontributions of this paper are as follows:

(1)We demonstrate that the POI embedding representation learned in the social- geographic heterogeneous graph during pre-training not only increases the interpretability but also has a good effect in the later deep model.

(2)In order to overcome the sparsity problem of the check-in data, we introduce the POI category and the geographical effect, and reduce the search space through a two-layer filtering structure.Three specific correlations are considered when POI candidate set is sorted.

(3)We conducted a number of comparative experiments on Gowalla and Yelp datasets to compare the performance of our model with existing recommendation methods.Experimental results show that this model has good recommendation effect and explanability.

2. Related Work

In this section, we will review the previous POI recommendation model.In POI recommendation system of geography, time, classification, and social context information modeling has proven to be the necessary steps to improve the quality of recommended results to develop context-aware application, Li and others [8] recommend POI task modeling for scheduling problems in pairs, and puts forward A kind of method using geographic information .Ye et al.believed that the check-in behavior of users was affected by the influence of location space, and proposed a unified location recommendation system integrating spatial and social influence to solve the problem of data sparse.However, this method does not consider the spatial information based on each user, but models it based on the check-in distribution of all users.

By referring to the attention method and RNN method proposed in the field of NLP, Xia et al. proposed an ARNN model, which used the attention method to give different weights to the usecheck-in information in different time periods [13].Liu et al. [9] used the Word2Vec framework to model the check-in sequence that captures the sequential check-in pattern.Feng et al.[6]proposed a potential representational model that can take into account the influence of geography.However, they do not include contextual information in the model and do not take into account the characteristicsof the POI.By contrast, our focus is to obtain interpretable POI embedding that integrates social information and geographic information through graph representation learning, and put it into the subsequent deep model as the initial value for further learning.In addition, POI category is used to filter the selected POI points, which alleviates the problem caused by data sparsity.

3. The Proposed Model: Casgd

In this part, we introduce the CASGD model, which is a deep continuous POI recommendation model based on category awareness and graph embedding. It simultaneously integrates social relations, geographic features and category information.Figure 1 illustrates the methodology proposed in the work to implement the recommended workflow.

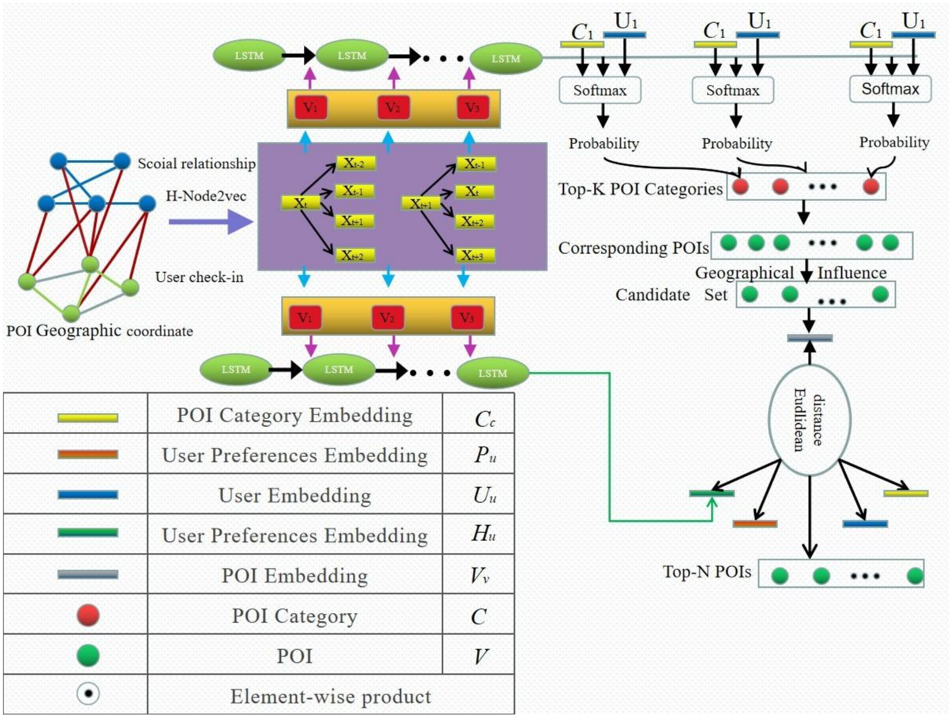

Figure 1: CASDG MODEL.

3.1. Problem Description and Preparation

Node2vec[9]:Node2vec combines the ideas of BFS and DFS to learn the network characteristics and node neighbor characteristics of LBSN, and output the vector representation of vertices in the network.Node2vec obtains the sequence of graph nodes through random walk.Graph embedding is a method to map each node in a Graph to a low-dimensional vector space， That's learning the mapping of a function.

$$f_G: V \to \mathbb{R}^d \text{ and } d \ll |V| \tag{1}$$

LSTM（Long-Short-Term Memory):LSTM is an artificial recursive neural network structure for deep learning.LSTM networks are well suited for time-based classification, processing, and prediction of sequence data, because there may be delays of unknown duration between important events in a time series.After initialization, the loop learns the t step, where the hidden layer is, and the hidden DeepWalk intend to generates user POIcheck in pseudo-sequence on the $G=(U,P,E_{UU},E_{PP},E_{PU})$ graph.The algorithm is shown above:

Since then we generate a pseudo sequence VS_i for each POI p_i . We regard the point in VS_i as the high correlation probability of each POI and the POI in the sequence can be repeated. The relevance of POI is proportional to the number of occurrences in VS_i . By entering the pseudo sequence VS_i into the Skip-gram model , we can obtain themaximization objective functionas follow:

$$\arg\max\ opt = \frac{1}{\beta}\sum_{i=1}^{\beta}\sum_{j\neq i}^{\beta} \log\ p(x_j \mid x_i) \tag{2}$$

Where β is the length of the pseudo sequence VS_i , and $p(x_j \mid x_i)$ is defined as the following Softmax function:

$$p(x_j \mid x_i) = \frac{\exp(w_i^T * v_j)}{\sum_\beta \exp(w_i^T * v_\beta)} \tag{3}$$

Where W_i and V_i are the embedding vectors of the POI,representing the target POI and the previous POI respectively.However, when β is too large, it causes the gradient calculation $\nabla(x_j \mid x_i)$ is hard to calculate. According to the Skip-gram negative sampling method proposed by Tomas , the formula 4 is modified as follows:

$$p(x_j \mid x_i) = \sigma(w_i^T * v_j) \prod_{k=1}^{E} \sigma(-w_i^T * v_k) \tag{4}$$

layer isupdated by the previous one.The formula of LSTM model is as follows:

$$\begin{aligned} i_t &= \sigma(W_{ix}xt + W_{ih}h_{t-1} + b_i) \\ f_t &= \sigma(W_{fx}xt + W_{fh}h_{t-1} + b_f) \\ o_t &= \sigma(W_{ox}xt + W_{oh}h_{t-1} + b_o) \\ c_t^{\wedge} &= \tanh(W_{cx}x_t + W_{ch}h_{t-1} + b_c) \\ c_t &= f_t \quad c_{t-1} + i_t \quad c^{\wedge} \\ h_t &= o_t \odot \tanh(c_t) \end{aligned} \tag{5}$$

Specially, i, f and o represent input gate,forgetting gate and output gate respectivly, $\sigma(x)$ and represent sigmoid function and element-wise function An LSTM cell calculates a combination of the current information and the information before time t.We use h_t as the final output of the LSTM and for later measurements.

$$p_u^{poi} = W_u^{poi} * h_j + b_u^{poi} \tag{6}$$

Definition 1(Pseudo sequence):It is a sequence obtained by sampling a real-world dataset.This sequence does not exist in the real world, but its distribution roughly corresponds to the distribution of the real world dataset.Therefore, this sequence can supplement the sparse dataset.

Definition 2(POI-category):The user tends to access different POIs in the same category that he/she likes.This access pattern, where users frequently access a particular POI category but rarely access each individual POI of that category, should be considered in subsequent POI recommendations.Therefore, effective use of POI categories can mitigate the impact of data sparsity.

3.2. POI Embedding based on H-Node2Vec

POI embedding is the first step of the CASGD model.According to the traditional project-based collaborative filtering idea, another feature in POI recommendations is that a user has a higher probability of visiting POIs visited by his/her friends[4].Therefore, we propose a POI embedding method based on H-Node2Vec to embed input information based on H-Node2Vec to generate the user's POI pseudo-check-in sequence through LBSN network.

Inspired by the Deepwalk method, H-node2vec learned the embedded representation of POI through random walk and skip-gram with negative sampling.On the basis of user check-in dataset, we first construct an LBSN heterogeneous graph containing user social relationship and POI geographical relationship.As shown in the Figure 2.

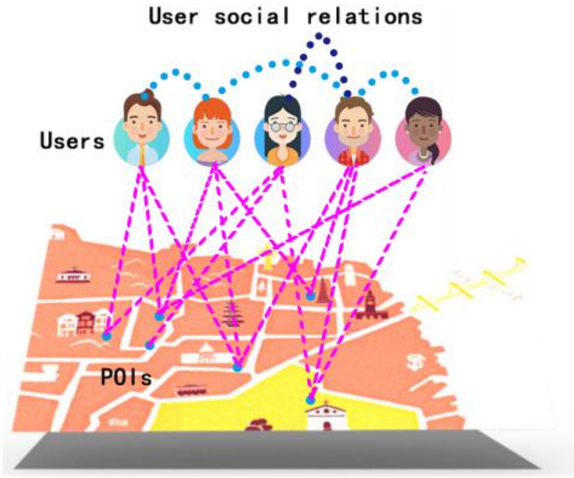

Figure 2: LBSN heterogeneous graph.

3.3. Deep Encoder for User Preference in POI Categories

The key to capturing user preferences in POI categories is to reduce the lookup space in POI recommendations.For this purpose, we designed an LSTM based encoder as follows:

$$I_j^{e,1} = W_u^{e,1}.U_u + W_c^{e,1}.C_j^u \tag{7}$$

$$H_j^{e,1}, S_j^{e,1} = LSTM(I_j^{e,1}, S_{j-1}^{e,1}) \tag{8}$$

Above, $U_u, C_j^u \in R^d$ represent User u and POI categories latent vector, respectively; $W_u^{e,1}, W_c^{e,1}$ are two weight metrics,measuring the potential impact of users andPOI categories, respectively. $I_j^{e,1}$ represents information extracted from the POI Category and hidden representation of the user ie C_j^u and U_u . $H_j^{e,1}$ and $S_j^{e,1}$ are the output (hidden state) and the state of the LSTM cell. In addition,the final output of the encoder $H_n^{e,1}$ can be viewed as user's current preference for the POI category.

Next, we look at this process in detail.In the first layer of filtering, we use user preferences in the POI category, learning the ranking of all POI categories for each user in the previous step.The main goal is to exclude categories of POIs that the user is not interested in.In the first filter, a binary classifier, the softmax function σ , is used to sort all POI categories.Given a set of POI categories:

$$input = W_n^{e,1}.H_n^{e,1} + W_c^s.C_i + W_u^s.U_u \tag{9}$$

$$Y_i^s = \sigma(W^s.Input + b^s);\ i = 1,2,...,P \tag{10}$$

$$\sigma(X)_j = \frac{\exp(x_j)}{\exp(x_1) + \exp(x_2)};\ j = 1,2 \tag{11}$$

Here,three weight metrics are used to capture user preferences in that POI category.At the first level, the search space of the model is reduced from all POIs to POIs belonging to top-k POI category, represented by $V_u^{l,1}$ .In addition, if the geographic location v of POI is far away from the user's current location, this POI can be excluded.The process is as follows:

$$V_u^{l,1} = layer_1(V_u) \tag{12}$$

$$V_u^{l,2} = layer(V_u^{l,1}) \tag{13}$$

3.4. Objective Function of Model

In order to accurately rank the POIs in the candidate set, we also consider three specific correlations :(1) the correlations between users and POIs;(2) Relevance between users and POI categories;(3) Correlation between POI and user's current preference representation.

$$E_{u,v}^n = \| U_u - V_u \|_2^2 + \| U_u - C_c \|_2^2 + \| H_n^{e,2} - V_v \|_2^2 + \| P_u^{poi} - V_v \|_2^2 \tag{14}$$

4. Experiment

Datasets: We evaluated the model on two real datasets: Yelp and Gowalla.They are represented by NYC and TKY,respectively.We removed POIs accessed by fewer than five users because they were outliers in the data.We measure the effectiveness of the recommendation task using two standard recommendation evaluation metrics: Precision@k for the top k recommended POIs and Recall@k for the top k recommended POIs. In Table 1, statistically significant results are shown, which achieved by performing a twotailed paired t-test at a 95% confidence interval ($p < 0.05$).Compared methods:

Table 1: H-node2vec algorithm.

Algorithm Hetegorgenus graph random walk algorithm

Input : Heterogenous graph G, Geographic distance thereold θ,The numbers of random walks α
Output: Pseudo-sequence set for all users' VS
1:Initialization set VS
2: for all $p_i \in P$ do
3: Initialization set VS_i
4: for j=0;j<β;j++ do
5: insert p_i into the pseudo sequence VS_i
6: Extract user u_i p_i in the set $Uu_{\in E_pU(p_i)}$ arrcoding to the normal distribution N(.)
7: Randomly walk α times on the G_U=(U ,E_UU) to get the user u_j
8: Use the N(.) to extract the POI point p_j in the check-in set $P_{p \in EPU(ui+\alpha)}$ of the user u_j, where p_i and p_j The distance between does not exceed the threshold θ
9: insert p_i into the VS_i
10: end for
11: insert VS_i into VS
12:end for
13:return VS

Table 2: Experiment results.

Method	Yelp						Gowalla					
	P@5	P@10	P@20	R@5	R@10	R@20	P@5	P@10	P@20	R@5	R@10	R@20
USG	0.0282	0.0244	0.0197	0.0281	0.0523	0.0753	0.0502	0.0471	0.0413	0.0517	0.0568	0.0625
MGMPFM	0.0197	0.0173	0.0136	0.0211	0.0293	0.0493	0.0281	0.0215	0.0197	0.0263	0.0291	0.0319
BPRFM	0.0285	0.0221	0.0185	0.0296	0.0361	0.0599	0.0493	0.0443	0.0342	0.0497	0.0529	0.0581
RankGeoFM	0.0421	0.0362	0.0292	0.0392	0.0673	0.0838	0.0567	0.0501	0.0492	0.0591	0.0642	0.0718
HGMF	0.0532	0.0491	0.0401	0.0478	0.0702	0.0915	0.0798	0.0711	0.0683	0.0715	0.0773	0.0819
Metric Factorization	0.0593	0.0552	0.0481	0.0533	0.0782	0.0974	0.0821	0.0782	0.0717	0.0784	0.0814	0.0862
CASGD-NOcat	0.0641	0.0613	0.0568	0.0589	0.0831	0.1013	0.0821	0.0782	0.0717	0.0784	0.0814	0.0862
CASGD	**0.0702**	**0.0692**	**0.0631**	**0.0621**	**0.0881**	**0.1121**	**0.0924**	**0.0894**	**0.0813**	**0.0872**	**0.0953**	**0.1283**

•USG. takes advantage of three modules of user-based CF,social influence, and geographical information.
•MGMPFM.combines geographical influence with Probabilistic Factorization Model (PFM), assuming a Multi-Center Gaussian Model (MGM) of the probability of a user's check-in behavior..
•BPRMF.adopts a Bayesian criterion to directly optimize for personalized rankings based on users' implicit feedback.
•Metric Factorization.places users and POIs in a low dimensional space and measures their explicit similarity using Euclidean distance.
•RankGeoFM.is a state-of-the-art ranking-based geographical factorization method. It incorporates the geographical information in a latent ranking model..
CASGD-NoCat is a variation of CASGD in which we remove the category module from the model. Therefore, it is trained using only the check-in module.

5. Performance Comparison

As seen in Table 1,CASGD significantly outperforms all of the baseline methods in terms of all evaluation metrics. This indicates that the check-in module is able to learn POI latent representation by modeling the context of users' visited POIs and the sequence of POIs. Furthermore, the results suggest that incorporating category information enables CASGD to model the characteristics of the POIs more effectively. It is worth noting that our proposed POI embedding model can be pre-trained on a large dataset of check ins to be used in various POI recommendation models. Also, it is seen that CASGD-NoCat is able to outperform all the baselines significantly, indicating that learning POI embeddings only based on check-in information is able to capture complex sequential relations between POIs.

6. Conclusions

In this paper, we introduced a novel POI embedding model and demonstrated the importance of characteristics of POIs in POI em bedding.Our model captures the sequential influence of POIs from check-in sequence of users, as well as, characteristics of POIs using the category information. The experimental results showed that our model contributes to improving POI recommendation performance

References

[1] Mohammad Aliannejadi and Fabio Crestani.2018.Personalized Context-Aware Point of Interest Recommendation. ACM Trans. Inf. Syst. 36, 4 (2018), 45:1 –45:28

[2] Xin Liu, Yong Liu, and Xiaoli Li. 2016. Exploring the Context of Locations for Personalized Location Recommendations..In IJCAI. 1188 –1194

[3] Yiding Liu, Tuan-Anh Nguyen Pham, Gao Cong, and Quan Yuan. 2017. An experimental evaluation of point-of-interest recommendation in location-based social networks. VLDB 10 (2017), 1010 – 1021.
[4] Mao Ye, Peifeng Yin, Wang-Chien Lee, and Dik-Lun Lee. 2011. Exploiting geographical influence for collaborative point-of-interest recommendation. In SIGIR. 325 – 334.
[5] J. Tang, M. Qu, M. Wang, M. Zhang, J. Yan, and Q. Mei, "Line: Large scale information network embedding," in Proceedings of the 24th international conference on world wide web. International World Wide Web Conferences Steering Committee, 2015, pp. 1067 – 1077
[6] Dumitru Erhan, Yoshua Bengio, Aaron Courville, Pierre-Antoine Manzagol,Pascal Vincent, and Samy Bengio. 2010. Why does unsupervised pre-training help deep learning? Journal of Machine Learning Research 11,Feb (2010), 625 – 660.
[7] Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. 2017. Neural collaborative filtering. In Proceedings of the 26th International Conference on World Wide Web. International World Wide Web Conferences Steering Committee, 173 – 182
[8] S. Zhao, T. Zhao, H. Yang, M. R. Lyu, and I. King, "Stellar: spatial temporal latent ranking for successive point-of-interest recommendation," in Thirtieth AAAI conference on artificial intelligence, 2016.
[9] Grover A , Leskovec J . node2vec: Scalable Feature Learning for Networks[C]// the 22nd ACM SIGKDD International Conference. ACM, 2016.
[10] Chen Cheng, Haiqin Yang, Irwin King, and Michael R Lyu. 2012. Fused Matrix Factorization with Geographical and Social Influence in Location-Based Social Networks.. In AAAI, Vol. 12. 17 – 23.