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Deep Knowledge-Embedding Network for POI Recommendation

Chengwen Zhang[1], Tang Li[1, a, *], Yunqing Gou[2] and Mo Yang[3]

[1]Beijing Key Lab of Intelligent Telecommunication Software and Multimedia, Beijing University of Posts and Telecommunications, Beijing, China;

[2]International School, Beijing University of Posts and Telecommunications, Beijing, China;

[3]State Key Laboratory of Networking and Switching Technology, Beijing University of Posts and Telecommunications, Beijing, China.

[a]Corresponding Email: 2017110747@bupt.edu.cn

Abstract

With the rapid development of location-based social network (LBSN), point of interest (POI) recommendation has become an important service and has received extensive attention in recent years. Most of the existing researches use recurrent neural network (RNN) to learn the user's interest preference according to the user's POI access sequence. However, the traditional RNN only inputs POI sequences according to the sequence of check-in times, without considering the check-in time interval between adjacent POIs. At the same time, if the user checks in more frequently at a certain interest point, the interest point is considered to be the user's "habitual" preference. Considering the check-in time interval and check-in frequency pair, this paper proposes a recommended framework KG-TIFLSTM based on the time interval and check-in frequency for the long-term and short-term memory network TIFLSTM (Time Interval and Frequency LSTM). Firstly, the knowledge graph embedding method is used to obtain vector representations of users and POI. Then, the POI sequence of the user is input into the TIFLSTM network to obtain the user preference vector. Finally, the probability of users accessing POI is predicted through the fully connected network for recommendation. Experiments were carried out on real LBSN data sets, and the experimental results prove the effectiveness of the algorithm.

Keywords

Knowledge graph, attention, embedding, POI recommendation, Gowalla.

1. Introduction (Heading 1)

In recent years, the rapid development of network technology and intelligent devices has triggered the vigorous development of social networks. Social networks like Facebook, Flickr and Gowalla have attracted billions of users to interact and share information on these platforms. The use of global positioning system (GPS) and technological progress have further promoted the emergence of Location-based Social Network (LBSN). Users can share their daily life and travel experiences on social network platforms by signing in. This form helped LBSN attract a lot of attention. Point-of-Interest (POI) refers to GPS-based locations in LBSN, such as hotels, hotels and shopping malls. Intelligent POI recommendation deeply explores the relationship between users and POI related information. By mining the user's historical check-in data, the user's interest preferences can be obtained, and then some nearby POI are recommended for the user according to the user's activity location range. It can not only improve the user experience, but also help businesses to expand their visibility and increase their operating income. Most of the existing research methods model user preferences based on historical check-in data combined with geographic information and social relationships.

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However, when modeling user preferences using historical check-in data, the interval between user check-in time and current time point and the influence of user check-in times on user preferences are not considered.

The user's historical check-in information is the most important information that reflects the user's personal preference and predicts the user's future travel. However, the sparsity and timing of the user's historical check-in data make it a challenge to model the user's check-in data. Most existing models use LSTM algorithm to extract user preferences from the user's check-in sequence. LSTM algorithm inputs the input sequence according to the time sequence, which is the most popular method [1]. The existing models use LSTM to model the user check-in sequence and apply it to POI recommendation [2]. However, the time interval between the user's check-in time and the current time is not considered, which will affect the extraction of user preference information. Previous studies have shown that user preferences will shift over time [3]. Things that users were interested in long ago are likely to be of less interest to users now. In general, the further check-in data from the current time point, the less influence it should have on the current user's personal preference. At the same time, the user's check-in times for a certain point of interest also reflect whether the user "really likes" a certain point of interest. The interest points that the user will not visit after checking in only once are likely to be the ones that the user failed to explore some new interest points. For an interest point that the user has checked in many times, the high probability is that the user really likes this interest point, and then the interest point can better reflect the user's real preference. Therefore, in order to model user preferences more accurately, we propose TIFLSTM model, which uses user check-in sequence, check-in time information and user check-in times to model and capture user preferences.

In addition, contextual information such as geographic location information and social information also have a great influence on the sign-in behavior of users. Knowledge graph is a complex network that integrates various contextual information (such as geographic location information, social information, etc.) and entity relationships (such as check-in relationships, friend relationships, etc.). The method based on knowledge representation can use the entity relation and entity context information in the knowledge graph to generate vector representation of entities. The knowledge graph embedding method is a method that takes the vector generated by knowledge representation as the embedding vector of neural network input. In this paper, our study used the knowledge graph embedding method to combine geographic location information, social relations and check-in relations to generate the embedding vectors of users and POI.

In this paper, we propose a deep learning framework (KG-TIFLSTM), which consists of knowledge graph embedding method and TIFLSTM network. The knowledge graph embedding method combines geographic location information, check-in relationship and friend relationship to generate embedded vectors of users and POI. TIFLSTM network builds user preference vector according to user check-in sequence, combining check-in time interval and check-in times. We have done a lot of experiments on real check-in data. The experimental results show that our model is superior to other methods.

2. Relatedwork

Many researches have been done in POI recommendation field. Initially, collaborative filtering algorithm was used in POI recommendation. Collaborative filtering algorithms are divided into memory-based collaborative filtering and model-based collaborative filtering algorithms. Paper [4-5] uses memory-based collaborative filtering method to recommend POI, and achieves good results. However, the memory-based collaborative filtering algorithm can only use information such as check-in or check-out, and cannot learn the latent preferences of users and

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POI. Matrix decomposition of model-based collaborative filtering algorithm can learn the latent semantic information of users and POI. Compared with memory-based collaborative filtering method, it has better recommendation effect [6] and has become the most popular solution adopted by recommendation system, but it does not solve the impact of data sparsity and cold start problem. Therefore, existing work combines contextual information such as geographic location information and social information to recommend POI [7-10]. Guo et al. [11] combined the user's social network information with the user's trust network to solve the problems of sparse data and cold start. Liu et al. [12] designed a recommendation system based on geographic location information to recommend POIs to users. Gao et al. [13] combined geographic location information, social information and other contextual information to recommend, improving the effect of POI recommendation model.

Knowledge graph has attracted extensive attention of scholars [14] because of its high coverage of entities and concepts and rich correlation, which can better integrate context information. Document [15] proposed a method of knowledge graph embedding, and expounded the idea and advantages of knowledge graph embedding combined with neural network. Therefore, this paper uses the knowledge graph embedding method to generate user and POI representation vectors and embed them into TIFLSTM network for recommendation.

According to the temporal characteristics of user check-in sequences, documents [16-17] propose a sequential recommendation method based on Markov chains, but they only consider the influence of the last check-in activity and cannot completely extract the information in the user check-in sequences. With the rapid development of deep learning, more and more researchers have used deep learning to recommend POI [18-19]. RNN is widely used in NLP as a popular model for processing time series [20]. Document [21] introduces RNN into POI recommendation, uses RNN to process user's check-in sequence and models user's preference, and achieves good results. However, RNN has the problem of gradient disappearance [1]. LSTM solves the problem of RNN gradient disappearance [1], and is used in POI recommendation [2]. Whereas both LSTM and RNN only input the POI check-in sequence of users in chronological order, without considering the influence of the check-in time interval and check-in times on user preferences. In this paper, TIFLSTM is proposed, which uses check-in time interval, check-in times and check-in sequence to model user preferences jointly.

3. Proposed Kdln Framework

In this paper, we propose a KG-TIFLSTM (Knowledge Graph-Embedded Time Inter-Cal and Frequency LSTM) framework, which consists of two parts: knowledge graph embedding and TIFLSTM network. Firstly, the embedding of users and POI are obtained by the knowledge representation method of knowledge graph. Then, the user check-in sequence is extracted, and the time interval and check-in times of each check-in point are calculated as the input of TIFLSTM model to generate the user preference vector. Finally, the user preference vectors and candidate POI vectors are input into the fully connected network for probability prediction.

Next, KG-TIFLSTM model will be introduced in detail in two parts. The first part is knowledge graph embedding method, which combines geographic context information, check-in information and friend information to generate POI embedding vectors and input them into TIFLSTM network. The second part is TIFLSTM network based on check-in time interval and check-in counts. Finally, the recommendation network based on fully connected neural networks will be described.

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3.1. Knowledge Graph Embedding

Our study constructed POI knowledge graph by extracting user entity, POI entity, friend relationship, check-in relationship, longitude and latitude information. POI knowledge graph consists of hundreds of thousands of triples in the following triplet form:

$$(h, r, t)$$

In which h, r and t respectively represent the head entity, relation and tail entity of the triplet. Given all triples in the knowledge graph, knowledge graph embedding is to learn a low-dimensional representation vector for each entity and relationship, which retains the structural information of the original knowledge graph. In this paper, translation-based knowledge representation model TransH is used to train triples to generate entity vectors, which are used to be embedded into neural networks

TransH makes entities to have different representations when different relationships are involved by projecting entity into the relationship hyperplane. When triplet (h, r, t) extists, then the formula $\boldsymbol{h}+\boldsymbol{r} \approx \boldsymbol{t}$ holds, where $\boldsymbol{h}, \boldsymbol{r}$ and $\boldsymbol{t}$ are the corresponding representation vectors of h, r and t. Therefore, TransH defines the scoring function:

$$f_r(h,t) = \|h_\perp + r - t_\perp\|_2^2$$

In which $h_\perp = h - w_r^\mathrm{T} h w_r$ and $t_\perp = t - w_r^\mathrm{T} t w_r$ *are* prediction of hyperplane w_r by h and t respectively, and $\|w_r\|_2 = 1$.

3.2. TIFLSTM

As shown in fig. 1 is the structural diagram of TIFLSTM cell, internal structure and reasoning formula of TIFLSTM in will be introduced in detail.

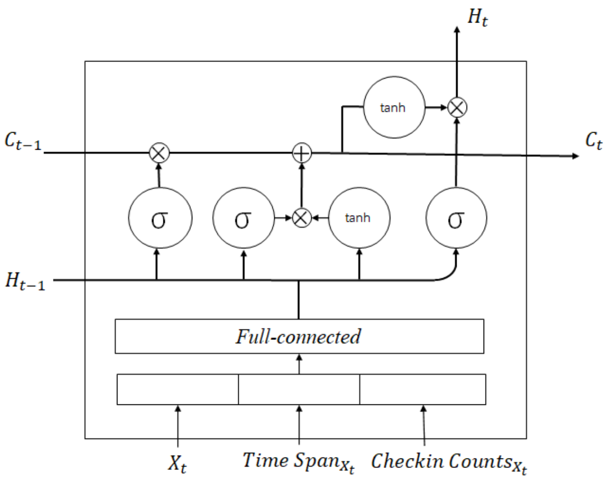

Fig 1. TIFLSTM cell structure

The input of TIFLSTM consists of three parts: the POI access sequence of the user $\{X_i | 1 \le i \le n\}$, the check-in time interval corresponding to each POI in the POI sequence $\{TS_{X_i} | 1 \le i \le n\}$, and the check-in counts corresponding to each POI in the POI sequence $\{CC_{X_i} | 1 \le i \le n\}$.

The embedding of each POI in the POI sequence is obtained by the knowledge graph embedding method. The check-in time interval is obtained by calculating. First of all, "days" are used as the time unit and the latest check-in time of the user as the benchmark to calculate how many time units the current POI check-in differs from each other, and represent the result using one-hot processing to generate vectors. Check-in Counts means counting the number of times the user has checked in the POI in the current check-in record. The check-in results are also expressed as one-hot. The POI vector X_i, the check-in time interval vector TS_{X_i} and the check-in counts vector CC_{X_i} are spliced and then passed through a fully connected network to output vector XC_t.

$$XC_t = W_{XC} \cdot [X_t, TS_{X_t}, CC_{X_t}]$$

XC_t and the cell state H_{t-1} at the previous moment update the cell state through the forget gate to remove redundant information in the cell state, where σ represents the sigmoid function.

$$f_t = \sigma(W_f \cdot [h_{t-1}, XC_t] + b_f)$$

XC_t and the cell state H_{t-1} at the previous moment update the cell state through the input gate, and add new information to the cell state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, XC_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, XC_t] + b_C)$$

Then the model shows that the cell state at the current time C_t is as follows:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Finally, the output vector is obtained from XC_t, H_{t-1} and the current cell state C_t:

$$\mathrm{o}_t = \sigma(W_o \cdot [h_{t-1}, XC_t] + b_o)$$

$$h_t = \mathrm{o}_t * \tanh(C_t)$$

The final output state of TIFLSTM UP represents the user's preference.

3.3. DNN Recommendation Net

We built a two-layer deep neural network, taking the output UP of the TIFLSTM network and the candidate POI vector generated by the knowledge graph embedding method as inputs, and we used the GeLU function as the activation function to output the probability P of recommending the candidate POI to users.

3.4. Parameter Learning:

The loss of each iteration is the cross entropy between $P_{u_k}$and$\hat{P}_{u_k}$:

$$loss\left(P_{u_k}, \hat{P}_{u_k}\right) = \hat{P}(i) log P(i) + \left(1 - \hat{P}(i)\right) \log\left(1 - P(i)\right)$$

Where $\hat{P}_{u_k}$is the output of the KEAN for u_k and $P_{u_k}$is the real posterior probability of the future check-ins of u_k that is estimated by:

$$P_{u_k}(i) = \begin{cases} 1, if\ u_k\ visits\ l_i\ in\ the\ future \\ 0, else \end{cases}$$

The objective of the Knowledge graph embedding and attention based network is as follow:

$$\theta = \min_{\theta} \sum_{u_k \in U} loss(P_{u_k}, \hat{P}_{u_k})$$

Where θ are the parameters of the network and updated using SGD.

4. Experiments

4.1. Setup

The data set for our experimental evaluation is the actual LBSN Gowalla data set. This data set collects the user's real check-in records, and records information such as check-in place, time, and user's social relationships[24].

We use the first 80% of the time embedded values to build the training set and the last 20% of the embedded values to build the test set. In the training set, we use the first 80% of the user's check-in as her most recent check-in, and the last 20% as her future check-in. In the test set, we also use the first 80% of each user's check-in as the most recent check-in and the rest as future check-ins.

Firstly, learn the knowledge embedding vectors of the user and POI. The knowledge representation algorithm of the model is TransH, the vector dimension is 256 dimensions, and the learning rate is 0.001. Secondly, train the TIFLSTM network. We also set the learning rate to 0.001, and the vector dimensions of time interval and sign-in times are set to 8 dimensions. In the output layer, we set the loss rate to 0.2.

4.2. Evaluation Metricss

We adopt three widely-used metrics for evaluation [30], Precision@K, Recall@K, where K is the number of POIs in the recommendation list of each user.

$$Precision@K = \frac{1}{|U|}\sum_{u\in U}\frac{|R_u^K \cap T_U|}{|R_u^K|}$$

$$Recall@K = \frac{1}{|U|}\sum_{u\in U}\frac{|R_u^K \cap T_U|}{|T_U|}$$

Where R_u^K is the set of top K POIs in the recommendation list of user u, and T_U is user u's ground truth set of POIs.

4.3. Contrast Algorithm

We compare the proposed method with the following POI recommendation methods:

FPMC [22]: factorizing personalized Markov chains, which linearly combines the user preference and Markov transition.

PRME [23]: personalized ranking metric embedding, which linearly fuses the user preference and Markov transition.

GeoIE [9]: It is a POI recommendation model exploiting POI-specific geographical influence. It incorporates the geographical influence between two POIs using three factors: the geo-influence of POI, the geo-susceptibility of POI, and their physical distance.

4.4. Experiment Results

4.4.1. The Performance of TopK Recommendation:

In the comparison experiment, we use the same method to segment the data set which could ensure the fairness of the comparison. Table I shows the evaluation metrics of the KG-TIFLSTM model and other comparison algorithms on the Gowalla dataset. (Precision@K; Recall@K), The values of K are 5, 10, and 20, respectively.

Table 1. Topk recommendation performance

Model	Precision				Recall				F1			
	Top-5	Top-10	Top-15	Top-20	Top-5	Top-10	Top-15	Top-20	Top-5	Top-10	Top-15	Top-20
FPMC	0.1049	0.0754	0.0665	0.0607	0.0707	0.0813	0.919	0.1100	0.0845	0.0782	0.1240	0.0782
PRME	0.1108	0.0812	0.0765	0.0573	0.0718	0.0886	0.1011	0.1183	0.0871	0.0847	0.0871	0.0772
GeoIE	0.1469	0.1072	0.0866	0.0764	0.0793	0.1003	0.1134	0.1268	0.1030	0.1036	0.0982	0.0953
KG-TIFLSTM	0.1684	0.1312	0.1248	0.1071	0.1038	0.1241	0.1371	0.1501	0.1284	0.1275	0.1307	0.1250

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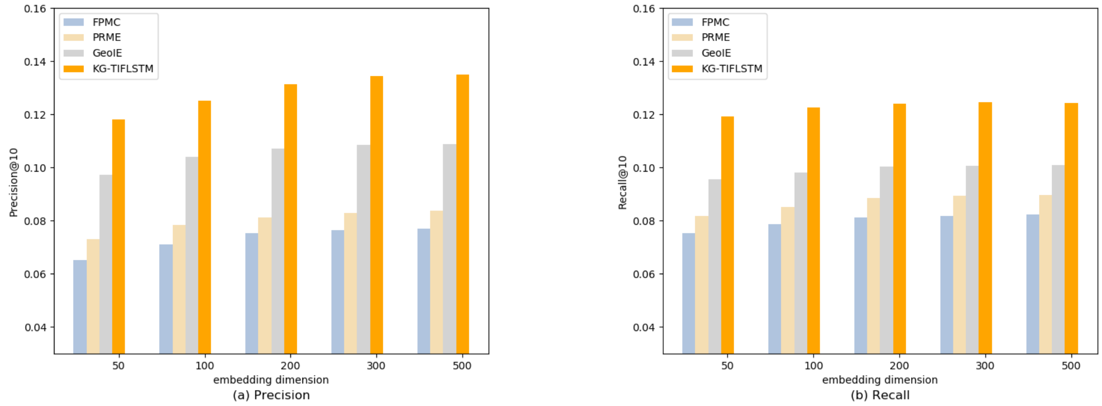

Fig 2. Performance in different dimension D

From Table I, we can see that all evaluation metrics of KG-TIFLSTM under different K values are higher than other algorithms, which proves the effectiveness of the KEAN model.

4.4.2. The Impact of Knowledge Embedding Dimensions on the Performance of the Model

This experiment is to evaluate the effect of the embedding vector dimension D on the algorithm. We compare the performance of the KG-TIFLSTM method with several other methods in different dimensions. The comparison results on the Precision and Recall metrics are shown in Figures 5 (a) and 5(b), respectively. As D increases, so does the performance of all methods. But when the dimension of D increased after 200 dimensions, the growth rate of the model tends to be flat. Considering the validity and time efficiency of the model, we choose D = 200.

4.4.3. The Effect of Time Interval Units on Model Performance

The time interval refers to the difference between the user check-in time and the current time. Here we use the last check-in time as the current time.

Time interval units This experiment is to evaluate the impact of the unit of check-in time on the model in KG-TIFLSTM. We choose different time interval units (eg 1day, 3day, 5day, 10day, 15day) under the same conditions of other parameters, and compare the performance of the model. The comparison results on the Precision and Recall metrics are shown in Figures 3 (a) and 3(b), respectively. The larger the unit of the model time interval, the worse the model performance. Considering the validity of the model, we set the calculation unit with the check-in interval in days.

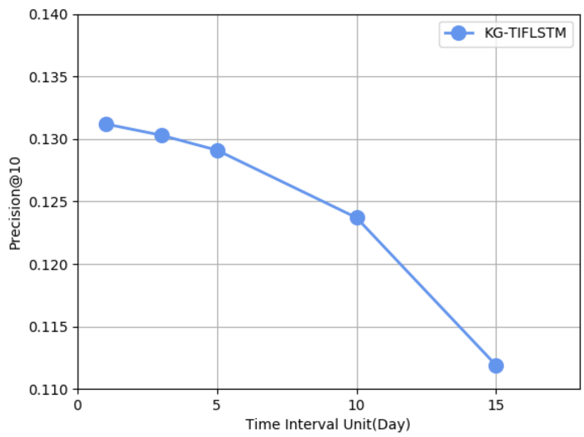

Fig. 3(a) Precision in different number of friends

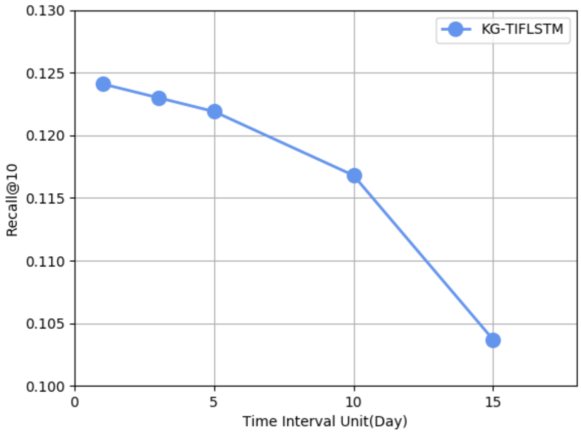

Fig. 3(b) Recall in different number of friends

5. CONCLUSIONS

In this paper, we propose a point of interest recommendation framework KG-TIFLSTM based on knowledge graph embedding and neural network. The framework consists of two modules: knowledge graph embedding module and TIFLSTM module. The knowledge graph embedding module is used to generate user and POI vectors by using geographic information, friend relationship, check-in information, etc. TIFLSTM module uses user check-in time interval and check-in frequency to model and generate user preferences for recommendation. KG-TIFLSTM has good expansibility, besides the information used in this article, it can also integrate other context information. The experimental results on the real-world Gowalla dataset show that our framework is obviously superior to other latest methods.

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