Received November 2, 2019, accepted November 18, 2019, date of publication November 27, 2019,
date of current version December 11, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2956138

Next POI Recommendation via Graph Embedding Representation From H-Deepwalk on Hybrid Network

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ABSTRACT With the rapid development of location-based social networks (LBSNs), point of interest (POI) recommendation has become more and more popular personalized service. Cold start problem and poor interpretability are two main challenges of the traditional recommendation system. In this paper, we propose a novel social and sequence-aware next POI recommendation model. Our model utilizes an improved DeepWalk on heterogeneous network to learn better POI representation which contains social relationship and geographical influence. In this way, the cold start problem and interpretability problem can be solved to some extend. As for the user preference learning, we use LSTM (Long Short-Term Memory) mechanism to infer user interest, taking both long term and short term intentions into consideration. The model is trained in a metric learning framework. The experimental results on two real LBSN datasets show our model has outstanding performance in terms of AUC, Recall, and ACC. Furthermore, we can obtain 20% performance improvement on spare dataset which indicates that our model can well solve the cold start problem.

INDEX TERMS LBSN, next-POI recommendation, LSTM, DeepWalk.

I. INTRODUCTION

In recent years, with the rapid development of mobile information networks, majority of user check-in data and users' social information data been generated. Therefore, the POI recommendation system based on LBSN plays an important role in solving information overload problems. Traditional recommendation algorithms (such as collaborative filtering, etc.) pay undue attention to the product features themselves, such as product rating information, etc.. When it is applied in the field of POI recommendation, the geographical location data and users' social information that belong to the LBSN network are not usually utilized well, and it is difficult to solve the cold start problem caused by data sparseness. In the real POI datasets, the dataset is too sparse for some users do not check in the POI location in time. As result, how to use the side information, such as social information in LBSN, to alleviate the sparseness of datasets is a very important and practical problem in the research of POI recommendation based on LBSN [1].

The existing work for POI recommendation can be divided into two categories: global recommendation and next-item recommendation [2]. The representative of the global recommendation system is the Collaborative Filtering. Such methods usually only consider the relationship between users and items from the static direction, so they cannot effectively capture the user's dynamic preferences. They also face the cold start problem. The recommendation system based on user behavior sequence has become a hot topic in recent research work because it has good performance when cooperating with a deep neural network to capture the dynamic features sequence.

For the POI recommendation system, it is crucial to model the users' check-in sequence features, and for the LBSN-based POI recommendation system, the user's social information and POI geographic location information also need to be considered. In my previous works, the social information of users and the geographical location information of POIs were regarded as low-dimensional embeddings, and they were usually combined with behavior embedding [3]. Although this method considers the user's social information and the geographical location information, but it concentrates the learning pressure in the subsequent neural network model. Therefore, this method makes subsequent networks lose performances to some extend, while also reduces the interpretability of the model.

The associate editor coordinating the review of this manuscript and approving it for publication was Jing Bi.

With the DeepWalk method and LINE method proposed [4], [5], large-scale network embedding has become an effective method to solve the complex relationship network structure. Applying the network embedding method to the LSBN-based POI recommendation system can help the system capture social and geographic-based association features, thereby improving the quality of recommendations and enhancing the interpretability of the model.

This paper introduces a POI recommendation model based on social-geographic two-layer heterogeneous graph and user behavior sequence modeling. We develop a model based on the social-geographic heterogeneous graph named SGBA(Social - Geographic Behavior Alliance model). The model proposes POI a pseudo-sequence that integrates the user's social information and POI's geographic information which is obtained by random walk. Then the sequence is input into the Skip-Gram model to learn the embedding representation of the POI. This method not only considers the second-order proximity problem of POI [5], but also expands the proximity range. Thus the POI embeddings with similar user groups are more relevant. At the same time, we limit the actual distance of POI in the sequence, so that POIs with similar geographical locations can be considered. In the aspect of user behavior modeling, we divide the user's sequence into long-term transfer sequence and short-term transfer sequence, so that the LSTM model can distinguish between user long-term behavior preference and user short-term behavior preference.

The main contributions of this paper are as follows:

1) We propose a embedding representation learning method based on LBSN network which can effectively mine the more relevant POI on the user's social level. This method considers the limitation relationship of POI's geographical proximity and therefore can effective alleviate cold start problem and improve recommendation accuracy at the same time. It also effectively alleviates the cold start problem caused by data sparseness while improving the accuracy of the model.
2) A time-based and geographically-based check-in sequence segmentation method is proposed. The user sequence is segmented into a short-term transfer sequence and a long-term transfer sequence, so that the subsequent neural network can better learn the short-term preference and long-term preference of the user respectively.
3) We conduct extensive comparative experiments on Gowalla and Foursquare dataset to compare the performance of our mode with the existing recommendation methods. The experimental results show that our model has better recommendation quality and interpretability.

II. RELATED WORKS

The POI recommendation system plays a vital role in LBSN-based services. For example, mobile Internet services such as Meituan and WeChat also incorporate the POI recommendation system. Recently, the POI recommendation system has received great attention in industry and academia. Research on the POI recommendation system can be divided into two main areas by task: global recommendation and next-poi recommendation.

A. GLOBAL RECOMMENDATION

The global recommendation is to recommend the top-N POI to the user. This method focuses on the static relationship between the user and the POI. The global recommendation is represented by the movie recommendation in Netflix.

The global POI recommendation method was first proposed by Ye *et al.* in the FCF model [6]. Just like the movie recommendation in the traditional recommendation, the FCF uses the collaborative filtering method to combine the user's social relationship to recommend the top-N POI for the user. In the past work, in addition to considering the FCF of the user's social relationship, there is also the Geo-FM proposed by Li *et al.* [7], which considers the influence of the POI geographic location on the user's check-in preference and quantifies the weight of the neighboring POI interaction. Nevertheless, in the traditional POI global recommendation, only the shallow impact of the side information is emphasized. But the relationship between the information and the deep meaning of the combination of the information are ignored.

In order to explore the deep meaning of information in the LBSN, Liao *et al.* proposed the UZT method for POI recommendation [8]. This model first uses the LDA topic model to extract the topic in the user comment information and combines the user's check-in temporal information. The user's interest preference for different POI points is obtained from the high-order singular value decomposition method, which greatly improves the prediction accuracy. Based on the POI-based geographic information and time information fusion method, Yuan *et al.* proposed a BPP-based GTAG method which embeds the user's time information and POI's spatial information [9]. This method also effectively alleviates the cold start problem. In view of the different contribution of each kind of information to user preferences, Bara *et al.* proposed two fusion models based on ranking and Matrix Factorization which effectively combine various side information and propose a new method for the utilization of side information [10]. With the development of the graph embedding method, Christoforidis *et al.* proposed the LBSN graph embedding method RLINE based on the LINE method which effectively embeds the side information such as user information [11], geographical location information and time series information of the LBSN into the low-dimensional space.

B. NEXT POI RECOMMENDATION

In the recent work, researchers gradually focus on sequential pattern mining. Typical successive POI recommendation methods are the next-basket method, the session-based POI recommendation method and the next-POI recommendation method.

Traditional next-POI recommendations mostly use Markov chain, Bayesian and other statistical methods to model the user's check-in behavior, such as the STELLAR model proposed by Zhao *et al.* [12], which recommends POI by providing a time series capture model based on Matrix Factorization. With the development of deep learning methods in recent years, the research on sequence data has gradually migrated to the method of deep learning. For example, the NLP field, the field of impact maximization, and the field of traditional commodity recommendation propose many effective deep learning models. By referring to the Attention method and the RNN method proposed in the NLP field,Xia *et al.* proposed the ARNN model which uses the Attention method to assign different weights to the user's check-in information at different time periods [13], and this model can treat the user's behavior preferences differently. Li *et al.* uses the Word2Vec method which widely used in the field of NLP [2]. It embeds the user's item interaction sequence and inputs the learned embedding into the subsequent LSTM neural network, which achieves excellent traditional product recommendation.

III. THE PROPOSED MODEL: SGBA

In this section, we introduce the SGBA model which is a next-POI recommendation model based on heterogeneous graph embedding and LSTM. We first introduce preliminary knowledge about Next-POI, DeepWalk and graph embedding and clarify the definition. Then we describe the main process of H-Deepwalk. Finally, we propose the method of Discriminative Scale User Preference Learning.

A. PROBLEM DESCRIPTION AND PRELIMINARIES

Next-POI recommendation [14]: In the LBSN scenario, when a user check-in at multiple POI points, the user's check-in sequence is generated. The context of these check-in sequences reflects the user's daily behavior preferences. We define the check-in records for all users as the set C, which is $C = S_1, S_2, \cdots, S_n$, where $|C| = n$ is the total number of users. Each user has a $S_i \in C$, where $S_u = p_1, p_2, \cdots, p_n$,$p_i$ is the i POI location checked by the user u. The Next-POI recommendation is a task that recommends the next point of interest to the user based on user history check-in data, similar to the Next-item recommended task.

DeepWalk [4]: DeepWalk learns a social representation of a network by truncating random walks and outputs the vector representation of the vertices in the network, and it's input is a graph $G = (V, E)$. Deepwalk obtains a sequence of graph nodes by random walk.

Graph embedding [5]: Graph embedding is a method to map each node $v \in V$ in the graph into a low-dimensional vector space R^d, that is, learn a function map $f_G : V \to R^d$, where $d \ll |V|$.

LSTM (Long-Short-Term Memory) [15]: LSTM is an artificial recurrent neural network architecture used in the field of deep learning. LSTM networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series. For the sequence $S_u = p_1, p_2, \cdots, p_n$, LSTM can effectively extract the features in the sequence, so that the sequence information of each sequence S_u is retained in the hidden layer of LSTM.

TABLE 1. Symbol table.

Symbols	Description
C	Check-in set for all users
U	Set of all users
P	Set of all POIs
E_{UU}	Set of all POI points
E_{PP}	Edge set of POI
E_{PU}	Edge set of all users' POI
p_i	The i-th POI point
P	The check-in POI set
VS	The pseudo sequence
S_i	Check-in sequence for user i
BE	block embedding set i
G	A heterogeneous map of LBSN that contains user social relationships and POI geographical relationships
v	Check-in sequence for user u
D_δ	Block check-in sequence distance threshold
D_τ	Block check-in sequence time threshold
$N(.)$	Normal distribution random generation function
$exp(.)$	Exponential function
α	The times of Random Walk
θ	The threshold of the distance of the POI point which selected by Random Walk
β	Maximum length of pseudo sequence generation
$\sigma(.)$	Sigmoid function
$start(.)$	Functions of taking the block head POI
$end(.)$	Functions of taking block tail POI
$tanh(.)$	Hyperbolic tangent function

Definition 1 (Pseudo Sequence): It is a sequence obtained by sampling the real world dataset. This sequence does not exist in real-world datasets, but the distribution roughly conforms to the distribution of real-world datasets. Thus this sequence can complement the sparse dataset.

Definition 2 (Block): For the user u_i, there is a historical POI check-in sequence S_i. Users who check-in a location within a region have high probability to attend locations that are proximate, so the sequence S_i has significant regional proximity. There is a check-in sequence SP_i and the distance of each POI in the sequence does not exceed the threshold D_δ and the check-in time for each POI in the sequence does not exceed the threshold D_τ. $C_i = SP_1 \cup SP_2 \cup \cdots \cup SP_n,\ SP_i \cap SP_j = \varnothing$, where SP_i is called a block.

B. POI EMBEDDING BASED ON H-DEEPWALK

POI embedding is the first stage in our SGBA model. One-hot encoding is widely used in traditional embedding methods. However, this One-hot encoding cause huge computational overhead. Another method is the implicit vector embedding. But implicit vector embedding is greatly dependent on the subsequent neural network, thereby leading to loss of information and degraded computational performance of the model.

According to the traditional idea of item-based collaborative filtering, there is also a feature that the user has a higher probability of accessing the POI visited by his/her

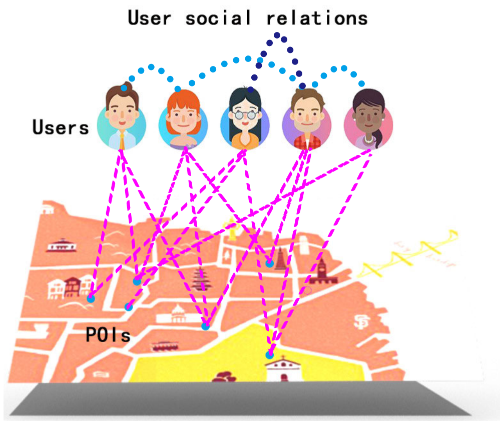

FIGURE 1. LBSN Heterogeneous Graph.

friend in the POI recommendation [16]. Therefore, we propose POI embedding based on H-DeepWalk for SGBA model to embed the input information representation, this means POI embedding based on H-DeepWalk generates the user's pseudo POI check-in sequence through the LBSN heterogeneous network.

Inspired by the DeepWalk method, H-DeepWalk learns the embedding representation of POIs in heterogeneous graphs by random walk and Skip-gram with Negative Sampling. Based on the user's check-in dataset, we first construct an LBSN heterogeneous graph, which contains the user's social relationship and the geographical relationship of the POI. This is shown in Figure 1.

H-DeepWalk intend to generates user POI check-in pseudo-sequence on the heterogeneous graph $G = (U, P, E_{UU}, E_{PP}, E_{PU})$. Firstly, H-DeepWalk inserts a POIp_i in the check-in set P into the pseudo sequence VS_i. Then it extract the user u_i in the check-in set $U_{u \in E_P U(p_i)}$ according to the normal distribution $N(.)$. It randomly walks α times on the graph $G_U = (U, E_{UU})$ and uses the $N(.)$ to extract the POI p_j in the check-in set $P_{p \in E_{PU(u_{i+\alpha})}}$ of the user u_j obtained by random walk. The geographic distance between p_i and p_j does not exceed the threshold θ and then p_j is inserted into VS_i, H-DeepWalk repeats the above steps for β times. Thus, a pseudo sequence VS_i of length β is obtained for the POI point p_i, and the algorithm is as follows.

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 point of the p_i point 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 [17], we can obtain the maximization objective function as follows.

$$argmax\ opt = \frac{1}{\beta}\sum_{i=1}^{\beta}\sum_{j \neq i}^{\beta} log\ p(x_j|x_i) \tag{1}$$

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

$$p(x_j|x_i) = \frac{exp(w_i^T * v_j)}{\sum_{\beta} exp(w_i^T * v_\beta)} \tag{2}$$

Algorithm 1 Heterogeneous Graph Random Walk Algorithm

Input: Heterogeneous graph G, Geographic distance threshold θ, The numbers of random walks α, Pseudo sequence length β

Output: Pseudo-sequence set for all usersVS

```
Initialization set VS
for all p_i ∈ P do
    Initialization set VS_i
    for j = 0; j < β; j++ do
        Insert p_i into the pseudo sequence VS_i
        Extract user u_i in the set U_{u∈E_P U(p_i)} according to the
        normal distribution N(.)
        Randomly walk α times on the G_U = (U, E_U U) to
        get the user u_j
        Use the N(.) to extract the POI point p_j in the check-
        in set P_{p∈E_{PU(u_{i+α})}} of the user u_j, where p_i and p_j
        The geographic distance between does not exceed
        the threshold θ
        Insert p_j into VS_i
    end for
    Insert VS_i into VS
end for
return VS
```

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 $\nabla(x_j|x_i)$ is hard to calculate. According to the Skip-gram negative sampling method proposed by Tomas [18], the formula 2 is modified as follows:

$$p(x_j|x_i) = \sigma(w_i^T * v_j)\prod_{k=1}^{E}\sigma(-w_i^T * v_k) \tag{3}$$

where $\sigma(.)$ is the Sigmoid function, ie $\sigma(.) = \frac{1}{1+exp(-x)}$, and E is the negative sample for each positive sample. The more times x_i appears in the check-in total C, the smaller the probability of being sampled, so we get the final objective function:

$$\begin{aligned} argmax\ opt &= \frac{1}{\beta}\sum_{i=1}^{\beta}\sum_{j \neq 1}^{\beta} log\ p(x_j|x_i) \\ &= \frac{1}{\beta}(\sum_{i=1}^{\beta}\sum_{j \neq i}^{\beta} log\sigma(w_i^T * v_j) \\ &\quad + \sum_{k=1}^{E} log\sigma(-w_i^T * v_k)) \end{aligned} \tag{4}$$

By this way, we can obtain high-quality POI embedding representations that integrate user social information and POI geographic location information via H-Deepwalk. The significance of this model is that the social information and geographic location information in the embedding representation we obtain are in a unified embedding space so that the subsequent neural network can effectively measure and

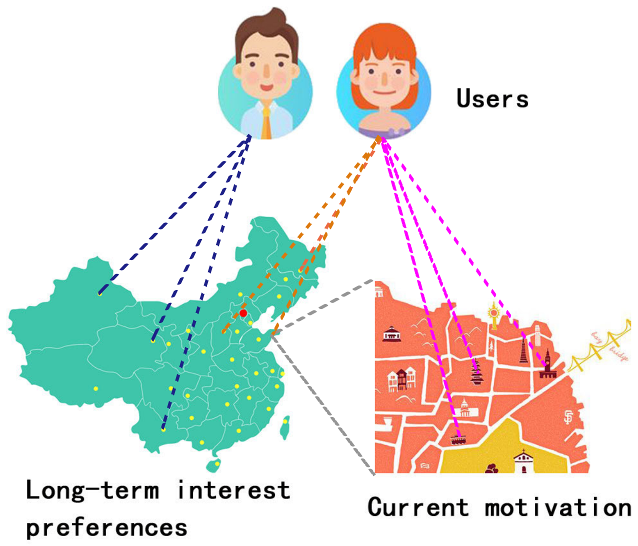

FIGURE 2. User Check-in Behavior.

adjust the embeddings. Finally, for each user u_i, we can use the embedding matrix combined with the check-in record to generate a POI history check-in embedding sequence $V_u = v_1, v_2, \ldots, v_n$, where v_i represents the d dimension embedding vector of x_i.

C. DISCRIMINATIVE SCALE USER PREFERENCE LEARNING

1) CHECK-IN SEQUENCE SCALE DIVISION

After obtaining the embedding representation of the POI, the Discriminative Scale Check-in Learning (DSCL) can use the check-in sequence as a priori knowledge to recommend POI that users are likely to be interest in.

As can be seen from Figure 2, a user's decision to reach a POI is mainly affected by two points: his/her current motivation and long-term interest preferences for different POI. Moreover, the user's travel motivation changes dynamically with time, and the recently checked POI will also have an important impact on the user's short-term preference. In this model, we divide the user's check-in sequence into two scales, short-term transfer sequence and long-term transfer sequence. At the same time, we consider that the user's historical check-in record does not fully represent the change of user's preference. We put the start and end of short-term transfer sequence into long-term transfer sequence and treat long-term transfer sequence as user's long-term transfer preferences.

Based on this, we develop a separate deep neural network structure based on LSTM. The user's interaction with the POI is a sequence, so we use LSTM to capture the dependencies between sequences [2]. Thereby, the long-term preference feature and the short-term preference feature of the user are extracted and unified in the same feature space.

2) SHORT-TERM TRANSFER SEQUENCE LEARNING

The short-term transfer sequence model focuses on the change of POI transfer within a block, which also reflects the POI check-in preferences of users in the recent period of time. According to the POI check-in sequence $C_i = p_1, p_2, \ldots, p_n$, we obtain user's check-in sequence. Short-term transfer sequence Learning combines the embedding matrix to get the embedding sequence $P_i = v_1, v_2, \ldots, v_n$ and obtain the block embedding set $BE = ((v_1, v_2, \ldots, v_j), (v_{j+1}, v_{j+2}, \ldots, v_k), \ldots, (v_{k+1}, v_{k+2}, \ldots, v_k))$.

In order to obtain the user's short-term transfer features, we use LSTM to learn the user's current POI transfer preferences. After initialization, the loop learns the j step, where the hidden layer is h_j, and the hidden layer h_j is updated by the previously hidden layer h_{j-1}, and the current input is embedding in v_j The LSTM model formula is as follows:

$$\begin{aligned}
f_j &= \sigma(W_f * [h_{j-1}, x_j]) + b_j \\
i_j &= \sigma(W_i * [h_{j-1}, x_j]) + b_i \\
\tilde{C}_j &= tanh(W_C * [h_{j-1}, x_C]) \\
C_j &= f_j * C_{j-1} + i_j * \tilde{C}_j \\
o_j &= \sigma(W_o * [h_{j-1}, x_j]) + b_o \\
h_j &= o_j * tanh(C_j)
\end{aligned} \tag{5}$$

where i_j, f_j and o_j are the input gates, the forgotten gate and the output gate for the j step. v_j is the embedded vector of the POI, c_j is the memory gate for remembering historical information, b is the bias term, and h_j is the hidden layer output of the j step. We use h_t as the final output of the LSTM and input it into a fully connected layer with the following formula:

$$P_{STPL} = W_{STPL} * h_j + b_{STPL} \tag{6}$$

So far we have the Next-POI prediction probability of the short-term transfer sequence.

3) LONG-TERM TRANSFER SEQUENCE LEARNING

The long-term transfer sequence model focuses on block-to-block transfer preferences, which can be seen as large fluctuations in user POI preferences. The method of obtaining the long-term transfer sequence is defined as follows:

$$D_{LTSL}(v_i, p_i, SP) = \begin{cases} p_i = start(SP_j) \\ p_i = end(SP_j) \end{cases} \tag{7}$$

Among them, $start(.)$ and $end(.)$ are functions of taking the block head POI and the block tail POI. The LSTM structure of the long-term transfer sequence learning model is the same as the short-term transfer sequence learning model, which uses LSTM to extract transfer behavior features and the last hidden h_j as the output of the LSTM. Finally LTSL input the output into a fully connected layer. The definition is as follows:

$$P_{LTPL} = W_{LTPL} * h_j + b_{LTPL} \tag{8}$$

Now we obtain the predicted probability of the long-term transfer sequence.

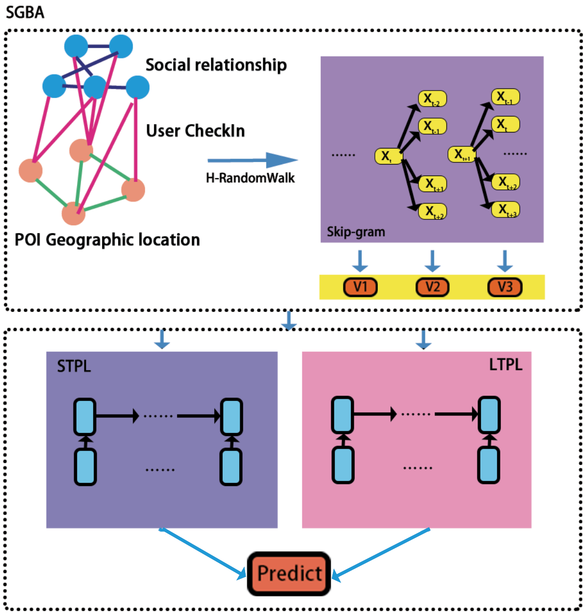

FIGURE 3. SGBA Model.

D. MODEL LEARNING OBJECTIVE FUNCTION

The outputs of the above models, P_{STPL} and P_{LTPL}, are a probability vector representing the probability of occurrence of the last POI of C_i. So we define the final probability prediction formula as follows:

$$P_{SGBA} = \gamma \odot P_{STPL} + (1-\gamma) \odot P_{LTPL} \tag{9}$$

where γ is a hyperparameter, which is used to adjust the influence coefficient of long-term transfer preference and short-term transfer preference, this parameter is set empirically in the experiment. P_{SGBA} is our final predicted probability vector for Next-POI, and we use Softmax for normalization calculation. SGBA uses Cross Entropy to calculate the loss and the formula is defined as follows:

$$y_i' = \frac{exp(x_i)}{\sum_j exp(x_j)}, \quad x_i, x_j \in P_{SGBA} \tag{10}$$

$$Loss_{SGBA} = -\sum_i y_i' log(y_i) \tag{11}$$

IV. EXPERIMENTAL EVALUATION

We demonstrate the effectiveness of our proposed framework from the following aspects:

1) The comparisons of baseline recommendation performance.
2) The analysis on cold-start scenarios and interpretability problem.
3) Analysis of the effects of different hyperparameters on the model results.

A. DATASET AND EXPERIMENT SETTINGS

We used two real-world datasets, Gowalla and Brightkite.

Gowalla is a location-based social networking site that users share their location by check-in. Among them, the user's social network is an undirected graph, and the data which includes the check-in records of Gowalla users from February 2009 to October 2010 is collected by Stanford's SNAP team through Gowalla's public API.

Brightkite is an LSBN-based network service provider that users share their geographic location by check-in. Among them, the user's social network is an undirected graph, and the data which contains the sign-in records of Brightkite users from April 2008 to October 2010 is collected by Stanford's SNAP team through the Brightkite public API.

The density calculation formula for the data Gowalla and Brightkite is as follows:

$$Density = \frac{|Check-In|}{|Users| \times |POIs|} \tag{12}$$

The dataset processing and the final model iteration learning are all done on the same machine. The experimental platform hardware configuration is as follows: QuadCore Intel Xeon E3-1230 v3, 16336 MB, GeForce RTX 2070. Experimental platform software configuration is as follows: Python (3.6.7), Pandas (0.24.2), Numpy (1.16.4), Tensorflow (1.13.0- Dev20181226).

B. COMPARATIVE MODELS AND PERFORMANCE INDICATORS

For each user in the test set, we treat all the POI that the user has not checked in as the negative items. Then each model outputs the user's check-in probability of the target POI. To evaluate the effectiveness of model, we adopt three widely used evaluation metrics: ACC, AUC and Recall. We evaluate the average user AUC as following:

$$AUC = \frac{1}{|U^{Test}|} \sum_{u \in U^{Test}} \frac{1}{|I_u^+||I_u^-|} \sum_{i \in I_u^+} \sum_{j \in I_u^-} \delta(p_{\hat{u},i} > p_{\hat{u},j}) \tag{13}$$

where $p_{\hat{u},i}$, and $p_{\hat{u},j}$ are the prediction probability for the positive case and the negative case. δ is the indicator function.

To illustrate the effectiveness, we compare our SGBA with the following methods:

1) **BPR-MF** [19]: The Bayesian Personalized Ranking was proposed by Rendela in 2009. This model trains the positive and negative examples of the user's interactive project and maximizes the difference posterior probability of the same user. The advantage of BPR-MF is that it can mine the user's potential association with the item, but not in complex scenarios and large numbers of interactions.
2) **LSTM-Rec** [20]: LSTM-based POI recommendation system we implemented. Different from the LSTM recommendation model proposed by Zhang in 2014, we use the implicit semantic embedding method to make the embedded project effectively participate in the gradient adjustment of the subsequent neural network. LSTM has good performance for processing sequence data, but is limited to the model itself, making it difficult to incorporate more side information.

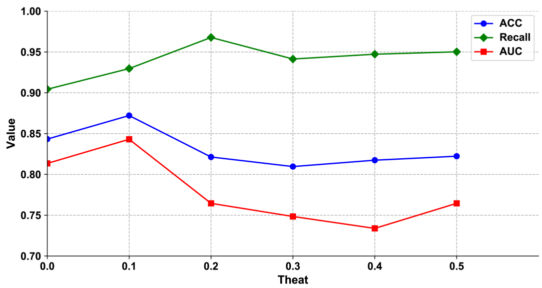

FIGURE 4. Performance of SGBA under different Theta.

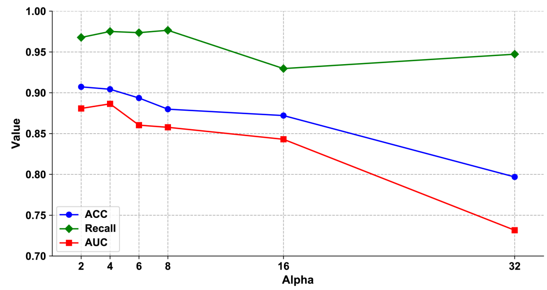

FIGURE 5. SGBA performance at different random walk times.

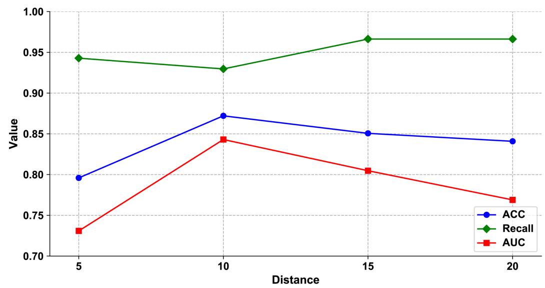

FIGURE 6. SGBA performance at different distances.

3) **ST-RNN** [21]: ST-RNN can model local temporal and spatial contexts in each layer with time-specific transition matrices for different time intervals and distance-specific transition matrices for different geographical distances. ST-RNN can better distinguish between user preferences over time periods, but it does not take into account the geography of POI and the user's social relationships.
4) **ATRank** [22]: Heterogeneous user behaviors are considered in ATRank that project all types of behaviors into multiple latent semantic spaces, where influence can be made among the behaviors via self-attention. Downstream applications then can use the user behavior vectors via vanilla attention.

By default, we allocated a 64-size embedding space for the POI and the user in BPR-MF. For LSTM-Rec, we use a 128-size embedding space, initial learning rate is 0.001 and negative sampling is 2. The parameters of our model as follows: α is 16, β is 64, θ is 10km, POI embedding size is 128, initial learning rate is 0.001, batch size is 32, LSTM maximum sequence length is 20, the number of LSTM hidden layers is 128.

1) MODEL COMPARISON

In the experimental results of Tables 3 and 4, we can see that the performance improvement of SGBA is particularly obvious on the sparse Gowalla dataset. The recommended performance for dense data sets has not decreased, so the SGBA model is robust and can be used for POI recommendation tasks on sparse data sets and dense datasets.

2) HYPERPARAMETER ADJUSTMENT

1) Long-short-term Harmonious
We can see from Figure 4. The model works best when θ is set to 0.1, which means that the user's long-term transfer sequence will also affect the user's Next-POI point decision. But users' long-term preferences are less influential. When θ is set to 0.1, although Recall does not reach the maximum value in the current chart, but ACC and AUC reached 87.207% and 84.2997% respectively. This indicates that the accuracy and robustness of the model are maximized under the current hyperparameters.
2) Random Walk Step
We can see from Figure 5. The model works best when α is set to 4, which means that a user's friend trust does not spread very far. The influence of users' friends on users decreases with the increase of friend dimension. When the random walk range is 4, the model not only retains the influence of users' friends on users, but also mines users' interest range as much as possible.
3) Distance Threshold
We can see from Figure 6. The model works best when distances is set to 10, which means that POI points within 10 km are highly correlated. This hyperparameter setting needs to work with different data sets. When the distance threshold is set to 10km, SGBA model performs best on the Gowalla data set, which reflects the distance correlation of POI points in the Gowalla data set.

3) INTERPRETABILITY AND COLD-START ANALYSIS

As we seen from Figure 7 and Figure 8, by using the H-DeepWalk method, the POI points on Gowalla and Brightkite reflect significant aggregation on the T-SNE view. The boundary between clusters is very obvious, indicating that different kinds of POIs are effectively distinguished. So that the user's social relationship and geographical relationship are also effectively reflected in POI embedding. This proves the effectiveness of the H-DeepWalk method.

From the T-SNE view we can see that the POI with similar features has this similar position in the embedded space, and the distant of POI points with different features be widened gradually. This explains the reason why the POI embedding method is effective. In other word, the POIs are close to each

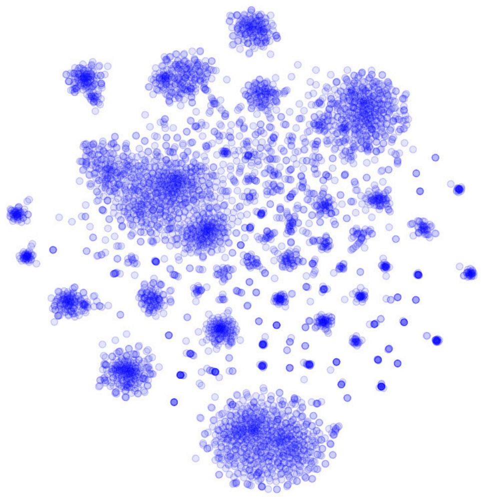

FIGURE 7. POI embeddings T-SNE view of the Gowalla dataset obtained by H-DeepWalk.

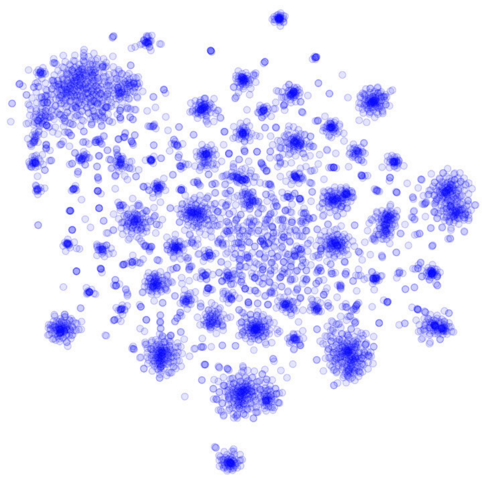

FIGURE 8. POI embeddings T-SNE view of the Brightkite dataset obtained by H-DeepWalk.

TABLE 2. Datasets Statistics.

Datasets	Gowalla	Brightkite
Total number of check-ins	6442892	4747281
Amount of users	107092	51406
Amount of POIs	1280969	772966
Dataset density	4.6966e-5	1.1947e-4

other and have similar geographical locations that are embedded in the adjacent embedding spaces, and the different POI will be farther apart in the embedding space. Thus, POI that are relatively adjacent in the embedding space have a higher probability of appearing in the Next-POI recommendation task.

In this paper, we use Gowalla and Brightkite datasets. From Table 2, we can see that the sparsity of the Gowalla dataset is an order of magnitude higher than that of Brightkite. In this experiment, the Gowalla dataset is treated as a sparse dataset.

TABLE 3. Performance on Gowalla.

Model	ACC	Recall	AUC
BPR	0.566232	/	0.698100
LSTM-Rec	0.724609	0.726686	0.717561
ST-RNN	0.849918	0.9040928	0.811500
ATRank	0.826626	0.710352	0.749477
SGBA	**0.872070**	**0.929618**	**0.842997**

TABLE 4. Performance on Brightkite.

Model	ACC	Recall	AUC
BPR	0.525279	/	0.579400
LSTM-Rec	0.828765	0.893343	0.791086
ST-RNN	0.858796	0.873867	0.809028
ATRank	0.851107	0.808686	0.810252
SGBA	**0.8652344**	**0.919354**	**0.838332**

TABLE 5. Performance change rate on Gowalla.

Model	ACC	Recall	AUC
BPR	/	/	/
LSTM-Rec	+27.97%	/	+2.79%
ST-RNN	+17.29%	+24.40%	+9.39%
ATRank	-2.74%	-26.65%	-7.64%
SGBA	**+5.50%**	**+30.87%**	**+12.48%**

TABLE 6. Performance change rate on Brightkite.

Model	ACC	Recall	AUC
BPR	/	/	/
LSTM-Rec	+57.78%	/	+36.53%
ST-RNN	+3.62%	-2.18%	+2.27%
ATRank	-0.90%	-7.46%	+0.15%
SGBA	**+1.66%**	**+13.68%**	**+3.46%**

We did not manually sample the dataset to achieve sparsity comparison in order to ensure that the authenticity of the dataset, manual sampling may destroy the true distribution of the dataset.

The test data from Table 3, Table 4, Table 5 and Table 6 respectively show the performance of the SGBA model on sparse data sets and dense data sets. SGBA has an ACC increase of 20.35% on the Gowalla dataset when compared to LSTM-Rec and the AUC is 27.76% higher than the BPR. It shows that the SGBA model has good predictive performance even on sparse data sets. When compared with the performance changes of the SGBA model on the Gowalla and Brightkite datasets, there is no significant performance degradation. It also proves that the SGBA model has good robustness in the face of different datasets.

V. CONCLUSION AND FUTURE WORK

In this paper, we propose a novel framework, namely SGBA, which combines the user's social information and the geographical location information of the POI with the check-in sequence information of the user's POI. The heterogeneous graph of LBSN contains a large amount of users' social information and POI's geographical location information. Along this line, we first used h-deepwalk method to obtain users' social information and POI's geographical location information from the heterogeneous graph of LBSN. Then we respectively developed LSTM-based neural networks to learn personal long-term preferences and short-term preferences. Finally, the SGBA model achieved excellent Next-POI recommendations on two publicly available real datasets, demonstrating the validity of our proposed model.

In the future, we will further explore how to utilize more side information of POI learned from POI knowledge graph to improve the next POI recommendation performance.

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