POI Recommendation Model Using Multi-Head Attention in Location-Based Social Network Big Data

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ABSTRACT

A point of interest (POI) recommendation model using deep learning in location-based social network big data is proposed. Firstly, the features of POI are divided into inherent features composed of attributes such as geographical location and category, and semantic features of relevance composed of spontaneous access by users. Secondly, the inherent attribute features and semantic features of POI are extracted by constraint matrix decomposition and word vector model respectively, and the two hidden vectors are spliced into the feature vectors of POI to solve the problems of data sparsity and cold start. Finally, the multi-head attention is used to obtain the key information of user preferences, and a deep learning recommendation framework is constructed to model the nonlinear interaction between features. Experiments show that when the recommendation list is 10, the precision and recall of the proposed method are 0.118 and 0.135 respectively, which are better than the comparative recommendation method.

KEYWORDS

Big Data, Deep Learning, Recommended Model, Multi-Head Attention, Points of Interest, Social Network

INTRODUCTION

The rapid development of information technology has made the digitization of human mobile behavior and sharing with friends easier (Xu et al., 2020). Many social media platforms of location-based social networks (LBSNs), such as Twitter, Facebook, Instagram and Foursquare abroad, Public Comments, and Alibaba Koubei in China, have become increasingly popular and are now everywhere in daily life (Feng et al., 2015; Yin et al., 2017). Users on LBSNs are willing to share their experience on POI with friends and make comments and scores (Qian et al., 2019). Users generate a large amount of data on these social media platforms, including text content with spatio-temporal information. The accumulation of massive user check-in data has given birth to the research on user recommendation POI (Yang et al., 2017). This information is particularly useful for understanding the user's behavior and preferences for POI (Chen et al., 2020; Yao et al., 2016). A POI is a specific location in which

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the user is interested. Mobile behavior can be used to understand and predict human movement and promote an individual's daily life experiences such as transportation and entertainment (Zhao et al., 2020). Many historical check-in data provide valuable information for service providers to help them understand users' preferences for the next actions (Zhang & Wang, 2016).

In recent years, with the rapid development and popularization of LBSNs, the number of their users has increased sharply (Islam et al., 2022). The acquisition and generation of POI information have exploded in geometric multiples. For example, Foursquare has more than 50 million active users, more than 8 billion POI signed in 2016, and Yelp has about 21 million users and 102 million comments with geographical coordinates (Guo et al., 2018). In this case, it leads to the "information overload" of the LBSN. For consumers, finding places of interest from massive POI will be interfered by redundant information. It would be difficult for businesses to make their locations stand out from a large amount of location information (Sun, 2021; Yang et al., 2017).

With the rapid development of LBSN services, users can check in real-world POI through mobile devices and share such check-in with friends to generate richer space, time, social, and content information to improve personalized POI recommendations (Hao et al., 2019; Wand et al., 2017). The deep learning method uses a large amount of data to train the model and mine the potential information from the data (Liu & Wu, 2021). Therefore, deep learning can better extract features and learn the high-order interaction between features. Hao et al. (2018) used the long short-term memory (LSTM) method to model the context sequence, determined the time series characteristics of users' access according to the spatio-temporal information of users' check-in records, and realized the prediction of users' next check-in POI. Xia et al. (2017) used recurrent neural network (RNN) to model the check-in sequence of users to realize personalized POI recommendations to users. Chang et al. (2018) proposed a content-aware hierarchical POI embedding model for POI recommendation using the characteristics of POI or the relationship between POI. The above-mentioned methods only use the user sign-in data and ignore the other information in LBSN. Feng et al. (2019) proposed a personalized recommendation method based on a deep interest network by capturing the dynamic characteristics behind user behavior. Liu et al. (2016) believed that the effective use of temporal and spatial context information could be helpful to predict the direction of users' access preference at the POI and proposed a spatio-temporal RNN recommendation model by extending the RNN. Zhang et al. (2021) combined content-based filtering with neural network-based collaborative filtering and proposed the collaborative filtering method DeepCCF based on deep learning for personalized resource recommendations. However, the above-mentioned algorithm does not consider the characteristics of user data and cannot effectively extract feature information from complex and diverse user data samples. Zhang, Wei et al. (2020) proposed a deep neural model based on transfer learning that integrated cross-domain knowledge to learn the complex user project interaction relationship and accurately capture the overall preferences of users for migration. Liu et al. (2021) proposed a personalized recommendation method based on the Seq2seq model of the LSTM network by combining personalized recommendation and collaborative filtering recommendation methods.

However, the above-mentioned methods can only extract shallow features and cannot extract deep features, resulting in low accuracy. To overcome the above problems, in this paper the author proposes a POI recommendation model based on the LBSN. The innovation of the proposed method lies in:

1. The features of POI are divided into inherent features composed of attributes such as geographical location and category and associative semantic features composed of spontaneous access by users. The inherent attribute and semantic features of POI are extracted by constraint matrix decomposition and word vector model, respectively, which significantly improves the feature extraction ability of the system.
2. The multihead attention mechanism is used to improve the ability of the model to obtain key information about users' preferences. A deep learning recommendation framework is developed,

the nonlinear interaction between features is modeled, and the accuracy of recommendation is improved.

The remainder of this paper is arranged as follows: The second section describes the problems the author studied; the third section explains the representation method of POI features; the fourth section provides the representation of user characteristics; the fifth section presents the proposed deep neural network recommendation framework; the sixth section details the experiments to verify the performance of the proposed model; lastly, the seventh section concludes the paper.

PROBLEM DESCRIPTION

Problem Definition

In this section, the author defines the user set $U = \left\{u_1, u_2, ..., u_p\right\}$, where 1~p are the indices of the users, and the location set is $L = \left\{l_1, l_2, ..., l_z\right\}$, where 1~z are the indices of POI locations. The comment information word set W is the vocabulary $W = \left\{w_1, w_2, ..., w_x\right\}$, where 1~x are the indices of the words. Each user uses C to represent their check-in history $C_u = \left\{c_1, c_2, ..., c_h\right\}$, where each check-in record c_i of the user u is composed of a tuple $c_i^u = \left\{l_i, t_i, s_i, p_i\right\}$. The check-in information indicates that the user u checked in at POI l_i at time t_i and commented on a sentence s_i at the same time. The sentence consists of a series of words commented by the user. Moreover, the check-in location is located at a position p_i, which is composed of longitude and latitude information α_i and β_i, respectively.

Given the top T check-in records of the user u, $\left(c_1, c_2, ..., c_T\right)$, the objective in this paper is to predict the next check-in location l_{T+1}:

$$y_i = f(l_i \mid c_1, c_2, ..., c_T, u) \tag{1}$$

where y_i is the POI l_i score calculated by the recommendation model. The final model will generate POI scores for all positions and select the top scores as the prediction results.

Definition of Input and Output of Point of Interest Recommendation Model

The input and output of the model in this paper take a subsequence approach. The maximum length of the subsequence of the user is m, and the value of m is set to 200.

The historical subsequence input for the user u in the model is $\left(c_1^u, c_2^u, ..., c_{m-1}^u\right)$. The historical subsequence output expected by the user u in the model is labeled as $\left(c_2^u, c_3^u, ..., c_m^u\right)$. This is a model setup where the sequence input corresponds to the sequence output.

REPRESENTATION OF POINT OF INTEREST FEATURES

Feature Extraction Based on Constraint Matrix Decomposition

In LBSNs, geographic location and category are inherent attributes of the POI. These attributes are important contents to describe the POI and directly determine the user's visit intention. A common description of the geographic location of POI is to directly express it according to latitude and longitude. Although this method is accurate for the representation of location information, the accuracy of expression makes the model ignore the spatial correlation of the POI. Likewise, the one-hot encoding of the categories of POI also struggles to capture the correlations between categories. Therefore, in this paper the author designs a model to jointly extract the geographic location and category features of the POI. Considering the spatial and attribute correlations of the POI, the author constructed a POI-POI geographic proximity matrix.

To express the spatial relevance of POI, the author defined a geographic proximity matrix $G \in N^{n \times n}$, where n represents the number of POI. To this end, the researcher set a spatial threshold m (km), and calculated the spatial distance between the interest points l_i and l_j first according to the latitude and longitude. If the distance is less than the threshold m, the value of the matrix $G_{i,j}$ is set to 1, otherwise, set to 0.

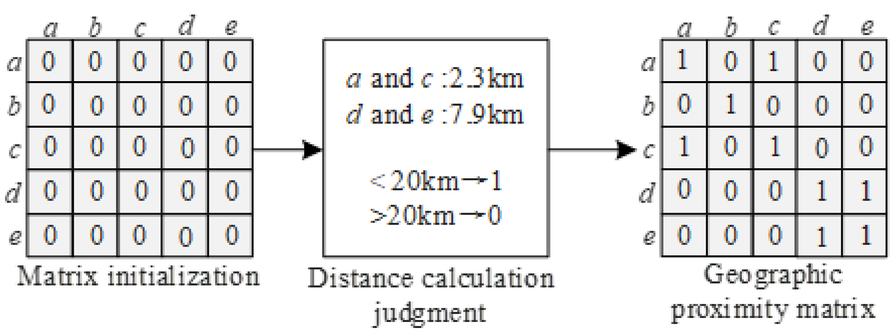
Figure 1 shows the detailed process of constructing the feature matrix. Figure 1 includes five POI from *a* to *e*, including the longitude, latitude, and category attributes to which they belong. Table 1 shows the category attributes and latitude and longitude values. Table 1 evidences that the category attributes of POI are not unique. First, the value of the geographic proximity matrix G is initialized to 0, and the size of the matrix is the number of POI, which is set to 5 in Figure 1. Then, the distance between POI is calculated according to the longitude and latitude of the POI. When the threshold m is set to 20km, the distances between *a* and *d*, and between *b* and *e* are all smaller than the threshold. In other words, the value of the corresponding position of the matrix is set to 1, indicating that the two are geographically related. Since the distance from POI to itself is also smaller than the threshold, the diagonal value is set to 1. At the same time, the POI with the same category is grouped into the same set to facilitate subsequent utilization.

Usually, the users' access preferences are concentrated in a certain area and a certain type of POI. In real life, the POI that are located in the same area with a short distance and similar category

Table 1.
POI Category Attributes and Latitude and Longitude Information

POI	Longitude	Latitude	Category
a	30.74	-70.12	Food
b	35.16	-120.07	Shop
c	33.5	-124.33	Movie
d	47.24	-78.23	Professional
e	24.63	-114.25	Service

Figure 1.
Feature Matrix Construction Process



attributes are more likely to be accessed. To express this correlation, the author proposed an improved constrained matrix factorization method. The category factors are added to matrix factorization as constraints to make the feature vectors of POI of the same category have higher similarity in order to combine geographical location and category features to represent POI. In the model training stage, the parameters of the model are trained by minimizing the following objective function:

$$L(G,E) = \frac{1}{2}\left(\chi_1 \left\|E\right\|_F^2 + \chi \left\|\sum_{i=1}^{N} E_i - \frac{1}{\left|C_i\right|}\sum_{v\in C_i} E_v\right\| + \sum_{i=1}^{n}\sum_{j=1}^{n} I_{ij}\left(G_{ij} - E_i E_j^T\right)^2\right) \tag{2}$$

where G represents the geographic proximity matrix constructed above and I_{ij} represents the value at the corresponding position of the matrix. If the spatial distance between l_i and l_j is less than the given threshold m, $I_{ij} = 1$, otherwise $I_{ij} = 0$. C_i is a similar set composed of POI that are spatially similar to l_i and belong to the same category. χ is used to constrain the normalization function. The purpose of the normalization function is to minimize the average distance between the target POI and the remaining POI feature vectors in the similar set, and ensure the similarity between the obtained feature vectors. χ_1 is used to control the regularization effect and is used to constrain the Frobenius norm of the latent feature matrix to prevent overfitting of the matrix.

To train the model, the stochastic gradient descent (SGD) method is used to iterate the objective function and optimize the model parameters. The first-order derivative of E_i in the optimization objective is:

$$\frac{\partial L}{\partial E_i} = \left(G_{ij} - E_i E_j^T\right)E_j^T + \chi\left(E_i - \frac{1}{\left|C_i\right|}\sum_{v\in C_i} E_v\right) - \sum_{\{v|v\in C_i\}} \frac{1}{\left|C_i\right|}\sum_{v\in C_i}\left(E_v - \frac{1}{\left|C_v\right|}\sum_{v\in C_v} E_w\right) + \chi_1 E_i \tag{3}$$

Once the parameters of the model are updated, a POI latent feature matrix E can be obtained. Each row represents the decomposed feature of the corresponding POI, that is, the original feature matrix is embedded into the feature space of dimension d. The value of d is much smaller than the scale n of POI, realizing the dimensionality reduction of features. After decomposing the normalized matrix, the eigenvector of the target POI l_i is the i row of the matrix E, which is denoted as $e_i^{g,c}$ for the convenience of marking.

Since the original matrix represents the spatial relationship of POI, in addition to its relationship with its neighbor POI, the spatial relationship meaning of dissemination is also included through the feature compression operation. It can reflect the spatial correlation between the target POI and other POI. At the same time, the addition of the normalization constraint of the same category to the matrix decomposition can also express the high similarity of POI of the same category within a specific region. Therefore, this method can efficiently preserve the potential associations of POI on spatial and category attributes. At the same time, feature extraction and dimensionality reduction are realized through the decomposition and reconstruction of the POI geographic proximity matrix. It can reduce the amount of calculation and the occurrence of overfitting of the subsequent model.

Feature Extraction Based on Word Embedding Model

The Word2vec word embedding model originated in the field of natural language processing. The model learns vector representations of words by maximizing the cooccurrence probability of words in the sequence. Skip-Gram uses the central word to predict surrounding words, and the input and output are in the form of word pairs during prediction. The number of model predictions is limited by the number of words and windows, and has better applicability to words that appear infrequently.

Firstly, in this study the author defined the user check-in sequence, target POI l_i, and context POI $C\left(l_i\right)$. Secondly, the researcher divided all the check-ins of the user u into time series to form user check-in sequences $M_u = \left\{C_u^1, C_u^2, \ldots, C_u^k\right\}$. Each check-in record can be represented by a triple $C = \left\langle u_i, l_j, t_k \right\rangle$, that is, the user u_i completes check-in at the location l_j and time t_k. Finally, the author selected a POI l_i in the user check-in sequence as the target POI. The POI at b positions before and after the target POI l_i are called its context POI, denoted as $C\left(l\right)$, where b is the predefined context window size. Moreover, the author used the Skip-gram algorithm to model the check-in sequences, and the method of negative sample sampling to improve the training speed of the model. Figure 2 shows the proposed network structure.

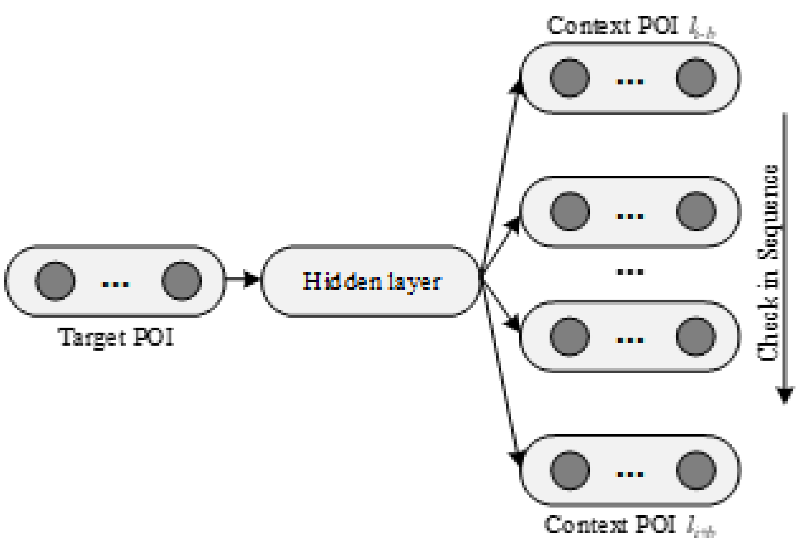
In Figure 2, l_i is the target POI, while l_{i-b} and l_{i+b} are the start and end points of the target POI context in the sequence, respectively. During the initialization, v_i represents the feature code of POI l_i.

By maximizing the cooccurrence probability of adjacent nodes in the sequence, the embedding representation of nodes can be learned so that the adjacent POI are similar in the feature space. Equation 4 expresses the objective of model maximization:

$$argmax \prod_{l \in L} \prod_{l_c \in C(l)} \frac{e^{v_{l_c}^T v_l}}{\sum_{x \in L} e^{v_x^T v_l}} \tag{4}$$

The loss function of model optimization is defined as:

Figure 2.
The Embedding of Target POI



$$loss = -\sum_{l \in L} \sum_{l_c \in C(l)} \left(\log \sigma \left(v_{l_c}^T v_l \right) + \sum_{l' \in neg(l)} \log \sigma \left(-v_{l'}^T v_l \right) \right) \tag{5}$$

where σ is the sigmoid activation function, $neg(l)$ represents the negative sample of the target POI l_i, and the size of the negative sample is set to be the largest. To ensure the accuracy of training, a small batch of data is used during model training. The parameters are updated using the SGD method to complete the training. The vector representation of the target POI l_i is obtained, which is spatially close to its context POI, and the influence of semantic features is obtained, denoted as e_i^s. All POI in the sequence are also embedded in a fixed dimension k, where the value of k corresponds to the size of the hidden layer.

POI Multifeature Representation

Given a POI $l_i \in L$, after the intrinsic attribute and semantic features of the POI are extracted by constrained matrix factorization and word vector model, respectively, the extracted embedding vectors are concatenated to aggregate all embeddings related to l_i. The overall characteristics of POI are expressed as:

$$e_i = \left[e_i^{g,c} e_i^s \right] \tag{6}$$

where $e_i^{g,c}$ and e_i^s represent the latent vectors of l_i in the geographic, category, and semantic feature spaces, respectively. By splicing these two latent vectors into the feature vector of POI, the recommendation method can simultaneously use the location, POI category and check-in semantic information of POI in the recommendation process. Thus, the problems of data-sparse and cold start are solved.

Representation of User Characteristics

To a certain extent, the places recently visited by users reflect the short-term interests and preferences of users. Modeling the users' short-term preferences is significant for understanding users' temporal preferences.

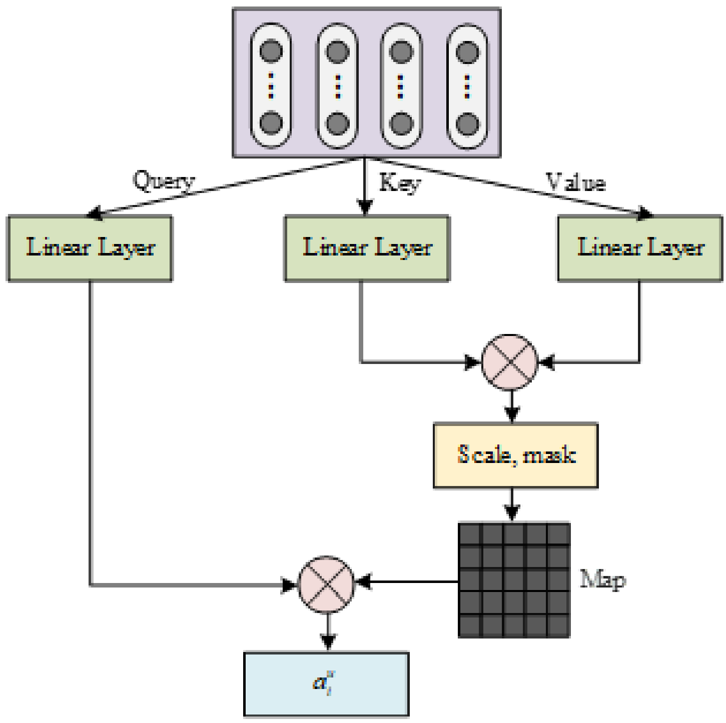
Figure 3 shows the attention module that constitutes the scaled dot-product attention mechanism. The inputs of the attention module are Query, Key, and Value, and the output is the sum of Value weights. The weight matrix is determined by Query and the corresponding Key value. In this section, Query, Key, and Value are the same, and they are all embedded vectors of sequences of locations, that is, matrix $M^{(u,t)}$.

If the researcher linearly transforms Query, Key, and Value, $Q' = W_Q M^{(u,t)} + b_Q$, $K' = W_K M^{(u,t)} + b_K$ and $V' = W_V M^{(u,t)} + b_V$, where W_Q, W_K and W_V are weight matrices and b_Q, b_K and b_V are biases, respectively.

The relationship matrix between locations can be obtained as:

$$R_t^u = soft\max \left(\frac{Q' K'^T}{\sqrt{d}} \right) \tag{7}$$

Figure 3.
Attention Module



At this point, the relationship between each location in the embedding matrix of the location sequence input is obtained, where $\sqrt{d}$ is used to scale the dot product attention. Finally, the final self-attention weight output is obtained by multiplying the calculated location relationship matrix with V':

$$a_t^u = R_t^u V' \tag{8}$$

where d is the embedding dimension. After a linear transformation, the output after the self-attention module can be obtained as:

$$M_t^u = M^{(u,t)} + a_t^u \tag{9}$$

RECOMMENDATION FRAMEWORK

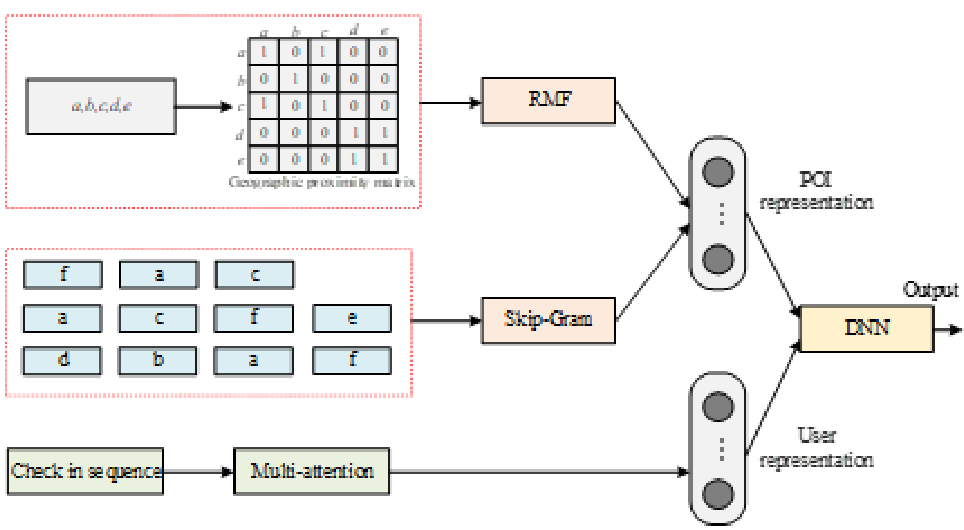
The features of POI are divided into inherent features composed of attributes such as geographical location and category, and semantic features of relevance composed of spontaneous access by users. After using constraint matrix decomposition and word vector model to extract the inherent attribute features and semantic features of POI. The user features with long-term preferences are obtained through the multihead attention mechanism. The results of POI features and user features can be used for similarity calculation to complete POI screening, friend recommendation, and other tasks. The commonly used similarity calculation methods include cosine similarity, Euclidean distance, and Jaccard coefficient. The cosine similarity method is used to express the consistency of feature vectors in the value direction, which is more suitable for POI screening. The inner product of the POI feature vector and user feature can also be used to calculate the recommendation results. However, preliminary experiments demonstrate that the vector inner product method is not suitable and unable to meet the expected requirements. Therefore, in this study the author designed a deep learning-based recommendation framework consisting of POI feature extraction and user feature extraction methods to further improve the accuracy of recommendations. The proposed framework takes the multifeature representation of POI and the user check-in feature based on the multihead attention mechanism as inputs and uses a deep network framework to fit the nonlinear interactions between users and POI. The neural network model uses the check-in data to construct the training dataset to complete the training and uses the SGD method to optimize the network parameters in the form of a Batch. Figure 4 shows the overall frame diagram of the proposed model.

The cross-entropy function is selected as the loss function for the training of the model, and its mathematical expression is:

$$L = -\sum_{(u,i)\in y^{+} \cup y^{-}} y_{ui} \log \bar{y}_{ui} + \left(1 - y_{ui}\right) \log\left(1 - \bar{y}_{ui}\right) \tag{10}$$

Since the users access only a small part of the POI, the number of negative samples is much larger than the number of positive samples. To achieve quick model convergence, the author used the negative sampling enhancement method and dropout strategy to train the model. The researcher generated the negative samples by randomly selecting some users who had not been visited from the POI set accessed by users' friends. The number of negative samples was set to 25. The random discard ratio of neurons in the dropout strategy was set to 0.8 to reduce the occurrence of the overfitting phenomenon. The fully connected layer adopted the structure of three hidden layers, and the input dimension of the first layer was 256. The number of hidden layer nodes in each layer was set in a manner that the number of nodes in the previous layer was twice the number of nodes in the next layer.

Figure 4.
The Overall Frame Diagram of the Proposed Model



The number of nodes in the embedded layer was twice the prediction factor of the model. The output layer activation function was Sigmod and the other layers used ReLU as the activation function. This model was trained by the sequential learning method, and all models were not trained end-to-end. The advantage of the proposed model is that the feature learning module and the recommendation system module are independent of each other.

EXPERIMENT AND ANALYSIS

Experimental Dataset

The experimental data was the BrightKite public dataset. BrightKite is an LBSN service provider. The check-in location dataset included 4491143 check-in records of Brightkite users from April 2008 to October 2010. The friend relationship network was composed of 58228 nodes and 214078 link edges.

The BrightKite dataset was preprocessed. The records with zero locations were removed. The records with less than 10 users and less than two different location points corresponding to each user were removed. The location records of continuous and repeated check-in of each user were removed and then the users without check-in records in the friend relationship network were removed. Next, cold start user dynamic data processing was performed. Based on the above normal user dataset, the sign-in records of users whose sign-in record was greater than 9 were randomly deleted until the number of user records was equal to 9. Specifically, the number of visits to each location in the training set was counted and the user record was deleted according to the location. Deleting it once would reduce the number of visits to the location by 1. When the number of visits to the location was equal to 2, that location was not deleted. The users who had no check-in record in the friend relationship network were deleted.

To divide the dataset into training and test sets, the places visited by each user were sorted according to time, the last place visited by each user was taken as the test set, and deleted from the training set accordingly. This is because it was necessary to ensure that the test set location of a user must be a location that the user has not visited before. The experiment was run on the server in the following hardware environment: Intel Xeon CPU E5-2630 @ 2.5GHz, 128G RAM and 1.5T hard disk. The running system was ubuntu-16.04, and the experimental code was in Python 3.

Evaluating Indices

To accurately evaluate the performance of each model in the POI recommendation task, in this study the author adopted two evaluation indices: Recall@K and Precision@K, where K represents the length of the recommendation list. To accurately evaluate the impact of different list lengths on the recommendation results, the author selected the report list length to take the values of each evaluation index at 5, 10 and 15. Recall is an important evaluation index in recommender systems. It represents the recall rate of the recommended items, indicating how many of all the items that need to be recommended are recommended. For each user u, recommend POI in the dataset that they have not visited and the Recall@K recommended by POI is:

$$\mathrm{Re}\,call\,@\,K = \frac{\sum_{u_i \in U} \left| P\left(u_i\right) \cap T\left(u_i\right) \right|}{\sum_{u_i \in U} \left| T\left(u_i\right) \right|} \tag{11}$$

where $P\left(u_i\right)$ represents the POI list generated by the model for the user u_i and $T\left(u_i\right)$ represents the list of POI visited by the user u_i on the test set.

For each user u, recommend its unvisited POI in the dataset, and the Precision@K of POI recommendation is:

$$\Pr ecision@K = \frac{\sum_{u_i \in U} \left| P\left(u_i\right) \cap T\left(u_i\right) \right|}{\sum_{u_i \in U} \left| P\left(u_i\right) \right|} \quad (12)$$

Convergence Analysis of the Model

In the case of Top K=10, Figure 5 shows the loss curves of the proposed method on the BrightKite dataset. It can be seen from the figure that the loss value of each type of user first decreases rapidly, then decreases gently, and finally tends to a certain value. The last converged value of cold-start users is lower than that of normal users. This is because the proposed method combines two latent vectors of geographic, category and semantic features into feature vectors of POI. The proposed recommendation method can simultaneously utilize POI's geographic location, POI category and check-in semantic information in the recommendation process, thus solving the problems of data-sparse and cold start.

Parametric Analysis

It is necessary to study the influence of the embedding dimension *k* on the performance of the proposed method, and it is necessary to choose the appropriate embedding dimension. To this end, the researcher conducted a large number of experiments on the BrightKite dataset with different embedding dimensions. The author compared the transfer learning (Zhang, Wei et al., 2020) and the CBF-NCF method (Zhang, J. et al., 2021) with the proposed method. The author used the evaluation indicators Precision@5 and Recall@5 to verify the impact of embedding dimension on the performance of each method. Figures 6 and 7 show the experimental results.

As Figures 6 and 7 evidence, the effects of the embedding dimension on the performance of the three methods are similar. When the embedding dimension *k* is low, it is difficult for the models to dig out the deep essential features of users and POI, and the performance is not ideal. With the gradual increase of the embedding dimension *k*, the performance of the models shows an upward

Figure 5.
Loss Curves of Normal and Cold-Start Users on BrightKite Dataset

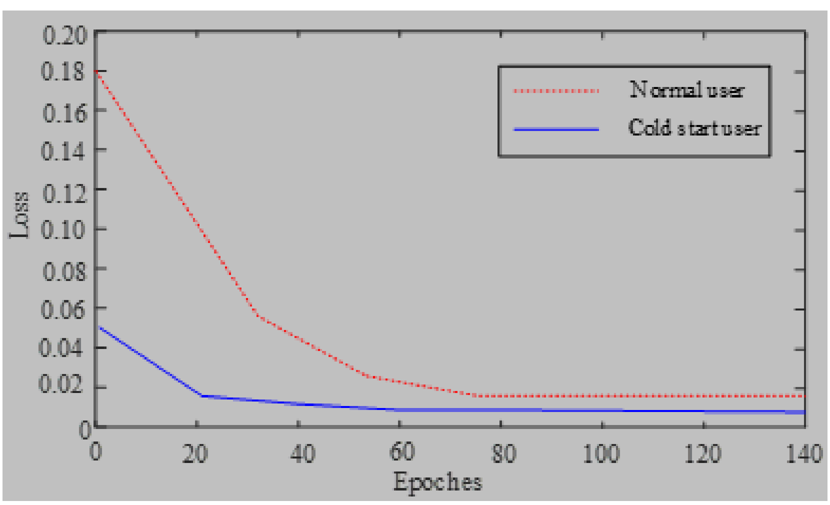


Figure 6.
Impact of Dimension k on Precision on BrightKite Dataset

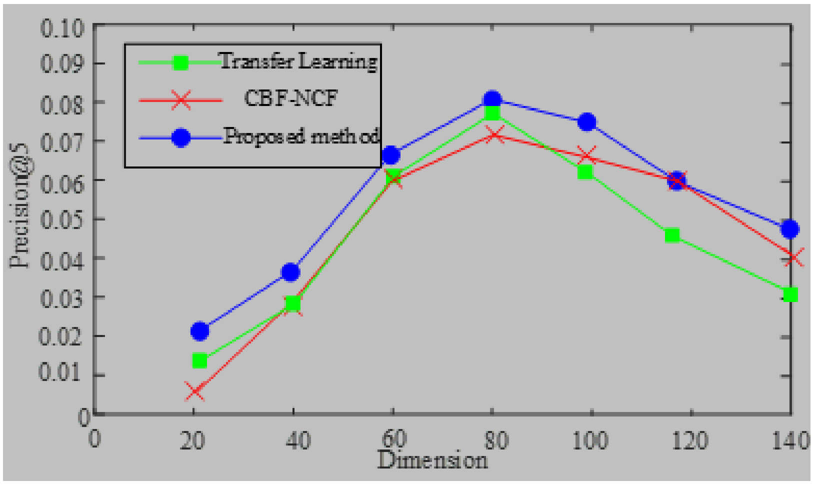
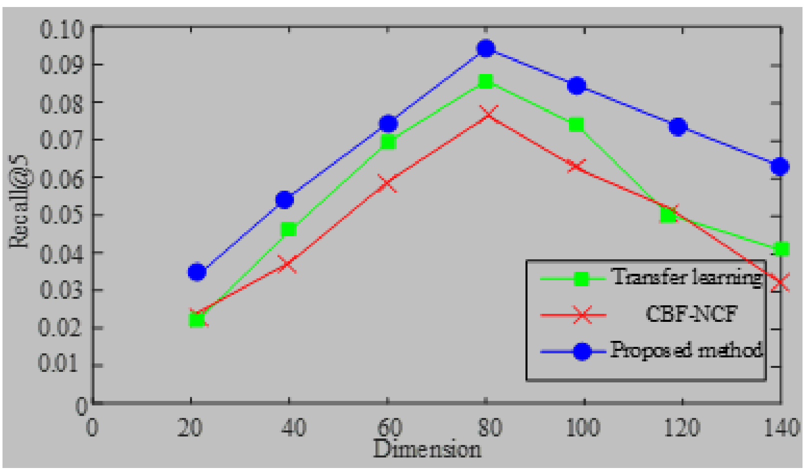


Figure 7.
Impact of Dimension k on Recall on BrightKite Dataset

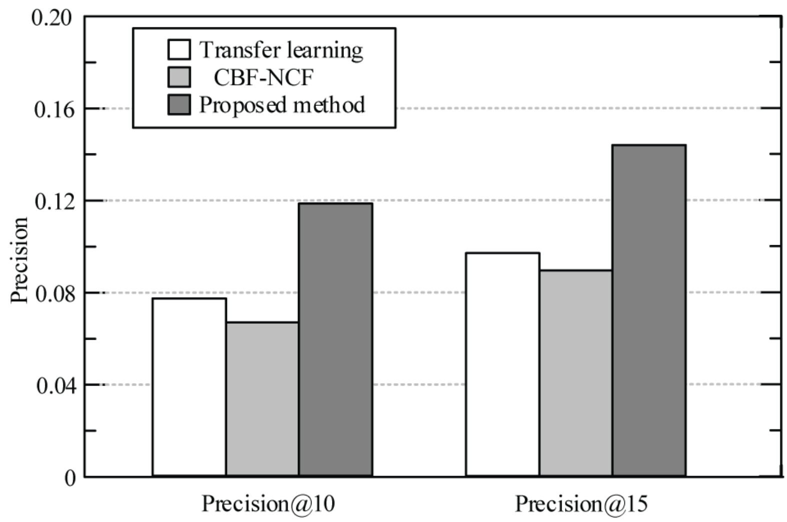


trend. The proposed model achieves the best effect when the value of k is 80. However, with the further increase in embedding dimension, the performance of the proposed model starts to decrease. This is because when the embedding dimension is too large, the model's feature extraction is too abstract, resulting in overfitting. Therefore, the author finally chose to set the dimension k to 80 to balance the performance and efficiency of the model. The author completed the rest of the comparison experiments under this parameter.

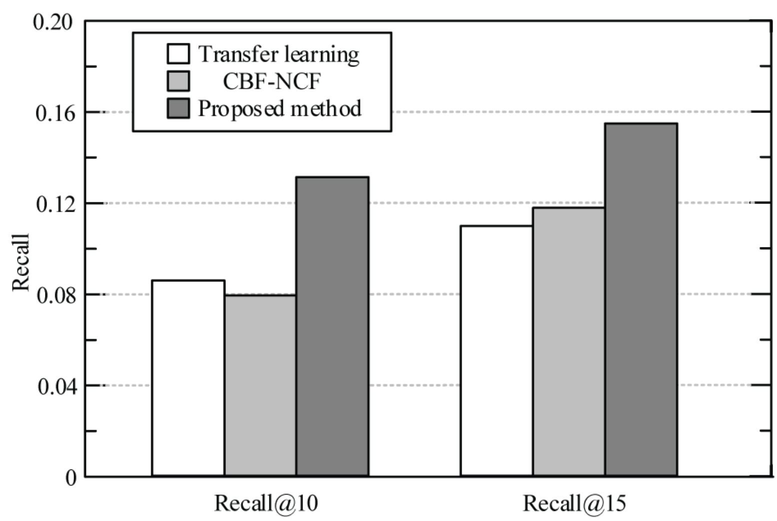
Result Analysis

To prove the advantages of the proposed personalized POI recommendation method, after analyzing the parameters of the experiment, the author completed a comparative experiment under the optimal parameters of each method. The recommended number K of POI was set to 10 and 15 to rule out the chance of the experimental results. Figure 8 shows the experimental results. The figure evidences that, on the BrightKite dataset, the proposed method consistently outperforms the other two methods in both precision and recall on Top-10 and Top-15 recommendation tasks. When the recommendation list is 10, the precision and recall of the proposed method are 0.118 and 0.135, respectively. When the recommendation list is 15, the precision and recall of the proposed method are 0.143 and 0.158, respectively, which are higher than that of the other two methods. This is because the proposed method uses a multihead attention mechanism to improve the model's ability to obtain key information about user preferences and improve the accuracy of recommendations. Moreover, the inherent attribute and semantic features of POI are extracted by constraint matrix decomposition and word vector model, respectively, to improve the feature extraction ability of the proposed method.

Figure 8.
Comparison of Precision@K and Recall@K Indices of Different Methods



(a) Precision@K



(b) Recall@K

CONCLUSION

The existing POI recommendation models in social network big data are unable to extract high-level feature information and have low precision and recall. To address these limitations, in this study the author proposed a POI recommendation model using LBSN. The author divided the features of POI into inherent features composed of attributes such as geographical location and category, and semantic features of relevance composed of spontaneous access by users. The researcher extracted the inherent attribute and semantic features of POI by constraint matrix decomposition and word vector model, respectively, and solved the cold start problem by multifeature representation. The author constructed a deep learning recommendation framework integrating the multihead attention mechanism for POI recommendation. The experiments demonstrated that, when the recommendation list is 10, the precision and recall of the proposed method are 0.118 and 0.135 respectively, which are better than the existing recommendation methods. The time factor is an important attribute of check-in. Considering the different preferences of users in different periods, the proposed framework is more in line with the law of use in real life. In future research, the author will introduce the time-aware POI recommendation method. Furthermore, the tensor-based method can be used to further improve the recommendation model since it regards different information as a whole and organizes the check-in behavior as a tensor.

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CONFLICTS OF INTEREST

The author declares that there is no conflict of interest regarding the publication of this paper.

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