Mathematical Biosciences
and Engineering

MBE, 20(9): 17428–17445.
DOI: 10.3934/mbe.2023775
Received: 03 April 2023
Revised: 01 August 2023
Accepted: 22 August 2023
Published: 11 September 2023

http://www.aimspress.com/journal/MBE

Research article

Point of Interest recommendation for social network using the Internet of Things and deep reinforcement learning

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Abstract: Point of Interest (POI) recommendation is one of the important means for businesses to fully understand user preferences and meet their personalized needs, laying a solid foundation for the development of e-commerce and social networks. However, traditional social network POI recommendation algorithms suffer from various problems such as low accuracy and low recall. Therefore, a social network POI recommendation algorithm using the Internet of Things (IoT) and deep reinforcement learning (DRL) is proposed. First, the overall framework of the POI recommendation algorithm is designed by integrating IoT technology and DRL algorithm. Second, under the support of this framework, IoT technology is utilized to deeply explore users' personalized preferences for POI recommendation, analyze the internal rules of user check-in behavior and integrate multiple data sources. Finally, a DRL algorithm is used to construct the recommendation model. Multiple data sources are used as input to the model, based on which the check-in probability is calculated to generate the POI recommendation list and complete the design of the social network POI recommendation algorithm. Experimental results show that the accuracy of the proposed algorithm for social network POI recommendation has a maximum value of 98%, the maximum recall is 97% and the root mean square error is low. The recommendation time is short, and the maximum recommendation quality is 0.92, indicating that the recommendation effect of the proposed algorithm is better. By applying this method to the e-commerce field, businesses can fully utilize POI recommendation to recommend products and services that are suitable for users, thus promoting the development of the social economy.

Keywords: social network; interest point recommendation; the Internet of Things; deep reinforcement learning

1. Introduction

As technology advances and intelligent devices become more prevalent, social networks have become an indispensable part of people's daily lives, with billions of users sharing and accessing information on social media platforms every day. However, among this vast amount of information, users often feel overwhelmed and finding content that interests them becomes increasingly difficult. Therefore, social network POI recommendation has emerged, aiming to help users discover content that they are interested. Point of interest (POI) recommendation, as one of the important means for businesses to fully understand users' preferences and meet their personalized needs, has laid the foundation for the development of social media [1,2]. The study of POI recommendation methods provides an unprecedented opportunity to analyze users' mobile behavior characteristics.

Traditional social network POI recommendation relies on techniques such as collaborative filtering, content filtering and hybrid filtering. Additionally, there are hybrid methods that combine collaborative and content-based filtering to improve the recommendation accuracy. However, these methods have some issues, such as data sparsity, cold start problem and scalability issue. Therefore, researchers have started exploring new technologies and methods to address these issues. In recent years, the development of Internet of Things (IoT) and deep reinforcement learning technology has provided new ideas and methods for social network POI recommendation. IoT technology can help collect user behavior data and environmental information to understand users' interests and needs. Deep reinforcement learning technology can learn the optimal recommendation strategy by analyzing users' historical behavior and environmental information and adjust and optimize it according to users' feedback [3]. The application of these technologies can make social network POI recommendation more intelligent, personalized and accurate, providing users with better recommendation services [4]. The proposed algorithm is innovative in its use of IoT technology and deep reinforcement learning (DRL) algorithm to improve the accuracy and recall of social network POI recommendation. By leveraging IoT technology, the algorithm is able to access multiple data sources and deeply explore users' personalized preferences for POI recommendation. The DRL algorithm is also applied to construct the recommendation model, allowing for more efficient and effective POI recommendations. These new elements are what sets the proposed algorithm apart from existing methods and contributes to its improved performance. Therefore, social network POI recommendation algorithms based on IoT and deep reinforcement learning have become a focus of researchers' attention, with great potential and development space.

The contribution of this paper is as follows: 1) Due to the high dimensionality and sparsity of the check-in matrix constructed by user check-in behavior, user interests change with different times and locations. To address this issue, I use IoT technology to mine user's time, location and category preferences, and obtain real-time social data to avoid the uncertainty of user check-in features, thus solving the problem of low recommendation accuracy of traditional algorithms. 2) Traditional recommendation algorithms ignore the effects of time and information popularity, which still need to be improved in terms of the quality of local and remote recommendations. To address this issue, we propose a joint recommendation model using DRL algorithm, which effectively integrates various influencing factors, simulates the dynamic behavior of user check-ins and solves the problems of recall and other issues that exist in traditional algorithms. 3) Different datasets are used to verify that the social network POI recommendation algorithm based on IoT and DRL can accurately POI recommendation, ensuring recommendation quality and efficiency.

The paper's organization is outlined as follows: Section 1 presents an overview of the proposed work; Section 2 discusses related works on the model; Section 3 provides a comprehensive discussion of the proposed algorithm; Section 4 covers the experimental analysis and results of the proposed work; and Section 5 concludes the future research directions for the model.

2. Related works

At present, research on the social network POI recommendation has made some progress. Islam et al. [5] proposes a POI recommendation algorithm based on deep learning. By collecting user check-in, opinion, photo and comment data, determining the user's main attributes and establishing a POI recommendation model based on the user's POI characteristics, POI recommendation is achieved by calculating POI scores. However, this algorithm has the problem of low accuracy in social network POI recommendation and there is still some gap with the ideal application effect. Liu et al. [6] proposed a collaborative filtering algorithm that combines temporal context information and user context, focuses attention on expanding and discovering user interests, and uses a popularity penalty function to weight the similarity between recommended short videos and historical short videos. Moreover, introducing the user situation into traditional collaborative filtering recommendation algorithms, considering the context information of users in the recommendation generation stage, and weighting the recommended candidate short videos. Finally, a diversified approach is used to generate top-K recommendation lists for users to achieve interest recommendations. However, it has a problem of low recommendation quality, and there is a gap between the expected research results. Du and Li [7] proposes a POI recommendation algorithm based on attribute networks. By analyzing social network and user attributes, the social network topology is determined, and the network structure and user attributes are encoded into low-dimensional representations. Relevant recommendation sequences are generated by determining the correlation between social network nodes, achieving short-term POI recommendation. However, in practical applications, it has a problem with root-mean-square error. Liao et al. [8] proposes a POI recommendation algorithm based on convolutional networks, accurately learning user and project tables from the user-project interaction graph and social graph to determine user historical data. The collected data is input into the POI recommendation model based on convolutional networks, and the model error is adjusted through model training to obtain relevant POI recommendation results. However, it is too complex and has a problem with long recommendation time, making it difficult to achieve the expected result. Sang et al. [9] proposes a visual-based POI recommendation algorithm. By collecting user photo and check-in data, a POI recommendation attention network is constructed, which adaptively considers the joint influence of user's long-term, short-term, and visual preferences, extracting long-term and short-term preferences from registration sequences. Finally, an adaptive attention mechanism is used to balance all extracted user preferences, combined with user preferences to recommend suitable products for users, achieving POI recommendation. However, it has the problem of low recommendation quality and still has some gap with the expected research results.

IoT refers to the connection of any object to the network through information sensing devices according to agreed-upon protocols, and the exchange of information and communication between objects through information transmission media to realize intelligent identification, positioning, tracking, supervision and other functions. It has the advantage of minimizing manpower and saving time. I mainly use IoT technology to deeply explore the personalized preferences of user POI recommendation to ensure the quality and speed of personalized preference mining. Deep reinforcement learning (DRL) combines the perceptive ability of deep learning with the decision-making ability of reinforcement learning, which can improve the accuracy of POI recommendation. Therefore, I propose a POI recommendation algorithm that combines IoT and DRL to effectively improve the performance of POI recommendation and optimize user experience.

3. Methodology

To better understand users' personalized preferences for check-ins and improve the quality of social network POI recommendations, I propose a social network POI recommendation algorithm based on the IoT and DRL. The overall framework of the algorithm is shown in Figure 1. From the analysis of Figure 1, we can see that the framework of the social network POI recommendation algorithm based on IoT and DRL is composed of two parts, the IoT part and the DRL part. The IoT part is mostly divided into three levels: the application layer, the network layer and the perception layer. The main function of the application layer is to calculate the fixed distribution value and user time similarity. The main function of the network layer is to calculate the geographic location score through a kernel density estimation function. The main function of the perception layer is to determine the user category preferences and the POI category preferences. After collecting this data, IoT technology [10,11], through various information transmission perception devices, connects people, objects and the environment in the network environment to form an information network connection, laying a solid foundation for social network POI recommendations. The DRL part mostly consists of the input layer, embedding layer, connection layer, feed-forward layer and output layer. Using user time, location and category preferences collected by IoT as the input for DRL, the POI recommendation model based on DRL is constructed. The input data is transmitted between the embedding layer, connection layer and feed-forward layer, and the final output is the personalized information push recommendation list (Top-N).

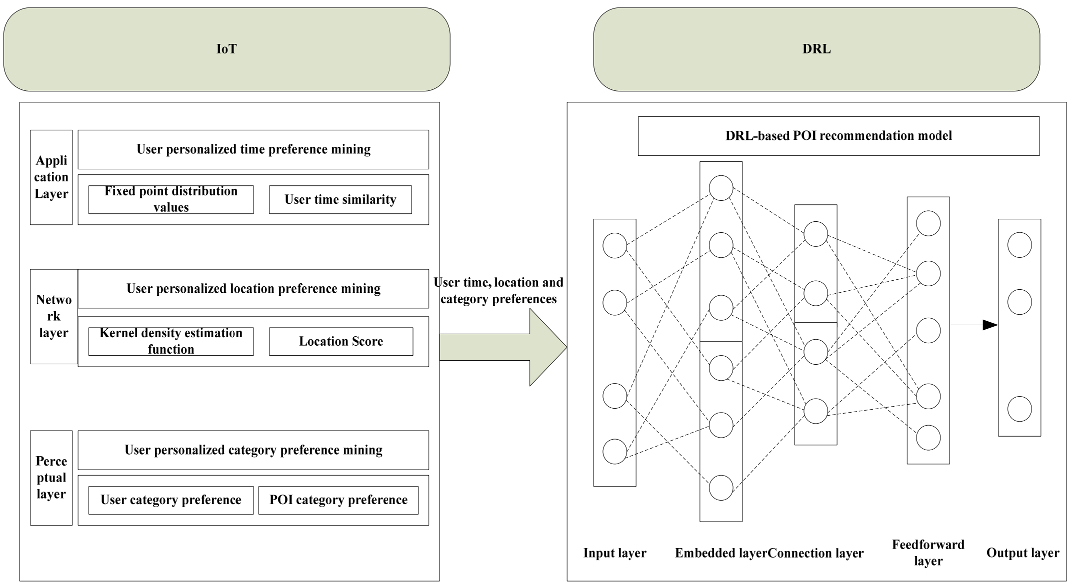

Figure1. Framework of proposed algorithm.

3.1. IoT-based personalized preference mining

According to Figure 1, the IoT is used to mine personalized preferences, thus laying a solid foundation for subsequent social network POI recommendations.

Time is one of the very important factors in the research work on POI recommendations. Because the purpose of selecting recommendations is to suggest social networks that may be of interest to users at a given time, it is said that it is very necessary to consider the time factor [12]. Therefore, the time of day is divided into 24 time points according to the number of hours. T is the set of all time points, $T = \{0,1,2,\ldots,23\}$. t denotes each time point. The 13:36 can be represented by the time point $t = 13$. $U = \{u_1, u_2, \ldots, u_m\}$ is the set of users. $L = \{l_1, l_2, \ldots, l_n\}$ is the set of POI. In the IoT platform, user time preferences are modeled by historical check-in data at various points in time and the similarity of users in terms of time [13]. In this paper, we consider the fixed distribution values (FDV), user time similarity (UTS), as defined below.

$$FDV_{t,1} = \frac{m_T}{\sum_{t \in T} m_1} \tag{1}$$

where m_T indicates the number of visits by a user in an information retrieval domain; m_1 is the total number of visits in the information retrieval domain; t is the time point. In user time similarity, let $V_{u,t} = \left(v_{u,l_1,t}, v_{u,l_2,t}, \ldots, v_{u,l_n,t}\right)$ be the access of user u in time period t. Each term denotes the number of times user u visits l in time period t. For user u, the equation for the similarity between time points t_i and t_j is shown in Eq (2)

$$\rho_u(t_i, t_j) = \left(V_{u,t_i} + V_{u,t_j}\right)^2 \left(V_{u,t_i} - V_{u,t_j}\right)^2 \tag{2}$$

where t_i and t_j denote the i th and j th time points.

Combining Eq (1) with Eq (2) yields the equation for calculating the user's personalized preference for time as

$$f_{time} = FDV_{t,1} \bullet V_{u,t} \tag{3}$$

where $FDV_{t,1}$ denotes the user fixed-point distribution value; $V_{u,t}$ denotes user temporal similarity. User location preference characterizes the phenomenon of spatial clustering of POI, which can to some extent be able to reflect the user for location preference, and to avoid the one-sidedness of mining, IoT technology is combined with kernel density estimation method to improve the accuracy of POI recommendation [14].

The set of user access locations is denoted by L_u, which is obtained from the set of user's historical accesses. Each POI $(x_i . y_i)^T$ is a two-dimensional vector with longitude and latitude. $K(.)$ is a kernel density estimation function, then the probability that user u goes to an unchecked location l is

$$z_u = \frac{1}{M} \sum C_{i,j} \tag{4}$$

where M denotes the number of positions. $C_{i,j}$ denotes the probability density function.

The personalized location preference of the user for the POI is shown in Eq (5).

$$f_{loc} = \sum(x_i . y_i)^T \bullet \frac{f_{Ge}(l/u_i)}{K(\theta^2)} \tag{5}$$

where f_{Ge} denotes the probability of a user's access to the same location; θ denotes the function bandwidth of a non-negative standard kernel function. $K(.)$ is calculated as follows:

$$K(X) = \frac{1}{\sqrt{2\pi}} exp\left(-\frac{1}{2}\right)^T \tag{6}$$

where T denotes the rotation matrix.

If two locations are closer to each other, the higher the geographical score is, the higher the final personalized location preference is obtained.

In the social network access dataset, each POI has its own category, and by viewing the information of the category to which the POI belongs, people can intuitively understand the style and characteristics of the POI. Researchers can also obtain the user's preference for a certain type of POI by observing the category characteristics of the user's access to the POI [15]. Therefore, the category information of the POI can be used to analyze the personalized category preference of the user.

This includes user category preference $\left(U_c(u, c_i)\right)$ and POI category preference $\left(P_c(c_i)\right)$, which are calculated as shown in Eqs (7) and (8)

$$U_c(u, c_i) = \frac{B(u,c_i)}{B(u)} \tag{7}$$

$$P_c(c_i) = \frac{B(c_i)}{M} \tag{8}$$

where $\frac{B(u,c_i)}{B(u)}$ is the total number of visits by user u on category c_i; $B(u)$ denotes the number of valid visits; $B(c_i)$ indicates the total number of user check-ins; M denotes the number of users.

User category preference is the degree of preference for each POI category in the user's historical social data, and the access preference of each user for each category is calculated by Eq (9), and a higher access preference indicates that the user prefers that category [16]. The calculation equation is as follows:

$$f_{cat} = U_c(u, c_i) \bullet P_c(c_i) \tag{9}$$

where $U_c(u, c_i)$ denotes the total number of visits by user u in category c_i POI; $P_c(c_i)$ denotes the maximum value of the number of visitors in all categories.

The top N results are selected as the input data of layer of the DRL algorithm by sorting them in descending order to prepare for the design of the POI recommendation model.

3.2. Design of the POI recommendation model

Based on the above personalized preference mining of users' POI using IoT technology, DRL algorithm is used to construct the POI recommendation model. The POI recommendation model is obtained by updating the state interval.

In this study, DRL is used to model user POI periodically, and the recommendation of POI is regarded as a problem of decision making, and the recommendation action of the model is rewarded by constructing a periodic reward function to improve the accuracy of modeling [17]. The embedding vectors of the model are converted into feature matrices of the same dimensional size to obtain the POI spatio-temporal encoding matrix with the following equation

$$X_{h,1} = F \bullet \sum W_{i,j}\left(X_{i,*}^{0}, X_{j,*}^{1}\right) \tag{10}$$

where F denotes user POI personalization preferences; $W_{i,j}$ denotes the parameters of the i-th order and j-th order interaction matrix; $\left(X_{i,*}^{0}, X_{j,*}^{1}\right)$ is the third-order interaction relation of the crawled embedding vector. After transforming the encoding matrix of the spatiotemporal feature through the POI, to build a recommendation model that contains historical sequence regularity information, it is also necessary to design the deep learning module and reinforcement learning module, ensuring the temporal dependency of POI [18]. Then, the loss function of the model is

$$L_{ce} = -\frac{1}{N}\sum_{l=1}^{N}\sum_{c=1}^{C} y_{tc}\, log\left(X_{h,1}\right) \tag{11}$$

where C denotes the fully connected layer dimension. y_{tc} denotes the sparse tensor of the input data.

Next, we can use a reward function to provide positive reinforcement for the model's periodically recommendation results. This can significantly improve the recommendation accuracy through DRL. Based on the loss function of deep learning, after completing the transformation of the dimension feature matrix, we can approach it from the perspective of reinforcement learning [19]. Considering that the fully connected layer of the network is a Q-value function, for a given state sequence $s_1 \to s_2 \ldots \to s_n$ and action sequence $a_1 \to a_2 \ldots \to a_n$, we have

$$Q(s_i, a_i) = L_{ce} + b \tag{12}$$

where b denotes the trainable parameters in the fully connected layer.

Based on the serial difference error, the loss function of the reinforcement learning part can be obtained as follows:

$$L_{rl} = |Q(s_i, a_i) - [max\, Q\,(s_i, a_i)]^2| \tag{13}$$

where $max\, Q\,(s_i, a_i)$ is the maximum value of the training parameters. In the modeling process, it is proposed to combine the loss functions of the deep learning and reinforcement learning components, and set a cycle for this process. To incentivize the model to recommend check-in locations that are consistent across cycles, a reward function can be used. This function will evaluate whether the recommended next check-in location a_* matches the check-in location from the previous cycle [20], and provide a reward accordingly.

$$r = \frac{1}{N-1} L_{rl} = \begin{cases} 1 \\ 0 \end{cases} \tag{14}$$

where $r = 1$ and $r = 0$ indicate that the recommendation locations are consistent and inconsistent with those recommendation in the previous cycle, respectively.

By integrating deep learning and reinforcement learning modules, we can effectively create a recommendation model for POI. This results in a DRL-based model, as illustrated in Figure 2.

According to Figure 2, the user check-in point sequence is composed of location, time and user ID, and generates corresponding check-in records. For the information of user check-ins, $V \in R^{N\times d}$, $U \in R^{M\times d}$ and $T \in R^{48\times d}$ are used to represent the location, user and time point of each place, respectively. Among them, d represents the embedded dimension, N represents the number of all locations and M represents the number of users.

By periodically dividing users' interests, calculating spatiotemporal encoding matrices and separately obtaining the deep learning loss function and the reinforcement learning loss function [21], setting the reward function based on the superposition of the two loss functions, determining the consistency of the recommendation locations during the cycle and completing the design of the POI recommendation model based on DRL. This lays the foundation for the implementation of subsequent POI recommendation algorithms.

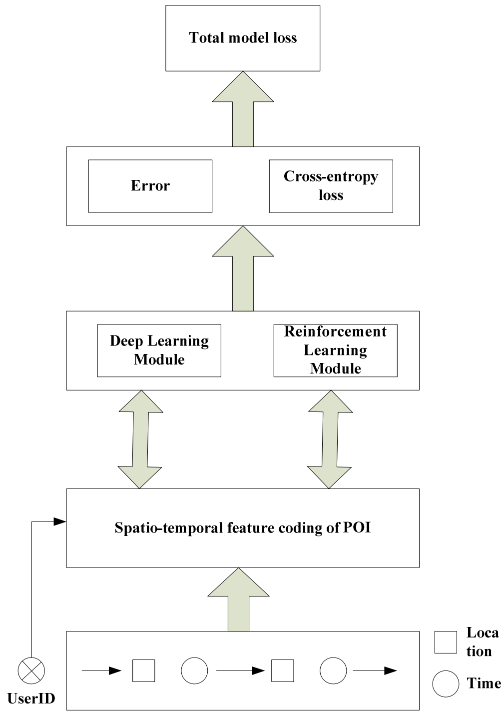

Figure 2. DRL based POI recommendation model.

3.3. The social network POI recommendation algorithm

Based on the results of personalized preference mining of user POI using IoT technology and the design of POI recommendation model based on DRL, I effectively combine the above two parts to construct a joint algorithm social network POI recommendation algorithm. The implementation steps of proposed algorithm are as follows:

Input: User data such as time, location and category preferences

Output: Social network POI recommendation results

The process of social network POI recommendation algorithm is shown in Figure 3. The implementation steps to get the POI recommendation algorithm construction process are as follows:

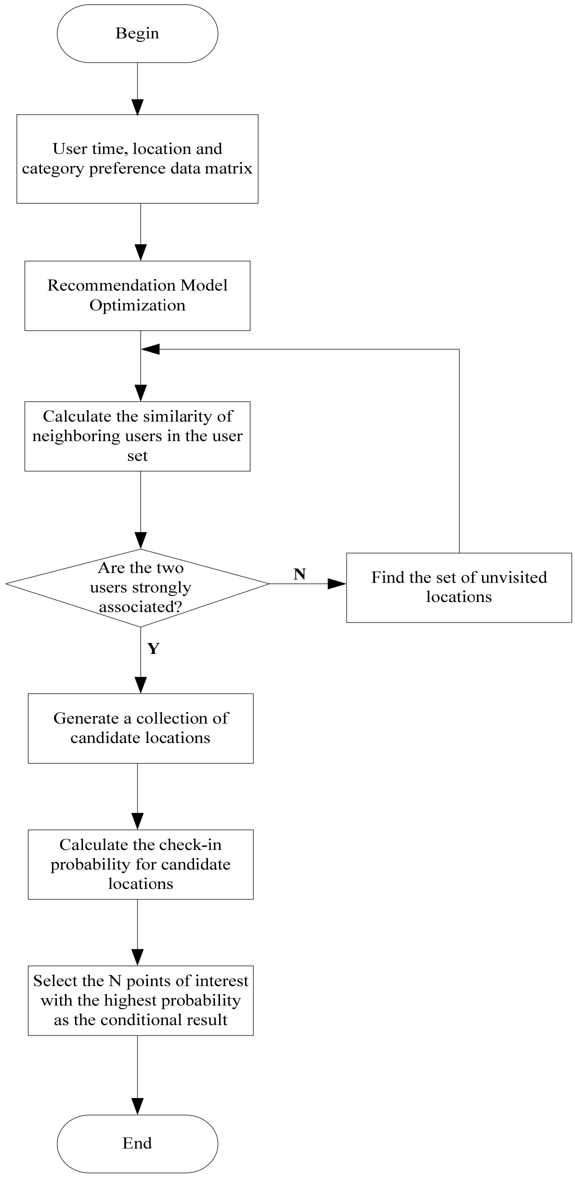

Figure 3. The process social network POI recommendation algorithm.

1) The relevant data matrix is determined by combining the user time, location and category preferences data collected using IoT technology [22].

2) Optimize the recommendation model using an activation function that retains the weights of the data features in the input layer of the model [23], and the optimization equation is as follows:

$$\zeta = \underset{u_i}{\Pi} P\iota\left[d\left(v_j, v_y\right)\right] \tag{15}$$

where $P\iota$ indicates the history of check-ins for user u_i; $d\left(v_j, v_y\right)$ denotes the distance between POI v_j and v_y.

3) Using the optimized model to calculate the degree of association between two users of the user concentration vector, the equation is as follows:

$$si\,m\,(a,b) = \frac{\sum r_i}{(rmin_{max})} \tag{16}$$

where r_i denotes the rating value of the user at the ith check-in; r_{max} and r_{min} are the maximum and minimum values of the rating, respectively.

Based on the calculation result of Eq (16), if it is a strong degree of association, the set of candidate locations is generated [24]; If it is weak association degree, the set of unvisited locations is found and the similarity degree is recalculated.

The equation for calculating the sign-in probability in the set of candidate locations is as follows:

$$p' = \frac{1}{n}\sum p(l_i, l_z) \tag{17}$$

where n denotes the number of local locations; $p(l_i, l_z)$ is the probability of a user moving from the current location l_i to the new location l_z, which is calculated as

$$p(l_i, l_z) = a \times x_{i,j}^{b} \tag{18}$$

where a and $b$denote distribution parameters; $x_{i,j}$ is the trajectory distance.

Using Eq (18), I calculate the check-in probability of users for each location in the candidate location set, respectively, and sort the calculated results in descending order, and select the top N POI as the final result of recommendation. This completes the design of the social network POI recommendation algorithm based on IoT and DRL.

4. Experimental results and analysis

4.1. Data sets

The data sets used in this article are the **Foursquare data set** and the **Gowalla data set**. The **Foursquare data set** contains 2,153,469 users, 1,143,090 venues, 1,021,966 check-ins, 27,098,488 social connections and 2,809,580 user ratings for venues. All this data was extracted from the **Foursquare** application through a public API. The **Gowalla data set** is a check-in data set for a social media app produced by Stanford University from February 2018 to October 2021, comprising a total of 9,874,814 data points.

The data in the **Foursquare data set** and the **Gowalla data set** were integrated and processed, and those users who visited more than 30 locations were retained, and the statistical information of the dataset is shown in Table 1.

Table 1. Statistical information of the data set.

	Foursquare	Gowalla
Check-in time	2020–2022	2018–2021
Number of users	14,423	16,352
Number of locations	501,161	122,564
Number of check-ins	2,554,875	2,356,487
Number of categories	80	100

Different social media platforms have different data formats and dataset sizes, so data preprocessing and cleaning are performed for different platforms. To improve the authenticity of the experimental results, abnormal and missing data in the experimental dataset are cleaned and filtered, and only users who have checked in more than 30 times are selected. The data density extracted from the two datasets is 6.60×10^{-3} and 3.25×10^{-3}, respectively, reflecting the extreme sparsity of the POI recommendation in the dataset, which increases the difficulty of POI recommendation. Based on the sample identification generated by the user and POI, the check-in behavior and activity records of users are aggregated.

In the check-in data, we can use IoT technology to mine users' personalized preferences, and then search for whether a particular user has time, location or category preferences for specific POI in the dataset. If there are, a positive sample will be generated; otherwise, it will be automatically classified as a negative sample. The positive and negative samples will be included in a set as the training set for the experiment, while the location set of reachable POI in the dataset will be used as the test set. Based on the above division of the dataset, we can obtain user IDs, POI locations, historical check-in data of all users at that point, feature weights and positive and negative samples with timestamps.

In the experiment, the time window size is set to $\tau = 12\, hours$, the dimension of the latent representation vector is $D = 200$, the number of negative samples for each actual check-in record is $N = 5$ and the learning rate is $\gamma = 0.001$. Then, we take the other check-ins within 48 hours before each user's check-in sequence in the training set as the user's recent check-ins (including the current check-in), and use the check-ins within the next 48 hours as the future check-ins to be predicted for training the network. During the network training process, we optimize the embedding layer parameters with a learning rate of 0.001, while the learning rate for the remaining parameters is set to 0.025. The size of the embedding dimensions for locations, time, and users is set to 200 and the size of the hidden units is set to 600. The parameters balancing deep learning and reinforcement learning losses are both set to 1.4. The learning rate decay is set to 0.1, and the dropout probability of the output layer is set to 0.5. By adjusting these parameters, the recommendation model can achieve the best output.

In the experiment, various devices, such as IoT sensors, servers, and computers, were employed to collect user behavior and environmental data, which underwent data preprocessing and cleansing. Additionally, DRL algorithms were employed for the recommendations, which require appropriate storage and computing resources. Furthermore, this research demands expertise from data scientists, machine learning engineers and software developers, among others, for the research and development. Therefore, the costs of this experimental setup primarily include device costs, labor costs and other necessary expenses. The cost-efficiency is in Table 2.

Table 2. Experimental costs.

Expense type	Specific value (yuan)
IoT sensors	5000
Server	10,000
Computer	2000
Storage resources	3000
HR cost	100,000
Data preprocessing	1000
Test data	500

As can be seen from Table 2, although the experimental setup cost for this research was high, the algorithm employed could improve the accuracy and diversity of social network POI recommendations, thereby enhancing user satisfaction and engagement. This can result in greater economic benefits such as increased advertising revenue, user retention rates and brand loyalty. Therefore, the proposed algorithm is believed to have a certain cost-efficiency.

4.2. Evaluation criteria

The algorithms of DLPOI [4], SVRA [5], ACRANE [6], SocialLGN [7], LSVP [8] and proposed algorithm are compared, and the practical application effects of different methods are examined by comparing the accuracy, recall, root mean square error (RMSE), recommendation time and recommendation quality of social network POI recommendations of different methods.

To evaluate the performance of the social network POI recommendation algorithm, the evaluation index of accuracy P_{acc} is selected to assess the recommendation quality of the algorithm, which is calculated as follows:

$$P_{re} = \frac{1}{M}\left(\frac{S_u \cap T_u}{K}\right) \tag{19}$$

where M denotes the number of users participating in check-in; K denotes the length of the POI recommendation list; S_u indicates the total number of POI; T_u denotes the number of valid check-ins.

Common metric used to evaluate the recommendation quality of a recommendation algorithm is the recall R_{re}. A higher recall indicates that the recommendation algorithm can reflect the user's preferences more accurately and the recommendation's quality is better. It is calculated by the following equation

$$R_{re} = \frac{1}{M}\left(\frac{S_u \cap T_u}{T_u}\right) \tag{20}$$

The smaller the RMSE, the better the recommendation quality of the recommendation's algorithm. The calculation equation of this index is as follows:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} \tag{21}$$

where m denotes the number of recommendations; y_i indicates the actual recommendation result; $\hat{y}_i$ denotes the recommendation results of different algorithms.

The shorter the time, the higher the recommendation efficiency, which indicates that the algorithm can more quickly mine the user's POI personalized preference, and then recommend the POI to the user according to the preference to ensure the recommendation quality.

The ranking evaluation index $nDCG$ was selected as the evaluation criterion. This indicator is one of the important indicators used to determine the quality of ranking in the field of information recommendation and retrieval. The calculation equation of ranking evaluation index $nDCG$ is as follows.

$$nDCG = \sum_u \frac{1}{Y_u}\sum\frac{2^{re}-1}{n+1} \tag{22}$$

where Y_u denotes the maximum $nDCG$ value of the user u; re denotes the relevance of the n th

POI to the user. $re = 1$ is relevance, otherwise 0.

4.3. Results and discussion

The comparison results of the accuracies of social network POI recommendations using six different algorithms are shown in Figure 4.

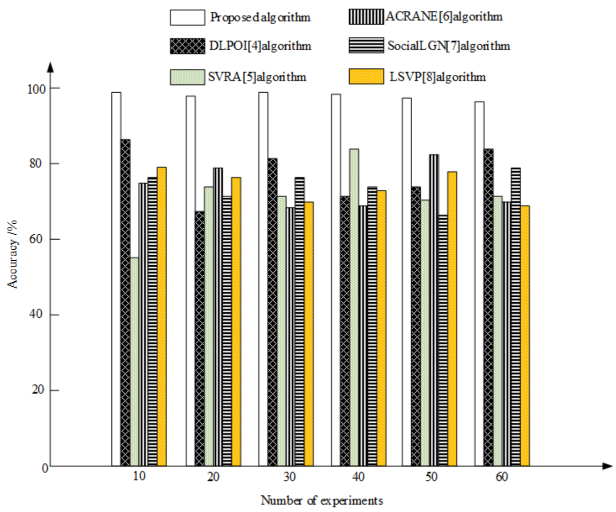

Figure 4. Comparison results of recommendation accuracy.

Analysis of Figure 4 shows that our algorithm consistently outperforms the compared algorithms across different experiment runs. Specifically, the maximum accuracy of social network POI recommendation achieved by our algorithm is 98%, while the maximum accuracy achieved by the algorithm in DLPOI [4] is 86%, in SVRA [5] is 85%, in ACRANE [6] is 83%, in SocialLGN [7] is 76% and in LSVP [8] is 79%. The maximum accuracy of proposed algorithm is respectively higher than that of the compared algorithms by 12%, 13%, 16%, 22% and 19%, indicating that our algorithm achieves higher accuracy in recommendation POI, while the lower accuracy of the compared algorithms can be attributed to the neglect of the relevance of user check-in behavior as a feature. This resulted in suboptimal internal structural parameters of the recommendation model, which ultimately affected the quality of the recommendations. In comparison, social network POI recommendation of proposed algorithm can accurately recommend POI to users with good quality.

Based on the experimental environment and parameter settings described above, we selected the algorithms from DLPOI [4], SVRA [5], ACRANE [6], SocialLGN [7], LSVP [8] and the proposed algorithm as experimental comparisons to evaluate the recommendation recall of different algorithms. The results of the comparison are shown in Figure 5. Analyzing the results in Figure 5, we can see that the maximum social network POI recommendation recall of the proposed algorithm is 97%, while the maximum social network POI recommendation recall for DLPOI [4] algorithm is 87%, for SVRA [5] algorithm is 89%, for ACRANE [6] algorithm is 85%, for SocialLGN [7] algorithm is 75% and for LSVP [8] algorithm is 74%. Overall, the recall of the proposed algorithm is the highest, surpassing the recall of DLPOI [4] algorithm by 10%, SVRA [5] algorithm by 8%, ACRANE [6] algorithm by 12%, SocialLGN [7] algorithm by 22% and LSVP [8] algorithm by 23%. This indicates that the proposed algorithm has a higher recommendation quality for social network POI recommendation.

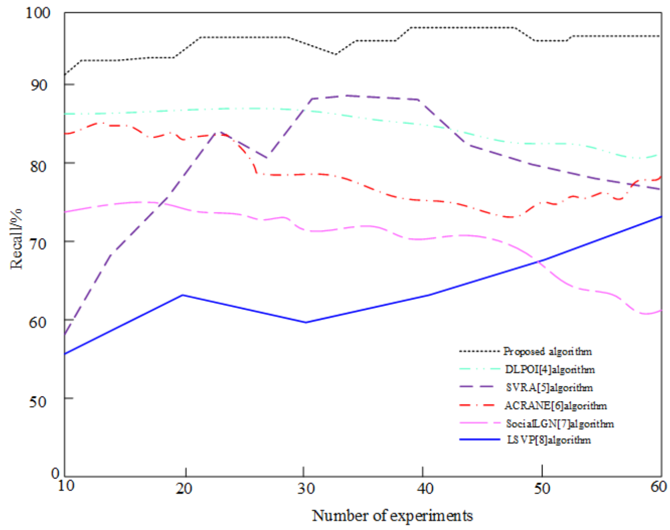

Figure 5. Comparison results of recommendation recall.

Analyzing the data in Table 3, it can be seen that the average RMSE of our algorithm is 0.278, which is 2.347 higher than the algorithm in DLPOI [4], 0.793 higher than the algorithm in SVRA [5], 2.301 higher than the algorithm in ACRANE [6], 2.746 higher than the algorithm in SocialLGN [7] and 1.061 higher than the algorithm in LSVP [8]. This indicates that compared to the experimental comparison algorithms, the RMSE of social network POI recommendation of proposed algorithm is much smaller, indicating that the recommendation effect of the proposed algorithm is better and the recommendation quality is higher.

Table 3. Comparison results of RMSE.

Number of experiments	RMSE					
	DLPOI [4] algorithm	SVRA [5] algorithm	ACRANE [6] algorithm	SocialLGN [7] algorithm	LSVP [8] algorithm	Proposed algorithm
10	2.727	1.365	2.654	3.665	1.247	0.214
20	2.624	1.012	4.781	4.124	1.445	0.366
30	2.754	0.536	2.635	3.694	1.362	0.241
40	3.201	1.247	1.478	1.471	1.478	0.331
50	2.887	1.012	1.556	2.554	1.223	0.247
60	1.556	1.254	2.369	2.634	1.278	0.271
Average	2.625	1.071	2.579	3.024	1.339	0.278

The comparison of the recommendation time of different social network POI under different experimental times are shown in Table 4. Analyzing the data in Table 4 shows that with the increase of experimental times, the recommendation time of different algorithms for social network POI has a changing trend. Among them, the maximum recommendation time for social network POI using our algorithm is 0.25 minutes. For DLPOI [4] algorithm, it is 1.69 minutes, for SVRA [5] algorithm, it is 2.36 minutes, for ACRANE [6] algorithm, it is 5.36 minutes, for SocialLGN [7] algorithm, it is 0.99 minutes and for LSVP [8] algorithm, it is 1.61 minutes. Compared with algorithms DLPOI [4], SVRA [5], ACRANE [6], SocialLGN [7] and LSVP [8], proposed algorithm is lower than 1.44 minutes, 2.11 minutes, 5.11 minutes, 0.74 minutes and 1.39 minutes, respectively. This result shows that proposed algorithm has excellent performance in recommendation efficiency, which can ensure the quality of the recommendations.

Table 4. Comparison of recommendation times.

Number of experiments	Recommendation time /min					
	DLPOI [4] algorithm	SVRA [5] algorithm	ACRANE [6] algorithm	SocialLGN [7] algorithm	LSVP [8] algorithm	Proposed algorithm
10	1.66	2.36	2.55	0.96	1.22	0.25
20	1.35	1.24	5.36	0.98	1.36	0.19
30	1.24	1.63	2.47	0.75	1.45	0.21
40	1.58	1.58	2.58	0.81	1.28	0.15
50	1.69	1.66	2.96	0.99	1.55	0.17
60	1.14	1.56	2.47	0.87	1.61	0.18

According to the data in Figure 6, it can be seen that the overall recommendation performance of the proposed algorithm is better than that of the experimental comparison algorithms. The maximum recommendation quality of this paper's algorithm is 0.92, while that of the algorithms in DLPOI [4], SVRA [5], ACRANE [6], SocialLGN [7] and LSVP [8] are 0.84, 0.76, 0.79, 0.87 and 0.68, respectively. Overall, the maximum recommendation quality of this paper's algorithm is 0.08 higher than that of the algorithm in DLPOI [4], 0.16 higher than that of the algorithm in SVRA [5], 0.13 higher than that of the algorithm in ACRANE [6], 0.05 higher than that of the algorithm in SocialLGN [7] and 0.24 higher than that of the algorithm in LSVP [8]. This is because proposed algorithm integrates users' social information by analyzing the differences in their check-in behavior as input data to the model, thereby recommending interests to users with better quality.

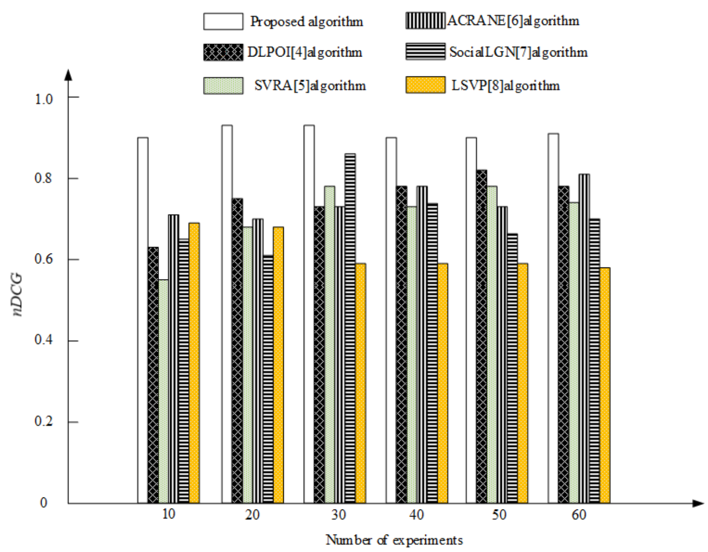

Figure 6. Comparison results of recommendation quality.

5. Conclusions

To address the low recommendation quality of traditional algorithms for social network POI recommendation, I propose a social network POI recommendation algorithm using the IoT and DRL. By designing multiple evaluation metrics and conducting comparative experiments with different recommendation algorithms, the results show that the maximum accuracy and recall of proposed algorithm are 98% and 97%, respectively. The average RMSE is 0.278, the maximum recommendation time is 0.25 minutes, and the maximum recommendation quality is 0.92, indicating that the recommendation effect of proposed algorithm is better. Despite the excellent performance of the algorithm proposed for POI recommendations in social networks, there are still some limitations in this study. These include limitations in data acquisition from the environment. I utilize IoT technology to collect environmental information from users, which may have certain acquisition restrictions and privacy issues that require device support and user authorization. The deep reinforcement learning algorithm used in this research may result in instability and over-fitting during the training process, and the implementation of proposed algorithm also requires certain hardware and software support, potentially presenting scalability issues. Based on the above limitations, the following directions for future work are proposed: Optimization of data acquisition and processing for environmental information and research can focus on more efficient and precise IoT technology to improve the efficiency of environmental information acquisition and processing. Additionally, it is necessary to consider how to protect user privacy and ensure data security. Optimization of algorithm stability and scalability: The training process can be optimized to improve the algorithm's stability and generalization ability. Additionally, more efficient and scalable implementation methods can be researched to cope with large-scale data and high-concurrency requests. In summary, the proposed algorithm has certain limitations and future areas for improvement. In future research, efforts will be made to optimize the performance and reliability of the algorithm, further improve recommendation performance to provide more personalized recommendations, and fully meet users' relevant needs.

Use of AI tools declaration

The author declares that no AI tools were utilized for data analysis, modeling, or decision-making processes.

Conflict of interest

The author declares that they have no conflicts of interest.

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