A Content-Aware POI Recommendation Method in Location-Based Social Networks Based on Deep CNN and Multi-Objective Immune Optimization

Xinxin Lu[1], Hong Zhang[2]

[1] School of Computer Science and Technology, Zhoukou Normal University, China
[2] School of Network Engineering, Zhoukou Normal University, China
zkxxl2016@126.com, 94640694@qq.com

Abstract

Aiming at the problem of sparse data and multi-attribute data in location-based social networks (LBSNs), a content-aware point-of-interest (POI) recommendation method based on deep convolution neural network (CNN) and multi-objective immune optimization is proposed. Firstly, three types of content information are modeled: Geographic information is modeled by location weighting strategy; Emotional information from users' comment texts is modeled by CNN; And user preferences are modeled by interaction matrix between comment content features and user potential features. Then, the three types of content information are inputted into a CNN based POI recommendation framework. To avoid adjusting too many weight coefficients at the same time, geographic information, user emotional information and user preferences are respectively optimized in three optimization objective functions. Finally, the non-dominated neighbor immune algorithm (NNIA) is used to solve the multi-objective optimization problem. Without adjusting any weight coefficients, a variety of POI lists can be respectively recommended for each user. In Foursquare and Brightkite datasets, the check-in records and comment texts data from New York (NY), Los Angeles (LA) and Austen were selected for experimental analysis. It can be seen from the experimental results that compared with other methods, the proposed method can ensure high recommendation accuracy under cold start and can achieve the accuracy and diversity of POI recommendation under different recommendation list length.

Keywords: Point of Interest, Location-based social networks, Deep convolutional neural networks, Multi-objective immune optimization, User sentiment classification

1 Introduction

With the explosive growth of network data and information, filtering out the information that we need efficiently from massive amounts of data is the key to improve daily work efficiency and facilitate life. The application of recommendation systems in e-commerce, information retrieval, mobile applications and online advertising has greatly improved the efficiency of information utilization and relieved the problem of information overload [1]. The function of the recommendation system is to predict the interest of users through the relevant information of the project and to recommend the most suitable project to them. The Point-of-Interest (POI) recommendation system predicts the user's interest based on the relevant information of the project. It captures the user's personalized preference for visiting new places to recommend the most suitable project to the user [2]. Meanwhile, it can also increase profits for merchants by providing intelligent POI recommendation services. Therefore, POI recommendation systems play an important role in location social networks [3]. Users can connect with their friends, upload photos, share their locations and post relevant reviews by signing into places of interest (such as restaurants, tourist attractions, shops, etc.). The new task of recommendation is to recommend the locations that users are interested in, which is called POI recommendation [4-5]. The POI recommendation system can not only capture the user's personalized preference for visiting new places, but also increase profits for businesses by providing intelligent POI recommendation services (such as location-aware advertising recommendations). Therefore, it plays an important role in the location-based social network.

The research hotspots of the current POI recommendation algorithm usually reflect the user preference by the check-in frequency of the location point. And they usually combine historical check-in behavior and context information to mine the preference information of users [6-7]. The context-aware recommendation system (CARS) introduces context information into the system to improve the accuracy of the recommendation [8]. In reference [9], a

*Corresponding Author: Xinxin Lu; E-mail: zkxxl2016@126.com
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hybrid approach that incorporates user preference, geographic influence and social trust into the POI recommendation system is proposed. The distrust links are exploited to investigate their propagation effects. A modified normalized Jaccard coefficient is used to measure the trust and distrust score. This approach performs better than traditional Collaborative Filtering in terms of accuracy and user satisfaction. Reference [10] incorporated geographic influence and social relationship information into a generalized matrix factorization model, which uses a multi-center Gaussian model to represent the check-in behavior of users. Reference [11] found that the spatial aggregation phenomenon of user sign-in behavior could solve the problem of the sparse matrix of user-POI. A weighted matrix decomposition POI recommendation model based on two-dimensional kernel density estimation was proposed. In real life, in addition to analyzing historical check-in data and contextual information of users, it can also analyze comment texts information [12]. Reference [13] proposed a new personalized successive POI recommendation model, called spatiotemporal sequential and social embedding rank model (SSSER). A hybrid deep learning model based on the convolution filter and multilayer perceptron model is used to mine the sequence pattern among the users' checked-in locations. The method of metric learning is used to model the social relationship among users. Finally, a unified framework is used for the successive POI recommendation by combining the users' personalized interests, the check-in sequential influence and social information simultaneously. This algorithm improves the accuracy of recommendation to a certain extent. However, when the amount of data is large, the algorithm is prone to over-fitting.

In recent years, using the Latent Dirichlet Allocation (LDA) model and stacked denoising autoencoders (SDAE) to extract comment texts features and make recommendations is a research hotspot. However, existing models cannot capture comprehensive information of comment texts [14-15]. For example, the following two sentences: "I trust this person" and "I betrayed his trust eventually". Because LDA and SDAE treat each word in the text as an individual and ignore the syntax and semantic relationship of the sentences, it is impossible to distinguish the different meanings of the word "trust" in the two texts. To solve this problem, reference [16] proposed a text recommendation based on convolution matrix factorization. This model integrates convolutional neural networks into the probability matrix factorization, which uses CNN and probability matrix factorization to learn the potential factors of the project and users respectively. Matrix factorization and convolutional neural network loss functions make up the objective function of the model. However, this model is only used for text recommendation, and it is not combined with other contextual information for POI recommendation [17].

Although the existing recommendation models have achieved good results, because they do not combine the comment texts and context information and do not consider multiple optimization goals, the results of POI recommendation lack diversity and accuracy. Therefore, this paper proposes a LBSNs content-aware POI recommendation method based on deep CNN and multi-objective immune optimization, which can improve the recommendation performance. The main innovations are as follows:

(1) Existing recommendation methods understand user preferences only at a shallow level due to sparse data. The proposed method uses CNN to build a content-aware POI recommendation model based on comment texts. The user preferences are mined by the interaction matrix between comment texts content features and user potential features.

(2) To analyze the influencing factors of the recommendation model comprehensively, attribute information of POI, user preferences and user sentiment classification information are introduced to improve the accuracy of LBSNs content-aware POI recommendation.

(3) Most recommendation methods require adjustable weight coefficients to determine the impact of each optimization goal on the results, and the proposed method uses a non-dominated neighbor immune algorithm to solve the multi-objective optimization problem in the recommendation model and achieve accurate and diverse POI recommendation without adjusting the weight coefficients.

Experimental results show that compared with other methods, the proposed method can guarantee a higher recommendation accuracy rate under cold start conditions and improve the accuracy and diversity of LBSNs content-aware POI recommendation under the different length of the recommendation list.

2 Content Information Modeling

Using content-aware service to recommend locations has been an important way to help people get their ideal location. However, the problem of data sparseness brings great challenges to the recommendation system [18]. To solve this problem, researchers have explored the methods of content-aware POI recommendation based on comment texts information. The existing methods are to process comment texts based on the document topic model, which can only shallowly understand user preferences [19]. To capture the deep preferences of users, this chapter proposes a content-aware POI recommendation algorithm based on convolutional neural networks (CNN). The algorithm uses CNN as the basis of a POI recommendation framework and introduces three types of information, including attribute information of POI, user preferences, and user sentiment classification information. The experimental results show that the convolutional neural network can extract semantic and emotional information from the comment texts content. Moreover, it proves that the relevant content information of review can improve the performance of the content-aware POI recommendation [20].

In the content-aware POI recommendation framework based on deep CNN, R is the check-in behavior, G is the impact factor of geographic location, S is the sentiment classification factor, V is the user potential factor and L is the potential POI. S, V and M can be obtained from the convolutional neural network [21-22].

2.2 Geographic Information Modeling

It assumes that the preference of user u_i for several neighbors of the location l_j represents the preference of user u_i for location l_j. The geographic location weighting strategy is used to complete the missing geographic location information in the matrix decomposition model [23]. Combining geographical feature and POI recommendation, the optimization goals of predicting the potential interest of users in unvisited locations are:

$$\min_{V,M} \frac{1}{2}\left(I \otimes \left(R - VGM^T\right)^2\right)$$
$$G = \beta VM^T + (1-\beta)\frac{sim\left(l_j, l_k\right)}{\sum_{l_k \in E\left(l_j\right)} sim\left(l_j, l_k\right)} \quad (1)$$

Where $I \in R^{M \times N}$ is the check-in weight matrix and $I_{ij} = 1$ is the check-in for user u_i at location l_j. V and M are matrix parameter. β is the weight parameter that controls the influence of adjacent locations. $sim\left(l_j, l_k\right)$ is the geographical weight of adjacent location l_k at the location l_j. It is a regularization term defined as $E\left(l_j\right) = \sum_{l_k \in E\left(l_j\right)} sim\left(l_j, l_k\right)$. The function can be expressed as Gaussian form:

$$sim\left(l_j, l_k\right) = e^{-\frac{\left\|x_i - x_j\right\|^2}{\sigma^2}}, \ \forall v_k \in E(v_j) \quad \textbf{(2)}$$

Where x_i and x_j are the latitude and longitude of the location l_i and l_j respectively. $E(v_j)$ represents the location of v_j. In real life, user is less likely to check-in in a region with longer distance. If the place to be recommended is not in the current position $E(v_j)$ of the user, the position is not considered. In the experiment, the distance variable D of the neighboring area is set to 10000 based on experience.

2.3 User Sentiment Modeling

The convolutional neural network is used to classify the sentiment of the comment texts. The input data of CNN is a word vector and the output is a predefined sentiment classification [24]. The network model includes input layer, embedding layer, convolutional layer, pooling layer, and output layer, as shown in Figure 1. The definition and function of each layer are as follows:

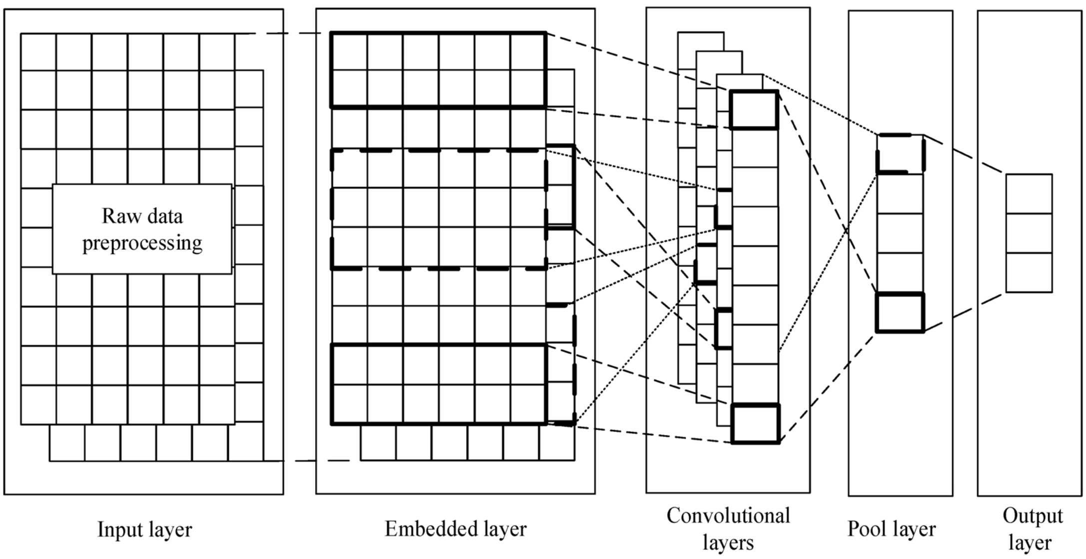


Figure 1. Sentiment classification using deep convolution neural network

Input layer. The word vector set of the comment text is inputted and preprocessed.

Embedded layer. According to the pre-trained word vector set, the word vector corresponding to each word is established, and the input matrix is generated.

Convolution layer. The convolution process of the convolution layer generates the word vector matrix. And each filter generates a series of feature values with context information.

Pooling layer. The pooling strategy generates fixed-dimensional features for each feature value.

Output layer. The text sentiment vector generated in the pooling layer is input into the softmax function. The softmax function is used to obtain the predicted probability of each sentiment and it is compared with standard experimental data to obtain the error. Through gradient descent and backpropagation, the error is transferred to the previous layers and the relevant parameters are updated [25].

The final output of the comment texts will be divided into three emotion categories, -1, 0, and 1, which represent dislike, neutral and like, respectively.

The reconstruction emotion category $\hat{I}$ is:

$$\hat{I} = I + \eta * S, \eta \in [0,1] \quad \textbf{(3)}$$

To ensure non-negativity, η is a scalar used to control the weights corresponding to the emotion of users. S represents a related sentiment score with a value between -1 and 1. According to the above formula, the check-in behavior is related to the corresponding emotional score of users [26].

2.4 User Preference and POI Attribute Modeling

CNN can deeply understand the comment texts content of the interested position by using a pre-trained word embedding model [27]. This paper adopts the method of extracting the characteristics of the comment texts $CNN(W, E_S)$, where E_S is comment texts set, W is the internal weights of CNN. The probability $P(f_{is} = 1 | u_i, E_S)$ of using softmax logistic regression function to define the reviews E_S posted by user u_i is

$$P(f_{is} = 1 | u_i, E_S) = \frac{\exp\left(u_i^T \cdot E \cdot CNN(W, E_S)\right)}{\sum_{E_k \in E} \exp\left(u_i^T \cdot E \cdot CNN(W, E_k)\right)} \quad \textbf{(4)}$$

where f_{is} represents whether E_S is published by u_i and $E \in R^{K \times d}$ is interaction matrix between the comment texts content feature and the potential feature of the user. This matrix can be used to distinguish the potential feature of the user u_i.

The softmax function is used to normalize the weight. With the meaning of probabilistic interpretation, the softmax function can normalize the output of the network (these outputs are between 0 and 1 and their sum is (1) and can be interpreted as the posterior probability of the classification target variable. To extract the potential feature vector u_i of user, the above formula is converted into an objective function:

$$\sum_{i=1}^{n} \sum_{E_k \in E_{Ni}} \log P(f_{ik} = 1 | u_i, E_k) \quad \textbf{(5)}$$

Similarly, the probability $P(h_{jp} = 1 | l_j, E_p)$ that comment E_p is related to location l_j is:

$$P(h_{jp} = 1 | l_j, E_p) = \frac{\exp\left(l_j^T \cdot P \cdot CNN(W, E_p)\right)}{\sum_{E_k \in E} \exp\left(l_j^T \cdot P \cdot CNN(W, E_k)\right)} \quad \textbf{(6)}$$

where h_{jp} indicates whether a comment E_p is associated with location l_j and $P \in R^{K \times d}$ is an interaction matrix between the comment texts content feature and the potential feature of POI [28]. To distinguish the potential feature l_j of POI, the above formula is converted into the objective function:

$$\sum_{j=1}^{n} \sum_{E_k \in E_{lj}} \log P(h_{jp} = 1 | l_j, E_k) \quad \textbf{(7)}$$

3 POI Recommendation

3.1 CNN Based POI Recommendation Framework

In the CNN based POI recommendation framework, R is the check-in behavior, G is the impact factor of geographic location, S is the sentiment classification factor, V is the user potential factor, L is the potential POI and P is the probability of users' comments. The appropriate S, V, and M are obtained through CNN learning. The relationship f_{is} between the comment texts and the user as well as the relationship h_{jp} between the comment texts and the location need to be considered to obtain a determined content-aware POI recommendation model [18-19]. The workflow of content-aware POI recommendation based on deep learning is shown in Figure 2.

The input of the framework is the user check-in behavior R. The experiment uses the well-known user check-in dataset and V, M, P and E are initialized. Firstly, use CNN to obtain the sentiment classification value S, and then calculate whether the geographic location information converges. If it converges, the derivation is used to update the parameter information and output the recommended content-aware interest points. Therefore, if G does not converge, it means that the preferences of the user are clear, so it does not need to judge.

To avoid the process of adjusting too many weight coefficients, the proposed method considers the attributes of POI, user preferences and user sentiment classification as three functions to optimize at the same

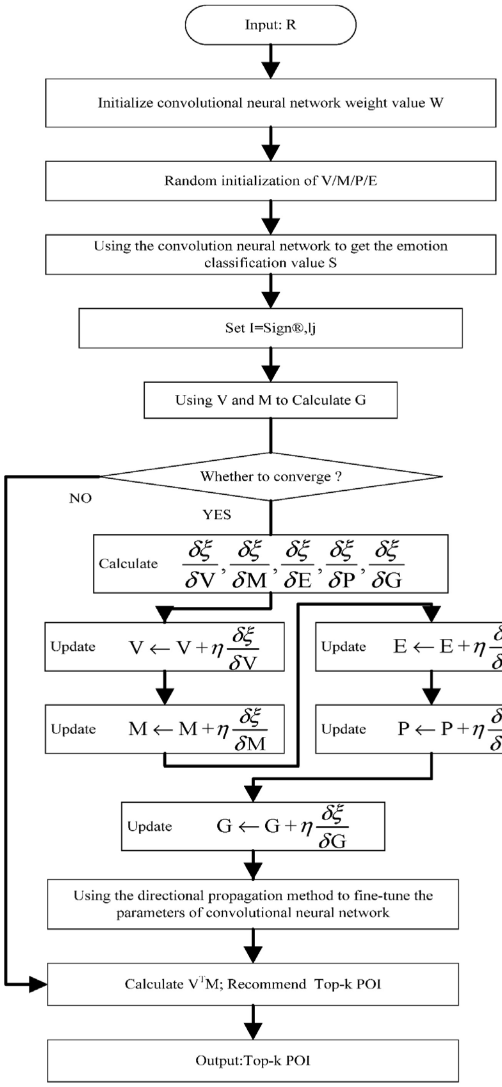


Figure 2. The framework of POI recommendation

time. Its goal is to improve one objective function without damaging another objective function value. The advantage is that there is no need to adjust any weight coefficients when providing a recommendation list for users. In this process, each generated recommendation list has different trade-offs among the attributes of POI, user preferences and user sentiment classification affected by geographic information [29-30]. Therefore, a diversified POI recommendation method based on multi-objective immune optimization can provide different POI recommendation lists for different users. Each list has different trade-offs among different objective functions, which can allow the list to compromise among different preferences. It can provide users with more options to choose and users can choose the best list from these non-dominated lists [31-32].

3.2 Objective Function Design

Most of the existing CNN based POI recommendation methods use weight coefficients to roughly evaluate the influence of each factor on the position of users, and the top places in the final ranking make up the POI recommendation lists [33-34]. For example:

$$\begin{aligned}\max_{V,M,G,P,E,CNN} \zeta = &-\frac{1}{2}\left\|\hat{I}\odot(R-VGM^T)\right\|_F^2 - \frac{\alpha_1}{2}\|V\|_F^2 - \frac{\alpha_1}{2}\|M\|_F^2 \\ &+\frac{\alpha}{2}\sum_{i=1}^{n}\sum_{E_k\in E_{ui}}\log P(f_{ik}=1\,|\,u_i,c_k) - \frac{\alpha_2}{2}\|E\|_F^2 \\ &+\frac{\alpha}{2}\sum_{i=1}^{n}\sum_{E_k\in E_{ui}}\log P(h_{ik}=1\,|\,u_i,c_k) - \frac{\alpha_2}{2}\|P\|_F^2 \\ &-\frac{\alpha_3}{2}\|W\|_F^2\end{aligned} \tag{8}$$

set $\alpha = 2\sigma^2$, $\alpha_1 = \frac{\sigma^2}{\sigma_u^2} = \frac{\sigma^2}{\sigma_l^2}$, $\alpha_2 = \frac{\sigma^2}{\sigma_P^2} = \frac{\sigma^2}{\sigma_C^2}$, $\alpha_3 = \frac{\sigma^2}{\sigma_W^2}$ to reduce parameters.

In formula (8), the importance of the influence of each factor depends on the size of the coefficient before each factor. The existing algorithms do not provide a unique weight vector for each user, and the entire system uses the same weight vector. This rough consideration assumes that all preferences of users for different factors are exactly the same, which does not meet the requirements of personalized recommendation [35-36]. Therefore, the proposed method considers the preference and sentiment classification of current active users and the probability density function of the check-in geographic information of current active users.

$$\begin{cases}\max & -\frac{1}{N}\sum_{i=1}^{n}\sum_{E_k\in E_{Ni}}\log P\left(f_{ik}=1\middle|u_i,E_k\right) \\ \max & -\frac{1}{N}\sum_{j=1}^{n}\sum_{E_k\in E_{lj}}\log P\left(h_{jp}=1\middle|l_j,E_k\right) \\ \max & I\end{cases} \tag{9}$$

Where N represents the length of the final recommendation list.

The content-aware service recommended by the proposed method needs to satisfy the greatest preference of users ($\max I$), that is, the most favorite location. The relationship between reviews and users as well as the relationship between reviews and locations should be closer, that is, the probability density function $P\left(f_{is}=1\middle|u_i,E_S\right)$ and $P\left(h_{jp}=1\middle|l_j,E_p\right)$ should be the largest [37].

3.3 Multi-Objective Immune Optimization

Based on the content-aware POI recommendation framework of a deep convolutional neural network, a non-dominated neighbor immune algorithm (NNIA) [38] is used to solve the multi-objective optimization problem of attributes, user preferences, and user sentiment classification of POI, which can get a list of recommendation.

The non-dominated neighbor immune algorithm simulates the mechanism of diversity antibody symbiosis and activation of a few antibodies in the biological immune system. It selects relatively isolated non-dominated individuals for activation. Proportional cloning operation is performed according to the crowded distance of activated antibodies. During the genetic operation, a search for sparse areas in the Pareto front is added to obtain a Pareto front with even distribution and good diversity [39]. The pseudo code of the NNIA algorithm is as follows:

Algorithm 1. Pseudo code of NNIA algorithm

Input: the maximum number of iteration: $G\max$; maximum size of dominant population: NM ; maximum size of active population: NA ; clone population size: CS

Output: Pareto optimal solution set

1. **Initialization**: initialize the antibody population B_0 of size NM , initialize the population $A_0=\phi$, $E_0=\phi$, and $D_0=\phi$, and set $t=0$
2. **Update dominant population**: According to the crowded distance in the population B_t , select the first NM individuals to enter the new population D_{t+1}
3. **While** $t \le G\max$ **Do**
4. $t=t+1$
5. Output population D_{t+1}
6. **Non-dominated neighbor selection:** **If** The population size of D_t is smaller than NA ,
7. **Then** $A_t = D_t$
8. **Otherwise** sort in descending order according to the crowding distance and select the first NM individuals to enter the population A_t
9. **Proportional cloning**: According to the population A_t , carry out proportional cloning to obtain the cloned population E_t
10. **Genetic manipulation:** Crossover and mutation in clone population E_t
11. Combine the population E_t and the population D_t to get the population B_t , and return to step 2.

The NNIA algorithm is used to solve the multi-objective function problem and the Pareto optimal solution set is obtained. Therefore, the diverse position recommendation of user in LBSNs can be obtained.

4 Case Verification and Result Discussion

Foursquare is currently the most popular social networking site based on POI. The proposed method selects the corresponding check-in records and comment texts data of New York (NY) and Los Angeles (LA) to demonstrate its performance. The statistical information of the two datasets is shown in Table 1. The two datasets are very sparse. There may be a problem of data sparseness of content-aware POI recommendation. However, the comment texts are very rich. Therefore, they can solve the problem of data sparseness and cold start. In addition, the Brightkite dataset, published by SNAP Labs, is a commonly used dataset for user interest recommendation based on geographic location. Brightkite was once a location-based social networking service provider, and users can share their locations by logging in. The Brightkite dataset is collected using their public API and consists of 58228 nodes and 214078 edges.

Table 1. The statistical information of LA and NY datasets

Datasets	LA	NY
The number of Users	30009	41260
The number of POIs	68573	86520
The number of Comments	154310	281430

4.1 Evaluating Indicator

Use the accuracy rate $Precision$, recall rate $Recall$ and F-value $F-score$ to evaluate the performance of the POI. $Precision$ and $Recall$ are defined as:

$$Precision = \frac{TP}{TP+FP} \tag{10}$$

$$Recall = \frac{TP}{(TP+FN)} \tag{11}$$

Where TP represents the number of samples predicted to be positive and actually positive. FP represents the number of samples predicted to be positive but actually negative. FN represents the number of samples predicted to be negative but actually positive.

When the recommendation list length N changes, the accuracy rate and the recall rate are often negatively correlated. Generally, as the recommendation list length N becomes larger, the test set accuracy rate decreases and the recall rate increases. In this way, when the length of the recommendation list is not fixed, the harmonic index $F-score$ is defined as:

$$F-score = \frac{2 * \Pr ecision * \operatorname{Re} call}{\Pr ecision + \operatorname{Re} call} \tag{12}$$

The proposed method uses Python for programming modeling and implements Keras library accelerated by Nvidia Geforce Titan X GPU. To obtain the weight coefficients of the convolutional neural network, the experiment uses the RMSprop mini-batch method. Each mini-batch includes 128 training samples, and each dataset is divided into three groups, including the training set, the validation set and the test set. 80% of samples in dataset are used as the training set, 10% are used as the validation set to adjust the hyperparameters, and the rest are the test set.

In addition, the parameters of the multi-objective immune optimization algorithm are set as follows: the length of the candidate list is 100, the number of iterations is 300, the maximum size of the active population is 30, the size of the clone population is 150, the maximum size of the dominant population is 60, the cross probability is 0.8, and the mutation probability is 0.1.

4.2 Sensitivity Analysis of Model Parameters

In the proposed method, the weight parameter β used to control the influence of location proximity has a greater impact on its performance. Therefore, an in-depth analysis of β is needed. The value of β is changed from 0 to 1. The recommended results obtained by the proposed method are shown in Figure 3.

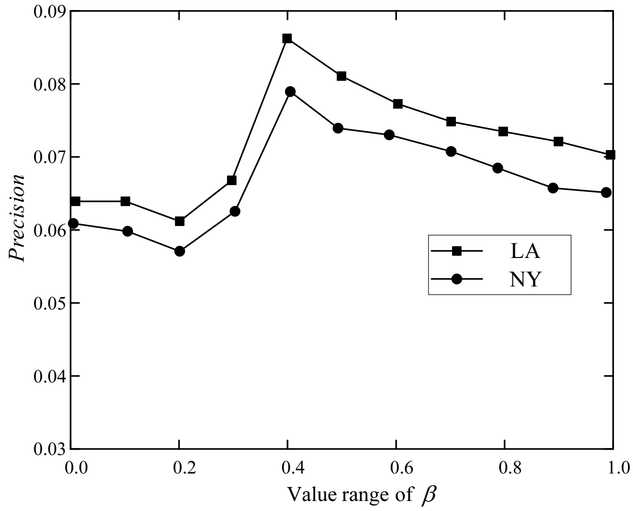
It can be seen from Figure 3 that when $\beta = 0$, the recommendation accuracy was the lowest because the geographical proximity relationship was not considered. Similarly, when $\beta = 1$, because too many geographical proximity factors are considered, the results were not accurate. Therefore, when $\beta = 0.5$, the accuracy of the proposed method was the highest, considering factors such as user preference and geographic location information. The proposed method has higher accuracy and lower recall rate, so it has better performance.

In addition, the proposed method achieves better results in the LA dataset than those in the NY dataset, but the numerical difference is not large, which may be due to a large number of comment texts in the NY dataset.

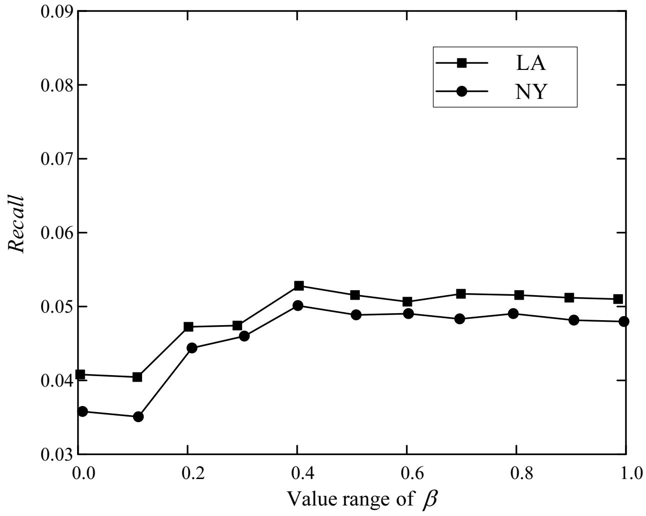
4.3 Cold Start Experiment

The proposed method can fuse the user preference, sentiment classification and POI attribute information to solve the cold start problem. Compared the proposed method with reference [9], reference [13] and reference [16], the results are shown in Figure 4 and Figure 5.

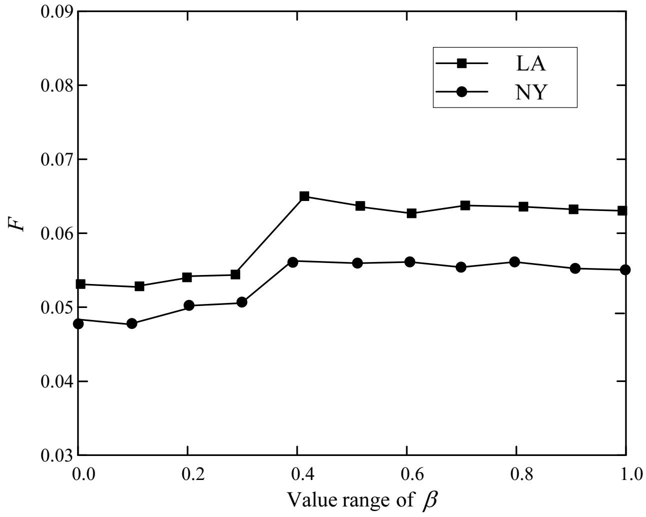
It can be seen from above Figure 4 and Figure 5 that compared with other recommendation methods, the proposed method performs best in solving the cold start problem of recommendation. For the cold start problem, the recommendation accuracy of all algorithms has different degrees of decrease. For example, the accuracy of the recommendations in reference [9] and reference [13] drops sharply, while the accuracy of the method in reference [16] slightly decreases. Because the algorithms in reference [9] and [13] do not consider the content information of the comment texts, compared with other methods, the performance degradations of the method in [16] and the proposed method are relatively small, and the performance of the proposed method decreases even less. Although the content of the comment texts is



(a) The test result of precision rate

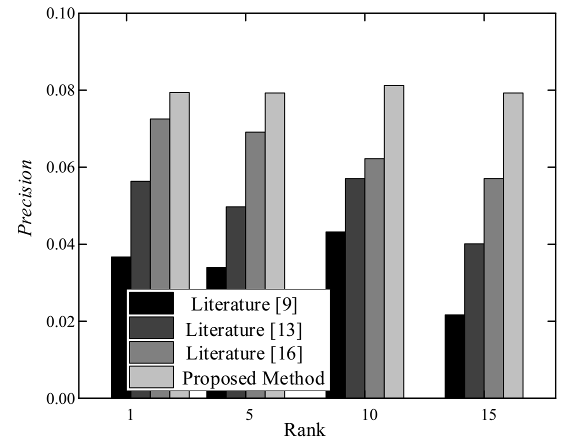


(b) The test result of recall rate

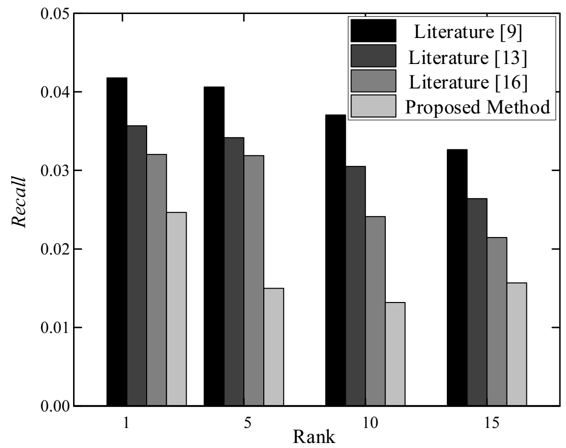


(c) The test result of F-score

Figure 3. The influence of parameter β on the recommended performance of the proposed method

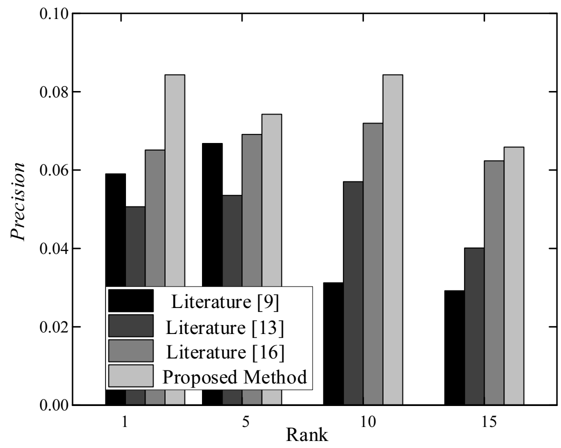


(a) The test result of precision rate

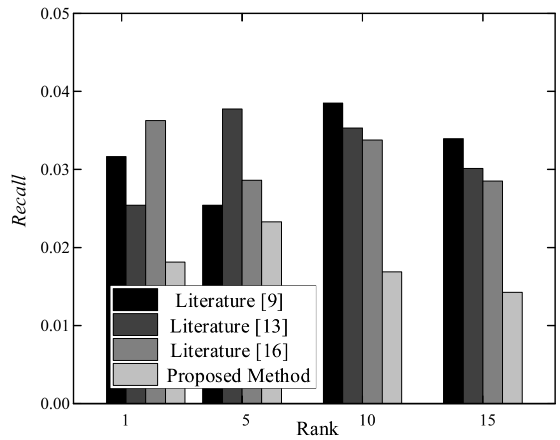


(b) The test result of recall rate

Figure 4. Performance comparison of LA dataset cold start problem



(a) The test result of precision rate



(b) The test result of recall rate

Figure 5. Performance comparison of NY dataset cold start problem

considered in the reference [16], because only the information of POI is considered, it is insufficient for the analysis of user sentiment classification. The proposed method combines three factors including sentiment classification, user preference and attribute characteristics of POI, and uses CNN to extract features from images. Then, it uses the extracted features to guide potential user and POI feature learning.

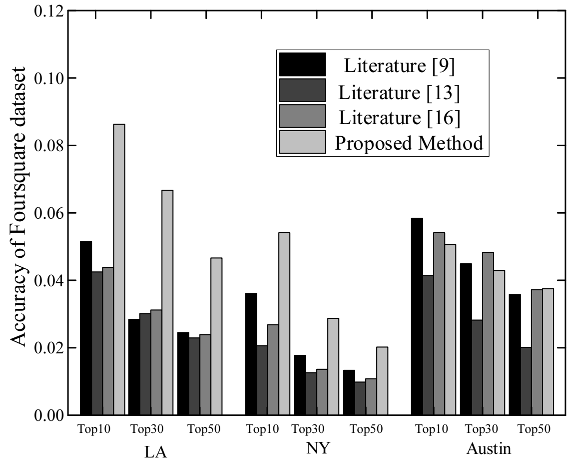
It can be concluded from the results that the extraction of image features can better understand user preferences, and then solve the cold start problem. The proposed method can extract user sentiment classification from images. Therefore, the proposed method shows better performance.

4.4 Experimental Results of Average Indicators with Different List Lengths

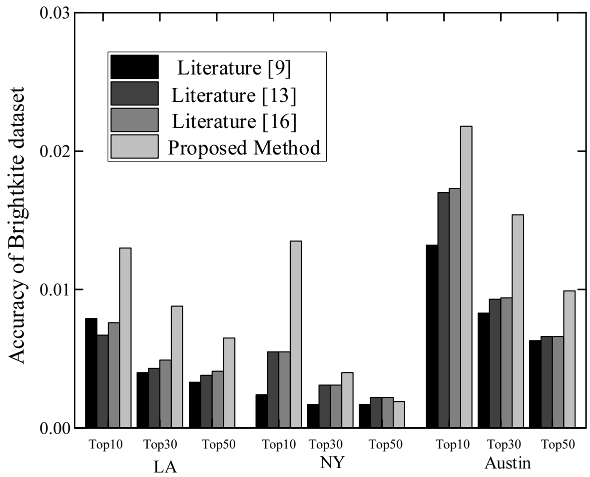
The objective optimization output of the proposed method is a set of non-dominated solutions. Therefore, the algorithm can recommend diverse solutions to each user. These lists have different trade-offs between different factors and cannot be simply described as one group is better than the other. The user can select a set of recommendation lists that best meets the current needs of these lists. And then, it forms a list of Top-N locations that are finally recommended to users.

In the experiment, the average value of the Pareto recommendation list evaluation index of all users in the dataset was selected to compare the experimental results with the algorithms in reference [9, 13, 16]. To illustrate the relationship between the length of the list N and other three factors including accuracy, recall and F-value, the range of N in the experiment is set from 10 to 50. To further demonstrate the performance of the proposed method, the proposed method was tested in the Brightkite dataset. A new check-in city Austen is added to demonstrate the generalization of the proposed method.

It can be seen from Figure 6 that as the length of the recommendation list N increases, the accuracy of each algorithm decreases. On the LA dataset, when $N = 50$, the accuracy of the proposed method is better than other algorithms. On the Austen dataset, the average accuracy of the proposed method is better than that of other comparison algorithms, and the proposed method can also generate highly accurate recommendation lists under different list lengths. As the check-in data is processed into binary data on the Austen dataset, it is more suitable for the multi-objective optimization algorithm. The accuracy of each method in Foursquare and Brightkite dataset has little difference in relative size, and the accuracy of the proposed method is the highest compared with other methods.



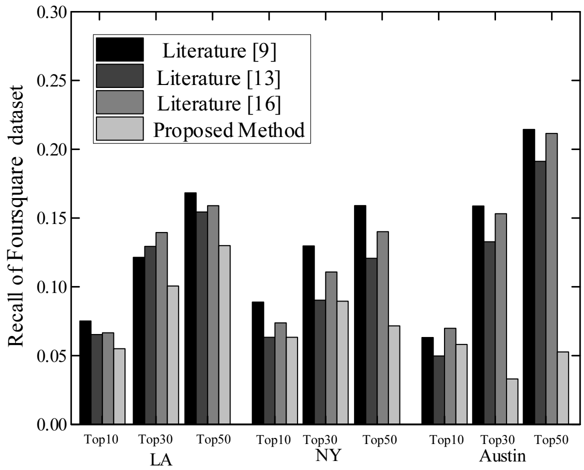
(a) The test result of precision rate on Foursquare



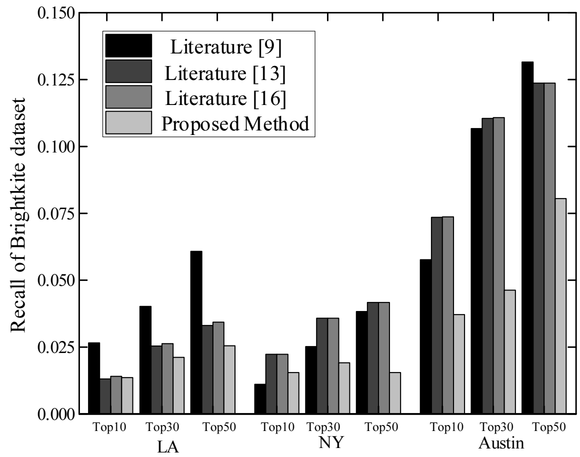
(b) The test result of precision rate on Brightkite

Figure 6. Comparison of accuracy rates under different recommended list lengths in different datasets

It can be seen from Figure 7 that as the value N increases, the value of the recall rate also increases. When $N = 10$, the recall rate of the proposed method is the best on the LA dataset. With the increase of N, the recall rates of other methods increase significantly. Although the proposed algorithm is not optimal on the Brightkite dataset, the recall rate is acceptable. On the NY data, the recall rates of all methods are not much different, especially in the Brightkite dataset. On the Austen data, the recall rates of the two datasets are high and the advantage of the proposed method is not obvious.



(a) The test result of recall rate on Foursquare

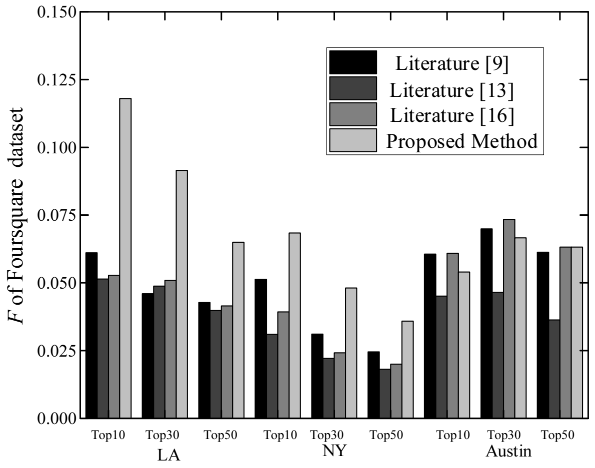


(b) The test result of recall rate on Brightkite

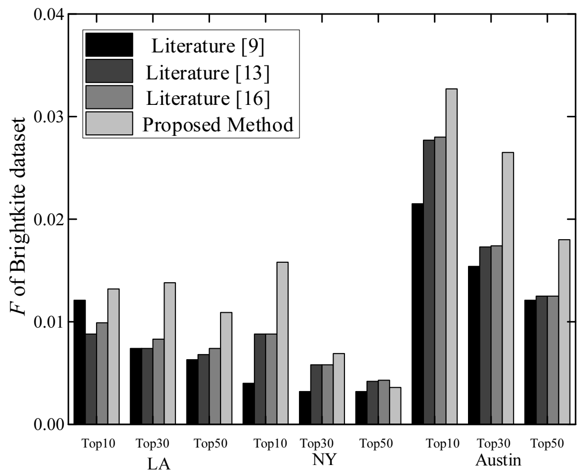
Figure 7. Comparison of recall rates under different recommended list lengths in different datasets

F value is a reconciliation indicator of accuracy and recall. It can be seen from Figure 8 above that with the change of the value N, the F value index is basically stable. For the LA and NY data in the Foursquare dataset, the F value result of the proposed method is far better than other comparison algorithms. In the LA dataset of Brightkite, because the accuracy and recall rate of the proposed method is very good, its F value is also better than the results of other algorithms. In the Austen data, the result of the proposed method is more prominent and the values of the other three methods have a small difference.

By comparing and analyzing the proposed method with other methods in the data of three cities of two datasets, the results show that the proposed method can guarantee a relatively good recommendation accuracy. Moreover, with the increase of the length of the recommendation list, the performance degradation is the smallest. Therefore, more recommended options can be guaranteed, and users can choose them in a variety of ways.



(a) The test result of F-score on Foursquare



(b) The test result of F-score on Brightkite

Figure 8. Comparison of F value under different recommended list lengths in different datasets

5 Conclusion

With the rapid development of the technology of internet, the recommendation system has been widely used in social media and other fields. As an information service technology, it has connected users and a large amount of information. To find the potentially interesting locations of users from massive and sparse data and place them to the appropriate users accurately, a LBSNs content-aware POI recommendation method based on deep learning and multi-objective immune optimization is proposed. The method first introduces CNN to process comment texts information and obtain user sentiment classification, user preferences and the attributes of POI. Meanwhile, it fuses geographic location information to determine a POI recommendation model. Then, it uses the NNIA algorithm to solve the above multiple goals and provides LBSNs users with recommended locations accurately. The experimental results in the Foursquare and Brightkite datasets show that the proposed method is superior to the existing POI recommendation models. Moreover, by using CNN combined with the comment content representation in the POI recommendation, the accuracy of the recommendation can be improved. In addition, the multi-objective immune optimization method can provide a set of recommendation lists that is long enough to ensure the diversity of content-aware POI recommendation.

In future work, other aspects can be considered to improve the performance of the algorithm. Firstly, user preference shifts can be considered. Secondly, attention mechanisms can be introduced into the proposed method to improve the accuracy of the recommendation. In addition, at the POI recommendation system of LBSNs, it should also consider more factors that affect user preferences. And these factors can be optimized simultaneously to improve the recommendation performance of existing algorithms.

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Biographies

Xinxin Lu, Master of Computer Science, Lecturer. Graduated from Guangxi Normal University. Worked in Zhoukou Normal University. His research interests include machine learning and computer applications.

Hong Zhang, Master of Computer Science, Lecturer. Graduated from China University of Geosciences Beijing. Worked in Zhoukou Normal University. His research interests include cloud computing, pattern recognition, intelligent optimization algorithm.