

Personalized Web Service Recommendation Method Based on Hybrid Social Network and Multi-Objective Immune Optimization

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Abstract

To alleviate the cold-start problem and data sparsity in web service recommendation and meet the personalized needs of users, this paper proposes a personalized web service recommendation method based on a hybrid social network and multi-objective immune optimization. The network adds the element of the service provider, which can provide more real information and help alleviate the cold-start problem. Then, according to the proposed service recommendation framework, multi-objective immune optimization is used to fuse multiple attributes and provide personalized web services for users without adjusting any weight coefficients. Experiments were conducted on real data sets, and the results show that the proposed method has high accuracy and a low recall rate, which is helpful to improving personalized recommendation.

Keywords

Cold Boot, Hybrid Social Networks, Personalized Recommendation, Multi-Objective Immune Optimization, Service Providers, Web Service Recommendation

1. Introduction

With the increasing number of network services, there are many services with the same function but different qualities-of-service (QoS), while users are left with no choice. Service recommendation can actively recommend to users unused web services with good service quality or high praise from other users, which effectively filters out many web services that are not be praised by users and narrows down the selection space. Service recommendation has attracted extensive attention from scholars at home and abroad [1-3]. However, how to infer the user's evaluation or the QoS when the user has not used the web service is a challenging problem. The existing web service recommendation methods are mainly based on collaborative filtering, and they are mainly divided into neighbor-based methods and model-based methods. On this basis, the context-aware method and the content-based method were developed [4,5].

Neighbor-based methods, also known as memory-based methods, mine similarity patterns between users or web services based on historical data and then make recommendations based on the experience results of similar users or similar services. Generally, methods based on the nearest neighbor have strong

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interpretability in theory and have played a great role in promoting the development of web service recommendation. However, in practice, because the historical data is usually very sparse, it is difficult to identify similar users or similar web services, and thus it is difficult to obtain high recommendation accuracy.

Model-based methods learn the potential patterns hidden in the data from the historical QoS or rating data, construct a prediction model to predict the unknown QoS or rating data, and then make a recommendation according to the prediction results. Zhang et al. [6] analyzed the potential characteristics among users, services, and time, and proposed a time-aware personalized QoS prediction method. Yu et al. [7] assumed that the QoS matrix was a low rank or approximately a low rank, and they proposed a trace norm regularized matrix decomposition method to predict the unknown QoS, and the web service recommendation is made according to the prediction results. Zheng et al. [8] integrated a similar user method and matrix decomposition method for personalized QoS value prediction. Kirchner et al. [9] proposed a web service recommendation model based on classification and a web service recommendation model based on regression, and they analyzed their respective adaptation situations. Xie et al. [10] used an asymmetric matrix to represent the potential association between users and web services and to alleviate the problem of data sparseness to further improve web service recommendation prediction accuracy. The model-based methods further improve the accuracy of web service recommendation; however, such methods often have high computational complexity, and there is a trade-off between model complexity and prediction accuracy.

To further improve the quality of recommendation results, information sources outside the user item matrix are also included in the collaborative filtering algorithm. Deng et al. [11] used a model-based collaborative filtering method to evaluate the trust degree among users in social networks, and then an extended random walk algorithm was designed to recommend web services. Wang et al. [12] used a cumulative sum control chart to detect malicious feedback scores, and they proposed bloom filtering to prevent malicious feedback scores and improve recommendation performance. Guo et al. [13] proposed a QoS prediction model using tensor decomposition based on service collaboration called Service-oriented Tensor. This prediction approach analyzes service collaboration from other similar services and relevant users by using a three-order tensor. Gonsalves and Patil [14] proposed a location-based QoS prediction method and used the k-nearest neighbor algorithm and support vector machine (SVM) as a collaborative filtering framework for web service recommendation. The method of context awareness is usually based on a collaborative filtering method. Generally, the prediction accuracy and recommendation quality have been improved in terms of their respective concerns and perceptions. Web service positioning (WSP) gives the specific function description of the service and publishes the service that conforms to the service level agreement; it can provide support for personalized recommendation and avoid taking the same approach as non-rated services.

This paper proposes a recommendation framework and algorithm based on a hybrid social network (HSN), which integrates service, WSP in the social network, user-user trust, and user-service trust. The trust between users and the WSP and the connection between WSP and service provide an HSN. Because the trust relationship between users and the provision of the WSP service contains rich information, it provides a reliable basis for improving the recommendation performance and improving the cold-start problem.

2. Hybrid Social Networks with Trust

The HSN model is constructed with trust, as shown in Fig. 1, and it is divided into two layers: the cloud layer and the user layer. The network consists of three types of nodes (users, web services, and WSP) and two types of contact (trust and provide). The links included are (1) user-service trust, (2) user-WSP trust, (3) WSP-service provision, and (4) user-user trust. The existence of a connection between two nodes means that there is trust or a connection is provided. The value range of the trust value is $[0, 1]$, and a value of 0 means that there is no connection. The value provided is either 0 or 1.

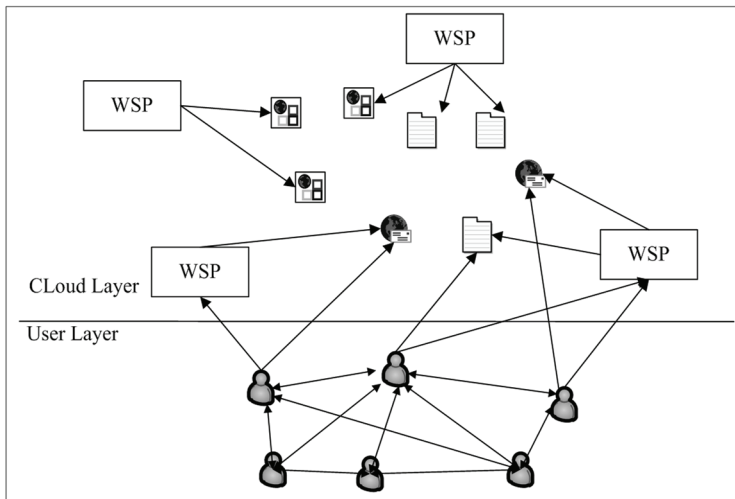


Fig. 1. HSN with trust.

In the user layer of the social network, the user is the node, and the trust relationship between users is the edge, which forms a user social network based on trust. It has the characteristics of domain relevance and transitivity.

- (1) Domain relevance: According to the functional domain, users have different trust values for the same user.
- (2) Transitivity: The trust between users is transitive.

The HSN is combined with the social network, service, and WSP, and an HSN is formed. While maintaining the characteristics of social network, it also has the characteristics of heterogeneity, personalization, mutual independence, and authenticity.

- (1) Heterogeneity: The network contains different types of nodes and connections, reflecting the heterogeneity of network structure.
- (2) Personalization: The trust value of users to the service and WSP reflects the personalized cognition of users.
- (3) Mutual independence: It is assumed that WSPs are independent of each other and will not share user information.
- (4) Authenticity: The information provided by the WSP is real and easy to obtain, which enhances the recommendation reliability.

2.1 Network Composition

The HSN is a directed graph, which can be formalized as $=(F, P, C, E, W, t)$. Here, F , P , and C represent the set of nodes in the graph; F is the service collection published in the registry, (f_1, f_2, \dots, f_m) ; P is the set of WSPs providing F , (p_1, p_2, \dots, p_n) ; C is the collection of all users in the registry, (c_1, c_2, \dots, c_o) ; E is the set of directed edges in the graph $E = \langle E_1 \rangle$; and $E_2 \rangle .E_1$ denote the WSP service providing the connection. When p_i provides service f_j , the value of the edge is 1; when there is no relationship provided, then there is no edge E_2 , which indicates the trust relationship between nodes. In $E_2 = (T_1, T_2, T_3)$, T_1 is the user-user-user trust, T_2 is the user-service trust, and T_3 is the user-WSP trust. W represents the weight set of all edges in HSN, and t marks a time window. In a certain period of time, the trust value is constant.

2.2 Network Trust Value Calculation

2.2.1 User-user trust

To recommend services with specific functions to the current user C , the premise of identifying the user group as C trust is that the user group with a high similarity to C is in the domain related to the recommendation task. Suppose you want to recommend a weather service for C , then a user who has used a weather-related service and has a high similarity with C is found, and that user's view on the weather field is credible. The trust value for trusted users c_i is expressed as follows:

$$T_1(C, c_i) = \text{sim}(C, c_i), \quad (1)$$

where $c_i \in C_i$, c_i belongs to the trustable set C_i .

Here, $C_i = \{c_i \mid \text{sim}(C, c_i) \geq \sigma, f(c_i, D(f)) = 1\}$. $\text{sim}(C, c_i) \geq \sigma$ means that the similarity threshold is set to σ , $\sigma > 0$. $f(c_i, D(f)) = 1$ indicates that c_i has used a service related to f , and f indicates a domain related to $D(f)$. The similarity $\text{sim}(c_i, c_j)$ is calculated by the Pearson correlation coefficient as follows:

$$\text{sim}(c_i, c_j) = \frac{\sum_{f \in f_g} (T_2(c_i, f) - \overline{T_{c_i}})(T_2(c_j, f) - \overline{T_{c_j}})}{\sqrt{\sum_{f \in f_g} (T_2(c_i, f) - \overline{T_{c_i}})^2} \cdot \sqrt{\sum_{f \in f_g} (T_2(c_j, f) - \overline{T_{c_j}})^2}}. \quad (2)$$

Here, f_g is the intersection of the services called by c_i and c_j , $\overline{T_{c_i}}$ and $\overline{T_{c_j}}$ are the average trust values of c_i and c_j called services, and the value range is $[-1, 1]$. When a negative value is taken, it is considered that there is no edge connection between users. The similarity between two users satisfies the symmetry below.

$$\text{sim}(c_i, c_j) = \text{sim}(c_j, c_i) \quad (3)$$

After obtaining the specified recommendation task, the similarity between any two users is calculated to form a weighted user social network to obtain C trusted user groups.

When traversing the social network, if there is no edge directly connected between two users, but there is path reachability, then the indirect trust can be calculated by Formula (4).

$$T_1(c_i, c_k) = T_1(c_i, c_j) \cdot T_1(c_j, c_k) \quad (4)$$

It is defined that the stage of the path between two users does not exceed the constant l . According to the small-world characteristics of social networks, l is set to 6. When there are multiple paths, the path with the largest indirect trust value is selected.

2.2.2 User-service trust

The user-service trust value measurement includes direct trust and indirect trust. Direct trust is the normalization of user experience and feedback on QoS indicators. According to the personalized characteristics of users, different weights λ_i are set for each QoS to form the direct trust value, which can be expressed as follows:

$$T_2(C, f) = \sum_{i=1}^q \lambda_i \cdot \text{QoS}_i^C, \quad (5)$$

where $\sum_{i=1}^q \lambda_i = 1$, $0 \leq \lambda_i \leq 1$.

Here, QoS_i^C is the evaluation value of C pairs of i QoS, and there are q indicators in total. Different users have different evaluations on the same QoS, which reflects the personalized characteristics of users [15].

The direct trust value changes dynamically with the increase of the number of users calling services. The calculation is as follows:

$$T_2^d(C, f) = \frac{\sum_{i=1}^N T_2(C, f)}{N}, \quad (6)$$

where N is the total number of times the user calls the service, and $T_2^d(C, f)$ is the average trust value after the user has called many times. The calculation of indirect trust value refers to the evaluation of service f by C trusted user groups, which is the average product of the trust value between C and c_i and the direct trust value of c_i to f , as shown in Formula (7).

$$T_2^{id}(C, f) = \frac{\sum_{i=1}^n T_1(C, c_i) \cdot T_2^d(c_i, f)}{n} \quad (7)$$

Here, $T_1(C, c_i) \geq \sigma$ and $\sigma > 0$, which denotes that c_i is a C trusted user. In our experiment, σ was set as 0.3. Besides, n is the number of users trusted by C .

When there is no direct trust value between users and services, C traverses the social network. When there is a path reachable between C and the user group, it is determined to be a trusted user group according to Formula (1). Suppose that c' is a trusted user and the nodes from C to c' pass through c_{i+1}, \dots, c_{i+n} in turn, then the trust value is calculated as follows:

$$T_{2,p}(C, f) = T_1(C, c_{i+1}) \cdots T_1(c_{i+n}, c') \cdot T_2(c', f), \quad (8)$$

where $T_1(C, c_{i+1}) \cdots T_1(c_{i+n}, c') \geq \sigma$ and $\sigma > 0$, which represents the threshold to be met by C trusted users. When there are multiple paths between C and c' , the user-service trust value is defined as the average trust value of multiple paths as follows:

$$T_2(C, f) = \sum_{p=1}^P T_{2,p}(C, f) / P. \quad (9)$$

There are P paths.

If there is a direct path between C and c' , then the trust value is not affected by the complex path, although there are other more complex paths (such as loops in the path).

2.2.3 User-WSP trust

For a service, WSP is the effective information. As important information of the service, a calculation method of the user-WSP trust value is proposed to provide the basis for the recommendation. The frequency of WSP usage reflects the implicit preference of users to select services. The frequency of users calling on the WSP can be used as the basis of the WSP trust value calculation. The quantitative relationship of service WSP follows a power-law distribution. The WS-Dream-QoSDataSet2 data set can be taken as an example (shown in Fig. 2). Based on the quantitative relationship between the service and the WSP, it is assumed that the frequency of WSP usage follows a power-law distribution, and there are a few WSPs frequently used. The usage frequency of user c' to p_j is the ratio of c' using p_j times and c' using all WSPs, which is expressed as follows:

$$\text{Fre}(c_i, p_j) = q_{i,j} / \sum_{j=1}^N q_{i,j}. \quad (10)$$

Here, N is the number of WSPs, and $q_{i,j}$ is c_i and p_j times of use.

The frequency of the user WSP usage is converted into the user WSP score. Using the linear function, the value range of the converted score is [0, 5]. For all the WSPs in descending order, the scores of c_i pairs of j -WSP are as follows:

$$r(c_i, p_j) = 5 \left(1 - \sum_{j'=1}^{j-1} \text{Fre}(c_i, p_{j'}) \right). \quad (11)$$

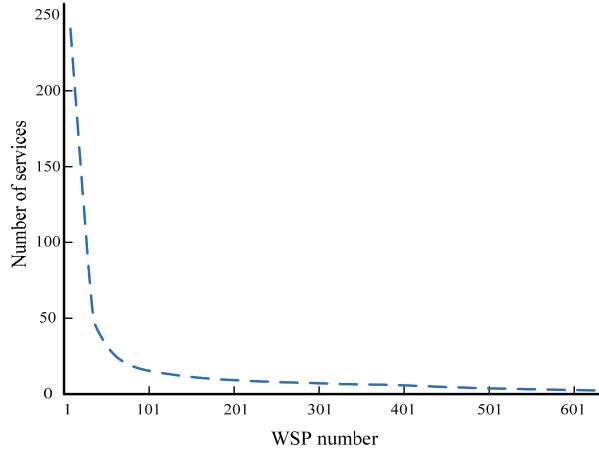


Fig. 2. Power law distribution of the service WSP number.

The trust value of the WSP can be obtained by normalizing the rating value as follows:

$$T_3(c_i, p_j) = \frac{r(c_i, p_j) - \min_{i,j} r(c_i, p_j)}{\max_{i,j} r(c_i, p_j) - \min_{i,j} r(c_i, p_j)}. \quad (12)$$

The Pearson correlation coefficient is used to calculate the similarity between any two users in the WSP selection to recommend the WSP for users.

$$g(c_i, c_j | \text{WSP}) = \frac{\sum_{k=1}^t (r(c_i, p_k) - \overline{r(c_i, p)}) (r(c_j, p_k) - \overline{r(c_j, p)})}{\sqrt{\sum_{k=1}^t (r(c_i, p_k) - \overline{r(c_i, p)})^2 \sum_{k=1}^t (r(c_j, p_k) - \overline{r(c_j, p)})^2}} \quad (13)$$

Here, t is the number of WSPs jointly called by users c_i and c_j .

According to the user WSP trust, the user-service trust value is predicted.

$$T_2(C, f) = \frac{m_j T_3(C, p_j) + \sum_{i=1}^N T_2(C, f_i)}{m_j + N}. \quad (14)$$

This is the number of services provided by N for C calling p_j , and m_j is the number of calls C to p_j . The more times the WSP is called, the more trust users have in it, and the more trust they have on other services provided by the WSP.

3. Service Recommendation Based on Multi-Objective Immune Optimization

To avoid the process of adjusting the weight coefficient, the proposed method regards the content attribute, user preference, and user sentiment classification as three functions and simultaneously

optimizes them. The purpose is to improve one objective function without damaging the value of another. In this process, each generated recommendation list has different trade-offs among the attributes of the web service recommendation points of interest, user preferences, and user sentiment classification affected by geographic information. Therefore, a web service recommendation method based on multi-objective immune optimization can provide different recommendation lists for different users. Each list has different trade-offs between different objective functions, which allows the list to compromise between different preferences. This provides users with more options to choose from, and users can choose the best list from these non-dominated lists.

3.1 Objective Function Design

Most of the existing literature has used a weight coefficient to roughly evaluate the impact of each factor on the user's location, and the top ranked sites constitute the location recommendation list. In this way, the importance of the influence of each factor depends on the size of the coefficient before each factor. The existing algorithms do not provide each user with a unique weight vector, but rather the whole system uses the same weight vector. This rough consideration assumes that all users' preferences for different factors are the same, which does not meet the requirements of personalized recommendation. Therefore, the proposed method comprehensively considers the currently active user preferences, sentiment classification, and the probability density function of the currently active user's registered geographic information.

$$\begin{cases} \max & -\frac{1}{N} \sum_{i=1}^n \sum_{G_k \in G_{N_i}} \log P(f_{ik} = 1 | c_i, G_k) \\ \max & -\frac{1}{N} \sum_{j=1}^n \sum_{G_k \in G_{j_i}} \log P(h_{jp} = 1 | l_j, G_k) \\ \max & I \end{cases} \quad (15)$$

Here, N is the length of the final recommended list.

The location aware service recommended by the proposed method needs to satisfy the user's maximum preference ($\max I$), that is, the favorite location to go to. Moreover, the association between comments and users and between comments and locations should be closer, that is, the probability density functions $P(h_{jp} = 1 | l_j, G_p)$ and $P(f_{ik} = 1 | c_i, G_k)$ should be the largest.

3.2 A Personalized Web Service Recommendation Method Based on Multi-Objective Immune Optimization

Based on the content-aware interest points of a deep convolution neural network to determine the service recommendation framework, the non-dominated neighbor immune algorithm (NNIA) is used to solve the multi-objective optimization problem of attributes, user preferences, and user sentiment classification of service recommendation interest points to obtain the recommendation list.

The NNIA simulates the mechanism of coexistence of diverse antibodies and the activation of a few antibodies in the biological immune system, selects relatively isolated non-dominated individuals to

activate, performs proportional cloning according to the crowding distance of activated antibodies, increases the search for sparse regions in the Pareto front in the genetic operation process, and obtains a uniform distribution and good diversity. The pseudo code of the NNIA algorithm is given below.

Algorithm 1. Pseudo code of the NNIA algorithm

Input: Maximum number of iterations, G_{max} ; Maximum size of potential population, NM ; Maximum size of active population, NA ; Clonal population size, CS

Output: Pareto-optimal set

1. **Initialization:** The antibody population of size NM was initialized B_0 , initialize the population $A_0 = \phi$, $C_0 = \phi$ and $D_0 = \phi$, and set $t = 0$.
 2. **Regeneration of dominant population:** According to the crowding distance of population B_t , the first NM individuals were selected to enter the new species group D_{t+1}
 3. **While** $t \leq G_{max}$ **Do**
 4. $t = t + 1$
 5. Export population D_{t+1}
 6. **Non-dominated neighbor selection:**
If the population size of D_t is less than NA , **Then**
 7. $A_t = D_t$
 8. **Otherwise** According to the descending order of crowding distance, the first NM individuals were selected to enter population A_t .
 9. **Proportional cloning:** According to population A_t , clone population C_t .
 10. **Genetic manipulation:** Crossover and mutation were performed in clone population C_t .
 11. Combine population C_t and population D_t to obtain population B_t . Return to step 2.
-

The Pareto optimal solution set is obtained by solving the multi-objective function problem by the NNIA algorithm, and personalized web service recommendation can be obtained.

4. Experiment

4.1 Experimental Environment and Configuration

A real data set, WS-Dream-QoSDataSet2, was used to remove the WSPs that only provided one service to form a new data set. It included 339 users, 4,000 services, and 883 WSPs. To form a candidate service set with a total number of 138, service filtering searched for services containing "search" by keywords with the query function. Since each user called the candidate service in the data set, the size of the candidate user set was 339 after user filtering.

A user-service trust matrix was established to normalize QoS value. The weights of the response time and throughput were set to 0.6 and 0.6 to form a matrix T' of 339×138 .

The WSP service supply matrix was established, information from the data set was extracted, and the 883×4000 0–1 matrix P was formed.

The user-user trust matrix was established according to the user-service trust value to form the 339×339 matrix U_T' .

The user-WSP trust matrix was established according to the power-law distribution of WSP usage times, and the usage frequency of WSP was simulated. According to Formula (11) and Formula (12), the score and trust value of user WSP were calculated to form matrix U_p .

4.2 Measurement Criteria

The accuracy *Precision*, recall *Recall*, and F value *F-score* were used to evaluate the performance of the recommended method. For target users u_i , *Precision* and *Recall* were defined as

$$Precision = \frac{\text{The number of user acceptance in the recommended list}}{\text{The number of user acceptance in the test set}} \quad (16)$$

and

$$Recall = \frac{\text{The number of user acceptance in the recommended list}}{\text{Quantity in recommended list}} \quad (17)$$

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

$$F-score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (18)$$

Each data set was divided into three groups, including a training set, an effective set, and a test set. In the experiment, 80% of the data set was used as the training set, 10% as the verification set to adjust the super-parameters, and the remainder was the test set.

Moreover, the parameters of the multi-objective immune optimization algorithm were as follows: the length of the candidate list was 100, the number of iterations was 300, the maximum size of active population was 30, the scale of clone population was 150, the maximum size of the dominant population was 60, the crossover probability was 0.8, and the mutation probability was 0.1.

4.3 Sensitivity Analysis of Model Parameters

In the proposed method, the weight parameter β , which is used to control the influence of position proximity, has a great influence on its performance, and thus it is necessary to conduct in-depth analysis on β . The value of β varied from 0 to 1, and the recommended results obtained by the proposed method are shown in Fig. 3.

As shown above, when $\beta = 0$, the recommendation accuracy was the lowest due to not considering the geographical proximity; similarly, when $\beta = 1$, the result was not accurate because too many geographical proximity factors were considered. Therefore, when $\beta = 0.5$, the accuracy of the proposed method was the best. The proposed method had high accuracy and low recall rate, and it had an ideal performance.

4.4 Analysis of the Experimental Results

The proposed method can solve the cold-start problem by fusing user preference, sentiment classification, and location interest point attribute information. The results are shown in Fig. 4.

As shown above, compared with the other recommendation algorithms, the proposed method performed the best in solving the cold-start problem. For the cold-start problem, the recommendation accuracy of all the algorithms decreased in varying degrees. For example, the recommendation accuracy of methods from prior work [10,13] dropped sharply, while the accuracy of methods from another study [14] decreased slightly, because these algorithms did not consider the content information of the review text.

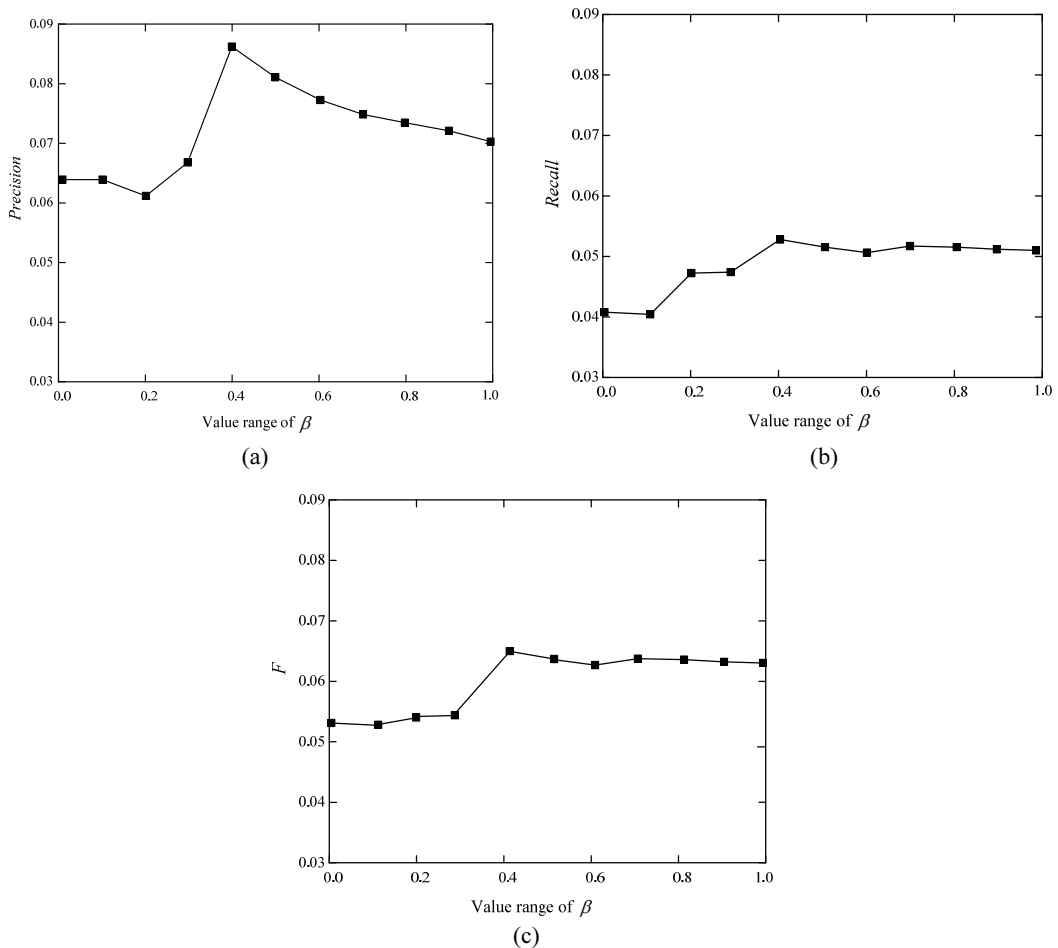


Fig. 3. The effect of parameter β on the recommendation performance of the proposed method: (a) precision, (b) recall, and (c) F-score.

Compared with the other methods, the performance degradation of the proposed method and the method from a prior study [14] was relatively small, and the performance of the proposed method was reduced even less. Because the content of the comment text was considered in the method from a prior study [14], only k-nearest neighbor algorithm and SVM were used as the collaborative filtering

framework for web service recommendation. Context awareness methods are usually based on a collaborative filtering method. Web service positioning gives the specific function description of the service and publishes the service that conforms to the service level agreement; it can provide support for personalized recommendation and avoid taking the same approach to non-rated services. However, such methods often have high computational complexity, and there is a trade-off between model complexity and prediction accuracy.

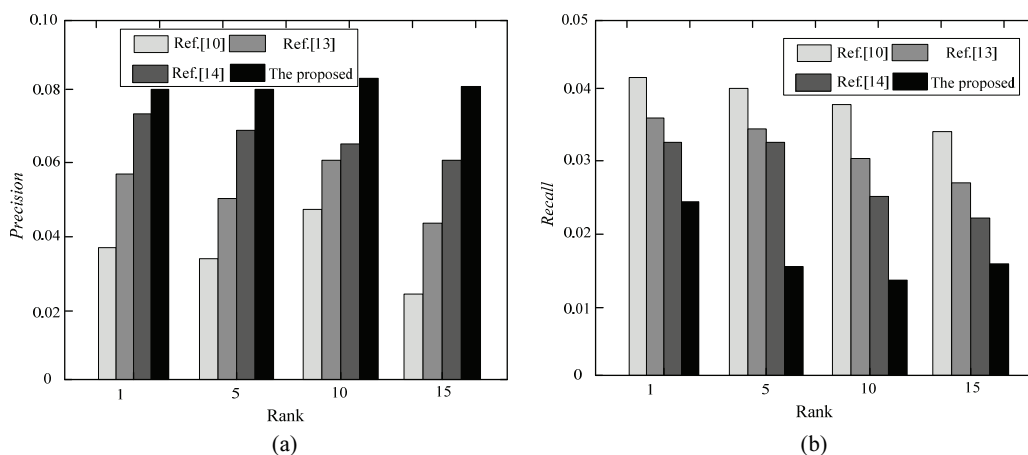


Fig. 4. Performance comparison of the cold-start problem: (a) precision and (b) recall.

It can be concluded from the results that the proposed method contained rich information due to the trust relationship between users and the provision of the WSP service, which provides a reliable basis for improving the recommendation performance and improving the cold-start problem. Therefore, the proposed method showed a better performance than the other methods.

5. Conclusion

Because trust can reflect the characteristics of personalized selection service, the combination of trust and HSN can alleviate common cold-start problems and matrix sparseness in recommendation. This paper establishes a web service recommendation framework based on HSN and proposes a personalized web service recommendation method based on an HSN and multi-objective immune optimization. Web service positioning is integrated into the social network, user, and user service. The trust between users and WSP and the connection between WSP and service provide an HSN. Moreover, the multi-objective immune optimization method can provide a long enough recommendation list to ensure the diversity of service recommendations.

There are still some areas worthy of further study, such as constructing a social network and a web service social network, taking a community structure as the center, recommending services for users, analyzing the game and sharing relationship between WSPs and applying them to recommendations. Besides, providers are common, and thus the method proposed in this paper should be extended to the research on the recommendation of general items.

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