A Service Recommendation Algorithm for Intelligent Community Combining Community Factor and Trust Degree

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Abstract

Service recommendation algorithm already exists in many fields, but its application in the field of intelligent community is relatively small. The existing recommendation algorithm treats the evaluation of each user equally, or only considers the similarity of the user's score, without regard to the user's domain correlation and the trust degree of the recommendation information. To solve above problems, this paper introduced the user's reputation and usage frequency of the service, to improve the traditional similarity calculation formula; established the trust relationship between users based on the user's trust model; for intelligence community users, introduced the community factor, constructed the trustworthy community, and put forward a kind of intelligent community oriented service recommendation method based on trustworthy community. Through the experiment, compared with the existing recommendation algorithm, the service recommendation algorithm for intelligent community combining community factor and trust degree has a higher accuracy.

Keywords

Intelligent community; Recommendation algorithm; Trust degree; Community factor.

1. Introduction

In order to provide a more convenient and comfortable community life experience for community residents, service recommendations are introduced into the intelligent community. Today, service recommendation [1] is available in many fields, such as e-commerce, news, movies, music, etc., but there are fewer applications in intelligent community. In recent years, a lot of research work around using history information about the problem of evaluating the quality of service, but these studies do not take into account the human factors too much: most studies rely on the different user feedbacks on the same service information [2] to evaluate the service trust degree, equally treat each user's evaluation, or just consider the similarity of user ratings, without regard to the user's domain correlation and recommend the trust degree of information.

For the above problems, while this paper is looking for users of behaviors similar and measuring users' similarity, the users' reputation and service frequency are introduced, so as to better reflect the user cognition process. Meanwhile, based on the existing trust theory and related trust model [3], the trust relationship between users is established and the construction of trustworthy community is completed. Then, in view of the intelligent community, in the recommended algorithm community factor is incorporated; and for users to realize reliable service recommendation, a kind of intelligent community oriented service recommendation method is put forward based on trustworthy community.

2. Related Notion

2.1 Similarity

Similarity is the recommended basis for collaborative filtering recommendation, and whether user-based or project-based collaborative filtering recommendation algorithm [4], its core is to calculate the similarity. Common similarity calculation methods include Euclidean distance, cosine similarity and Pearson similarity. In this paper, Pearson similarity is used to calculate the similarity, with user reputation [5] and usage frequency of service [6] introduced.

2.2 Trust Degree

In the environment of intelligent community, trust degree can be affected by many uncertain factors. The main factor influencing users' trust is the evaluation of people's trust value [7] and time weight. In general, the higher the trust value, the higher the trust degree. The evaluation of users' reference is more recent, and the time weight of evaluation should be reduced in terms of long time evaluations.

2.3 Suggested Users

The service evaluation for User u_i is as shown in formula (1):

$$EV_i = \left(WS_i, \delta_i\right) \tag{1}$$

Where WS_i is a finite set of services that users u_i accesses, and δ_i is a service evaluation function. The current service evaluation of user u_i is EV_i, the service evaluation of user u_j is EV_j, and ws_{jk} is the k^{th} collection of the service set WS_i. If the $\exists ws_{jk} \in WS_j$ and $ws_{jk} \notin WS_j$, and user u_i wants to be able to get the evaluation information of the service ws_{jk}, then the user u_i is the recommendation user for service ws_{jk} of user u_j.

2.4 Recommendation Degree

If the user u_i is the recommendation user for service ws_{jk} of user u_j, then recommendation degree for service ws_{jk} that the user u_i provide to user u_j is as shown in formula (2):

$$R_{u_i \to u_j}\left(ws_{jk}\right) = \delta_j\left(ws_{jk}\right) S_{u_i \to u_j}\left(1 + \mu + \lambda\right) \tag{2}$$

Where μ is the value-added coefficient generated according to the user, $0 < \mu < 1$; λ is the value-added coefficient generated by user from its related domain.

3. The Construction of Trustworthy Community for Intelligent Community

Trustworthy community refers to in the service recommendation system, for the target user u_i, according to a recommendation strategy to select a set of users that are adjacent to the user u_i: $U = \{u_1, u_1, \cdots, u_n\}$. Where the recommendation behavior of the adjacent user is trustworthy and is similar to the service usage behavior of user u_i.

3.1 The Calculation of User Similarity

The degree of similarity can be calculated by the Pearson correlation coefficient that is a method to calculate the similarity by linear fitting degree, which can also get a better similarity calculation result when the data is not very normal.

Assuming that there are users u_1, u_2, $\cdots$, u_n and service s_1, s_2, $\cdots$, s_n in the recommendation system, then the similarity between the user u_i and the user u_j is as shown in formula (3):

$$Sim(i,j)=\frac{\sum_{s_k\in S}\sqrt{\theta\frac{1}{r_{s_k}^2}+\varphi\frac{1}{f_{s_k}^2}}\left(EV_i-\overline{EV_i}\right)\left(EV_j-\overline{EV_j}\right)}{\sqrt{\sum_{s_k\in S}\left(EV_i-\overline{EV_i}\right)^2}\sqrt{\sum_{s_k\in S}\left(EV_j-\overline{EV_j}\right)^2}} \tag{3}$$

The EV_i is the service evaluation of the user u_i, EV_j is the service evaluation of the user u_j, the $\overline{EV_i}$ and $\overline{EV_j}$ is the mean evaluation of the user u_i and the user u_j for all the services, the s_k is a certain service in all of the services, S is the set of all services, r_{s_k} and f_{s_k} are the user's reputation and the frequency of service usage, and the parameters θ and φ are the weighting factors of the reputation and the frequency of use respectively. So the user's similarity can adjust the parameters θ and φ according to the application scenario, so that the user's similarity has different results in different scenes.

3.2 The Trust Degree Calculation Between Users

The trust degree between users refers to the target users' subjective cognition degree on the authenticity, validity, and reliability of recommendation behaviors of recommendation user. To establish the trust relationship between users, it is necessary to select similar adjacent users by evaluating the similarity of behavior.

User's direct trust degree refers to when user u_i and user u_j have the same service evaluation set, the user u_i's satisfaction for user u_j's recommended service. The value is between 0 and 1, recorded briefly as RDT. As shown in Figure 1, user u_i and user u_j have the same set of service evaluations, so user u_i and user u_j established a direct trust relationship. The total number of recommendation times by user u_j to user u_i is $n_{i,j}$, where the number of times of correct recommendation is $t_{i,j}$, the number of times of error recommendation is $f_{i,j}$, the parameter x is the correct service recommendation event that u_j provides to u_i, with $0\le x\le 1$, and $\overline{x}$ is the wrong service recommendation event that u_j provides to u_i, with $x+\overline{x}=1$, then direct trust degree of u_i and u_j is as shown in formula (4):

$$RDT(i,j)=\frac{\Gamma\left(n_{i,j}\right)}{\Gamma\left(t_{i,j}\right)\Gamma\left(f_{i,j}\right)}x^{t_{i,j}}\overline{x}^{f_{i,j}} \tag{4}$$

Where Γ is a gamma function.

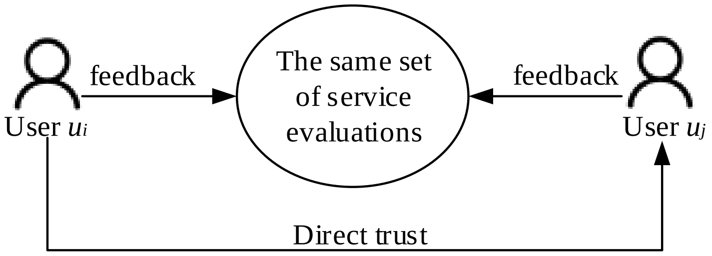

Fig. 1 User's direct trust relationship

The user's indirect trust: in the case that the user u_i and the user u_j have no direct interaction of service evaluation, u_i can recommend u_j by u_k that has interaction of service evaluation with it, and the trust degree of u_i and u_j can be got through direct trust between u_i and u_k and that between u_k and u_j, then the satisfaction of recommendation service for user u_i to user u_j is the user's indirect trust degree. The value is between 0 and 1, recoded briefly as RIDT. As shown in Figure 2, both user u_i and user u_k and user u_j and user u_k have direct trust relationship, so user u_i and user u_j established an indirect trust relationship through user u_k. The indirect trust degree between the user u_i and the user u_j is shown in formula (5):

$$RIDT(i,j) = RDT(i,j)\omega_k \tag{5}$$

Where ω_k is the trust weight of the user u_k to the target user u_i .

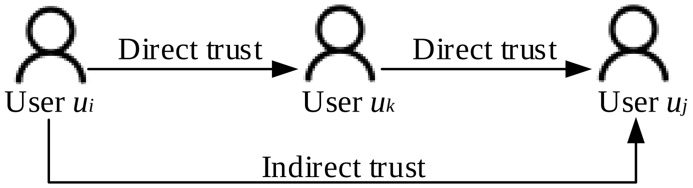

Fig. 2 User's indirect trust relationship

The trust degree between users is determined by direct trust degree and indirect trust degree. The trust degree $RT(i,j)$ between user u_i and user u_j is as shown in formula (6):

$$RT(i,j) = \alpha RDT(i,j) + (1-\alpha) RIDT(i,j) \tag{6}$$

Where α is the weight of the direct trust degree, and $1-\alpha$ is the weight of the indirect trust degree, $0 \le \alpha \le 1$. The larger $RT(i,j)$ indicates that the user u_i trusts the user u_j more.

3.3 The Calculation of Community Factors

The community has fixed the user's living environment and social relations, which largely leads to the user similar living habits and daily necessities and services, and community factors allows community users to have similar differences in habits and needs, so community factors can provide a critical role for service recommendations for intelligent community. The community factors extracted in this paper include the city of the community, the community grade, the age structure of the community, and the gender of the community. The community factor f is as shown in formula (7):

$$f = \frac{\sum f_i}{n} \tag{7}$$

Where f_i is the factor $\{f_1, f_2, \cdots, f_n\}$ that affects the service recommendation in the community.

3.4 The Construction of Trustworthy Community

According to the similarity $Sim(i,j)$ of users, the trust degree $RT(i,j)$ and the community factor f between the users calculated above, we can calculate the comprehensive weight $weight(i,j)$ of the user u_j to the user u_i , thus a trustworthy community can be constructed, and the calculation of $weight(i,j)$ is as shown in formula (8):

$$weight(i,j) = \frac{|Sim(i,j)| \times RT(i,j)}{|Sim(i,j)| + RT(i,j)} f \tag{8}$$

The construction of trustworthy community is as follows:

(1) Input: user u_i , the user's evaluation information;

(2) Output: the trustworthy community of the target user;

(3) Select the user u_j in the user set to calculate the similarity $Sim(i,j)$ of the user u_i and the user u_j ;

(4) According to the trust relationship of the users, the direct trust degree $RDT(i,j)$ and the indirect trust degree $RIDT(i,j)$ are calculated, and then the trust degree of the user u_i to the user u_j is calculated as $RT(i,j)$;

(5) According to the difference between the intelligent community to calculate the community factor f that impacts service recommendation;

(6) According to the similarity $Sim(i,j)$, the trust degree $RT(i,j)$ and the community factor f, the comprehensive weight $weight(i,j)$ of the user u_j to the user u_i is calculated.

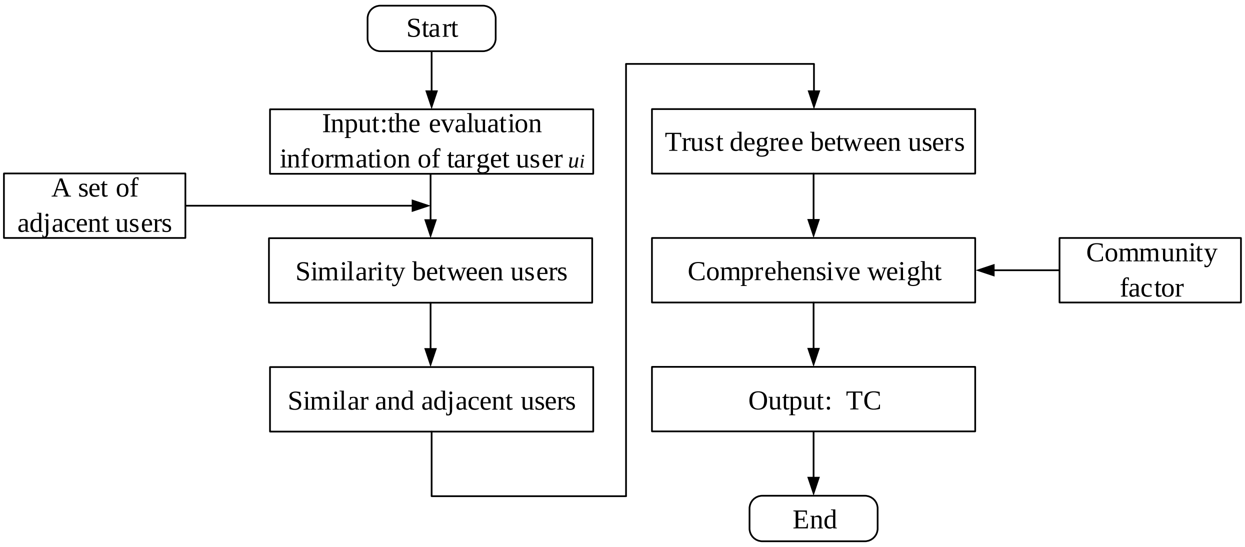

Fig. 3 The flow chart of constructing trustworthy community

Figure 3 gives a flow chart for constructing a trustworthy community TC for the target user u_i. First enter the evaluation information of target user u_i, then find a set of adjacent users, and then determine the similarity between users. According to the similarity between users, find similar and adjacent users, so that the trust degree between users can be obtained. At this time, the community factor is introduced to calculate the comprehensive weight $weight(i,j)$. Finally, output trustworthy community TC.

4. The Construction of Trustworthy Community for Intelligent Community

In the intelligent community, recommendation degree for service ws_{jk} that the user u_j provide to user u_i is as shown in formula (9):

$$R_{u_i \to u_j}\left(ws_{jk}\right) = \frac{\sum_{j \in TC} weight(i,j)\left(EV_i - \overline{EV_i}\right)}{\left|weight(i,j)\right|} \tag{9}$$

Where EV_i is the service evaluation of the user u_i, EV_j is the service evaluation of the user u_j, $\overline{EV_i}$ and $\overline{EV_j}$ is the mean evaluation of the user u_i and user u_j for all services in the trustworthy community TC. If $R_{u_i \to u_j}\left(ws_{jk}\right)$ is greater and the user u_j on the user u_i recommendation degree is greater, then the user u_j will be more satisfied on the service ws_{jk}. For a set of service set $\left\{ws_{j1}, ws_{j2}, \cdots, ws_{jn}\right\}$, you can calculate the recommendation degree of user u_j to the user u_i about a variety of services, and then sort according to the degree of recommendations, to select the larger recommendation degree of service for the user u_i to recommend.

Based on the above work, a method of service recommendation based on trustworthy community is proposed, which introduces the community factors according to the characteristics of the community, constructs the trustworthy community, and provides the service recommendation to the target user. The specific algorithm steps are as follows:

(1) Input: the trustworthy community of the target user u_i;

(2) Output: the recommendation service set for the target user u_i;

(3) Select the user u_j from the users among trustworthy community, to calculate the similarity $Sim(i,j)$ of the user u_i and the user u_j;

(4) Calculate the trust degree $RT(i,j)$ of user u_i and user u_j;

(5) Calculate the community factor f according to the characteristics of the community;

(6) Converge the community factor, to calculate the comprehensive weight $weight(i,j)$ for user u_j to the user u_i;

(7) According to the comprehensive weight and service evaluation, calculate the recommendation degree $R_{u_i \to u_j}(ws_{jk})$ of user u_j on the user u_i on the service ws_{jk};

(8) Sort according to the set of recommendations calculated by different services, and select the larger recommendation degree of service for the user u_i to recommend.

5. Simulation Experiment and Analysis

5.1 Experiment Preparation

5.1.1 Experimental Data Set

The MovieLens data set is one of the most widely used data sets in the recommendation algorithm experiment, which is a collection of film scores collected by the GroupLens project team at the University of Minnesota for many years. In order to ensure that the user in the training set and the test set has a score data, each user's score data are randomly divided into training set and test set according to a certain percentage. This paper in the data set u.base of MovieLens randomly selected 100 users * 100 movies, 100 users * 200 movies, 200 * 100 movies, 200 users * 200 movies, 400 users * 100 movies, 400 users * 200 movies six sets of data as input data, that is, training set; in the data test set u.test of MovieLens, it randomly selected 20 users as the target user, that is, the test set.

5.1.2 Evaluation Indicator

The current recommendation algorithm measures are mainly predictive accuracy and classification accuracy. Predictive accuracy measures the degree of similarity between the algorithm predictive score and the user's actual score, including the mean absolute error MAE, the mean squared error MSE, the root mean square error RMSE, and so on. This paper adopted mean absolute error MAE as the quality standard to measure the quality of the recommendation and the accuracy of service recommendations. The smaller the MAE, the higher the recommendation quality. The calculation of MAE is shown in formula (10):

$$MAE = \frac{1}{N}\sum_{i=1}^{n}\left|p_{i,s} - r_{i,s}\right| \tag{10}$$

Where $p_{i,s}$ is the predicted score of the user u_i for the service s, $r_{i,s}$ is the true score of the user u_i for the service s, and N is the number of the recommendation services.

5.2 Experimental Results and Analysis

5.2.1 Comparison of Satisfaction of Three Service Recommendations

This paper choses the Trustworthy Services Selection Based on Preference Recommendation proposed by Zhu et al. and An Improved Chain Recommendation Algorithm Based on Cloud Model proposed by Liu et al. as representatives, which simulates the service recommendation algorithm for intelligent community combining community factor and trust degree proposed in this paper, and compares their performance difference. Figure 4 is the MAE value of the line chart drawn under three recommendation methods in the different numbers of users and the different numbers of films.

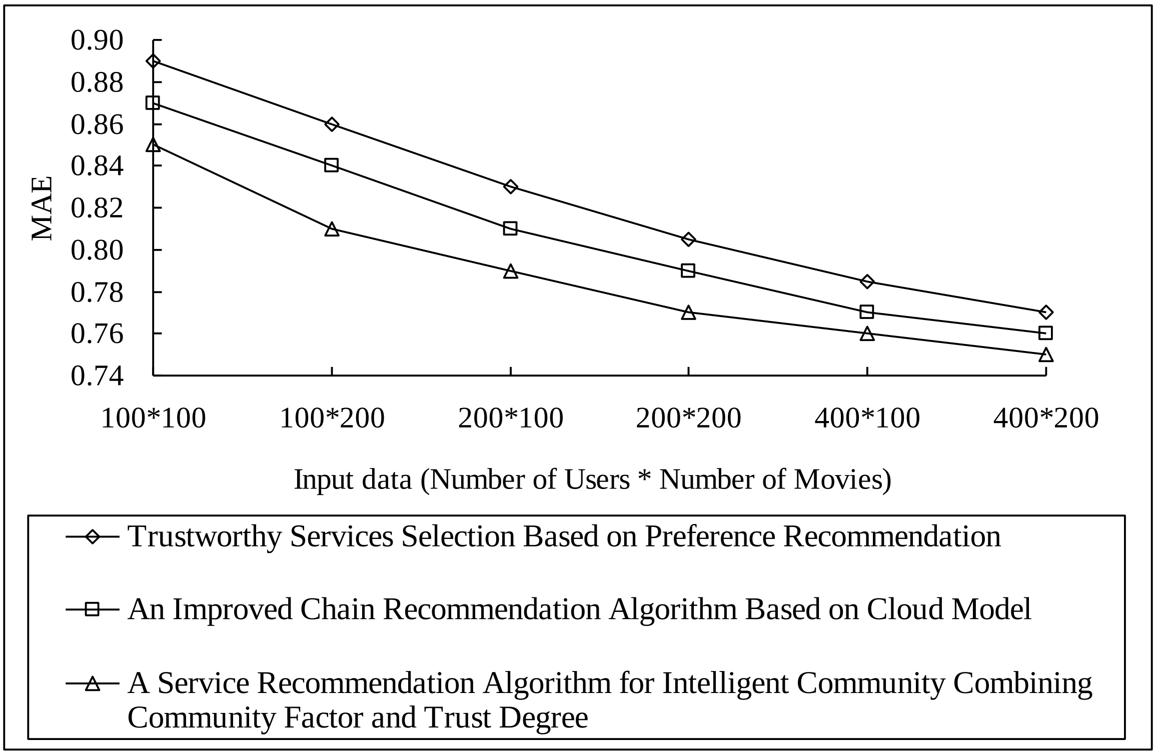

Fig. 4 Comparison among the MAE value of recommendation algorithm

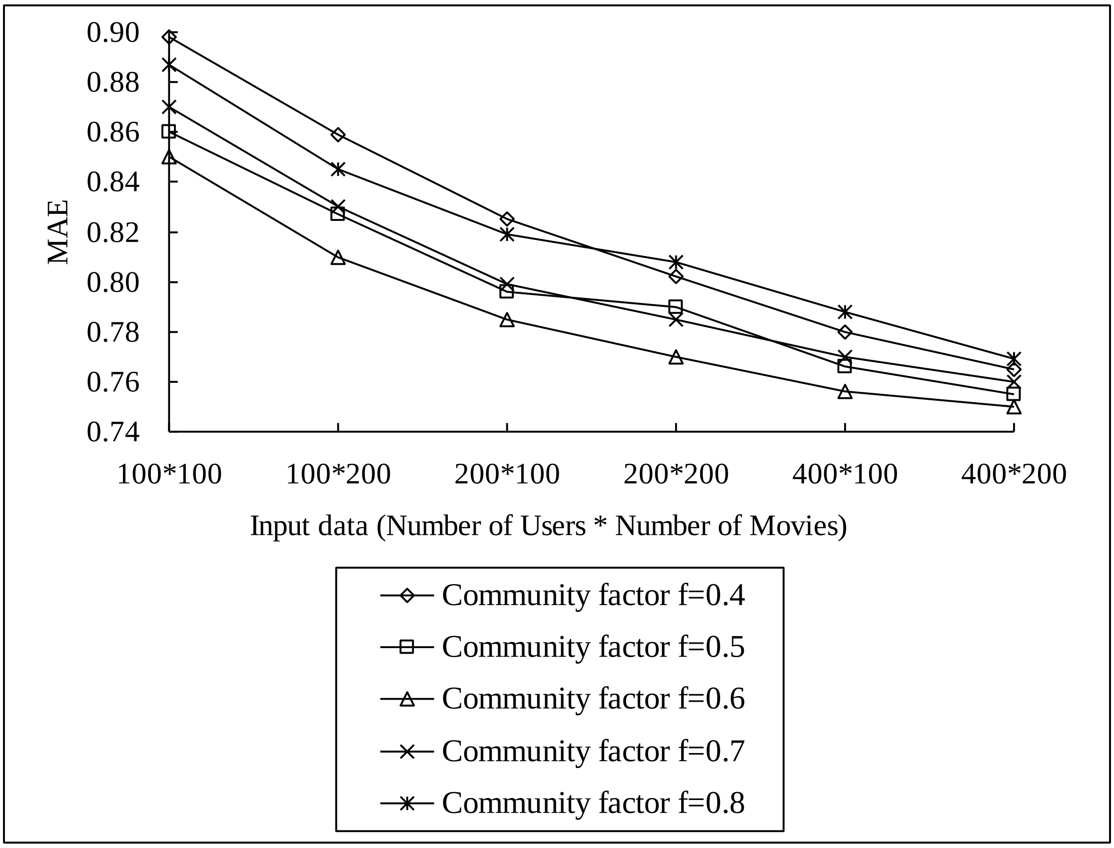

Fig. 5 The impact of community factors on the recommendation algorithm

From the figure we can see that the MAE value of the three recommended methods is not particularly significant in the case of a small number of users, but with the increase in the number of users, the recommendation accuracy of the service recommendation algorithm for intelligent community combining community factor and trust degree has improved significantly. Therefore, the recommendation algorithm integrating community factors can be recommended in the intelligent community to make users more satisfied.

5.2.1 Adjust The Impact of Community Factors on The Recommendation Algorithm

In intelligent community, community factors can provide a critical role for service recommendations. After calculation, this paper chose the community factors 0.4, 0.5, 0.6, 0.7 and 0.8 respectively to conduct the experiment. Figure 5 is the MAE value broken line graph drawn by different community factors in a trustworthy community service recommendation algorithm for intelligent community.

As we can see from the figure, starting with community factor 0.4, the MAE value decreases as the community factor increases, and the MAE value increases when the community factor increases to 0.7. Therefore, through the experiment, we chose a community factor with a value of 0.6 to be integrated into the recommendation algorithm, which can make the recommendation service more accurate and make users more satisfied.

6. Conclusion

This paper presents a service recommendation algorithm for intelligent community combining community factor and trust degree. Considering the similarity of users, the trust between users and the community factor, the user’s similarity is calculated by the improved Pearson similarity, and then the trustworthy community is built through the trust between users, with the integration of community factors, and ultimately for the target users more accurate service recommendations are provided. Compared with the existing recommendation algorithm, this recommendation algorithm based on trustworthy community service for intelligent community has a higher accuracy. In the future work, we will be more in-depth study of the trustworthy community that will be better applied to the intelligent community, to provide community users with more accurate service recommendations. The reason is that community factors are related to the composition of community users. When the community factor is 0.6, the number of similar users in the community is more, the number of users of trustworthy community is more, and the recommendation algorithm is more accurate.

Acknowledgements

This work is supported by the research and design of security operation protocol for variables based on household Internet of things (cstc2016jcyjA2069), the Chongqing City Board of Education Science and technology research project (KJ1602910) funding, and the Special Scientific and Technological Innovation Project of Social Undertakings and People's Livelihood Guarantee in Chongqing in 2017 – “Key Technology Research and Demonstration Application in Smart City” (cstc2017shmsA0841).

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