QoS-Aware Web Service Recommendation using a New Collaborative Filtering Approach

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Predicting Quality of Service (QoS) of web services through recommendation systems for accessing the information required by users is possible. But the utmost challenging in such systems is how to find the optimal service corresponding with the needs and requests of the users among a variety of web services. Satisfactory in quality of web service depends on its performance and this performance is measured through QoS. Collaborative Filtering (CF) plays important role in recommendation system. In general performance of CF is manipulating of a bunch of candidates with similar functionalities in predicting data distinguished by them, which is calculated by Pearson Correlation Coefficient (PCC). In this paper, we introduce a new collaborative filtering approach for predicting of the values of QoS of web services, also we introduce a Web service recommendation by taking in account of advantages of using of candidates foregoing experiences. In purpose of increasing accuracy of CF, values of similarity of main item and average of items were added to CF of candidates. This method which is called New Pearson Correlation Coefficient (NPCC), which is a combination of user-based and item-based methods. In purpose of investigating the accuracy of our proposed predicting of QoS, we have used a subset of the WSdream dataset to predict the QoS values. The outcomes of using our proposed method indicate the better performance and results compared to other methods outcome.

Keywords: Web Service, Collaborative Filtering, QoS, Recommender Systems, The Item Similarity, Service Selection.

1. INTRODUCTION

The Internet has begun to grow at a very high pace, providing an opportunity for sharing knowledge, as well as creating the social networks. In predicting web services, it has been attempted to obtain the later set of web services, likely to be used by the user, based on the knowledge obtained by the previously used web services. What is important in prediction of web services is the quick response to visitors and presenting useful information to them. The main purpose of recommender systems is to produce meaningful recommendations to a group of users, to whom that group of web services and items are interested in. The recommender systems are trying to guess the interests of the user, and then propose the nearest and most appropriate item to the users preferences. As the presence and use of web services in the global networks increases, the QoS is becoming an important task to describe the non-functional characteristics of web services. The web services with software components have been designed for interacting machine-to-machine adaptation on the network.

By increasing the presence and use of Web services on global networks, service quality is becoming an important issue for describing the inefficient features of the Web service. Web services are designed with software components for interacting with machine by machine on networking (Zeng, Benatallah, a H. H. Ngu, Dumas, Kalagnanam, and Chang, 2004). Web service is a part of software that make itself available in internet, which uses a standard messaging system XML[1]. XML is used to coding of all communications with web service. Web services are autonomous, integrated, scattered, vibrant applications that can be described, published, placed,

[1]eXtensible Markup Language

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or appealed over the network to create products, methods, and supply restraints. Web services are communication systems based on XML that using internet for direct associating with applied program (MENDONA, SILVA, MAIA, RODRIGUES, and VALENTE, 2008). With the increasing presence of Web services in the World Wide Web, demand is being sought for proper advice, as optimal web services are recommended for users through a large number of available Web services.(Zeng et al., 2004). Among different QoS properties of web services, some properties are independent of the user, having identical value for various users, such as cost, popularity, and availability. The values of user-independent QoS properties are usually presented by service-providers. On the other hand, some QoS properties are dependent on the user, having different values for different users, such as response time and failure rate. Attaining the user-dependent QoS properties is a challenging task, as the evaluation of web services in the real world is on the side of service receiver, and measuring the performance of user-dependent QoS properties is necessary in the web services. Evaluating the web service on the side of service receiver requires recalling of web service in the real world, having the following deficiencies (Chen, Zheng, and Lyu, 2014):

- ✓ In the real world, recalling the web service imposes costs on the service users, consuming the providers resources.
- ✓ There might be several web services to be surveyed, and some suitable web services might not be available, while existing in the evaluation list of the users.
- ✓ Many web service users are not experts in the field of web service evaluation and the common time constraint limits the careful evaluation of web service.

However, the exact values of user-dependent QoS properties could not be obtained without enough evaluation from the service-receiver, and selecting a desirable web service and its recommendation would be difficult. To analyze this significant challenge, we represent a collaborative filtering approach to predict the QoS value for service users. Our method requires no recalling from web service and could help users in line with discovery of suitable services by analyzing QoS information from the similar users. To carefully predict the QoS value of web services without requiring for a service web recalling in the real world, we should collect the previous QoS information from their other service users.
The collaborative filtering is a method that predicts the values of current users by collecting information from the similar users or items automatically (Herlocker and Konstan, 1999). The methods of collaborative filtering are as follows: user-based and item-based methods. In the proposed method, a combination of user-based collaborative filtering and item-based methods has been used, in which the web service would be predicted when the QoS value similarities are measured, and at the end, the predicted QoS values and the recommendation results would be received by the active user.

This method can be used in many real-world cases. One of them is the web service composition. Because if for some reason the values of some of the service quality parameters are not specific to one or more candidate services, the web service composition system, in view of the inability to estimate uncertainties, eliminates the candidate's services, and in the process of interfacing will not be taken in account. While the service is set aside due to its other parameters, it is possible that one of the candidate services selected for the composite service is improved. In fact, estimating uncertainties in the quality of service with the proposed method provides the chance for the candidate's services that are selected as a member service in the final composite service and even increases its quality.

The paper continues in the following way: In Section 2, the statement of the problem is presented; The related works and the method of calculating the similarity has been presented in

Section 3 and section 4, respectively; In Section 5, the prediction of QoS values of web service has been presented as a new method. The implementation and test results are shown in Section 6. The Section 7 is dedicated to concluding remarks.

2. STATEMENT OF THE PROBLEM

Although collaborative filtering is the most mature and most widely applied method in the recommender systems.The process of identifying similar users and similar web services and recommending what similar users like is called collaborative filtering. The collaborative filtering suggested the web services to the user, on the basis of past web service history. A user can hardly invoked all services, meaning that the QoS (round-trip time i.e. RTT) values of services that the user has not invoked are unknown. Hence, providing accurate Web service QoS prediction is very important for service users. Based on the predicted QoS values, desired service selection can be made. In Web service recommendation, the primary issue of CF is to find a group of similar users, a group of similar services and to build a user-service matrix about the QoS value of services used by users. The user-service matrix is actually very sparse in practice. Based on such a sparse matrix, the prediction accuracy of QoS values of services will decline distinctly. So we Firstly predict the missing QoS values of the matrix by finding historical QoS data from similar users or similar services and then recommend Web services with optimal QoS values to the active user (Puri and Bhonsle,).

In this paper, we propose a new similarity measure for collaborative filtering, emphasizing on the performance improvement of users interest predictions. The proposed method selects the users similar to the active user among service users. The service user explains those users who have stored QoS values in the dataset and are employed for predicting the QoS values of the active user. The service users requiring the prediction of QoS values in the services are called active users. The proposed method predicts the QoS values of web service for the active user, and at the end, the active user receives the predicted QoS values, as well as the recommendation results. In this study, a hybrid recommender system with a new similarity measure has been designed for collaborative filtering concentrating on the improvement of QoS prediction on the web service. This method is a combination of user-based and item-based collaborative filtering methods. To improve the precision of prediction, a combination of the similarity rate of service users and the similarity rate of QoS in the web services, as well as median values of QoS ranks in the web services have been considered. When the similarities among users is obtained, the QoS of web services would be predicted. By this strategy, we are going to increase the precision of estimating the values of Quality of Service parameters in the web services by using the proposed collaborative filtering.

3. RELATED WORKS

Z. Zheng. et al. (Chen et al., 2014) has presented a method for predicting QoS values of web services by combining user-based and item-based collaborative filtering methods. Although the traditional methods of user-based and item-based collaborative filtering present acceptable results, in measuring the similarities they occasionally employ users that are actually not similar. Significane Weight was used in this paper to overcome this issue. They increased the calculation precision of similarity between users and items. In calculation prediction stage, two reliability weights were used, one for the users, and the other for the items in order to balance the results of these two prediction methods. The proposed method has improved the prediction in the recommender systems.

S. Xia. Et al. (Xia, Chen, and Wang, 2015) has presented a new filtering collaborative method by considering the time factor. It is likely that the interests of the users change as the time passes. In other words, the time of item selection can affect the similarity among the users. Therefore, the nearest time to the present time better reflects the real situation. In this paper, by adding a linear function of time to the calculation of user-based similarity, a more precise similarity was received from the users, leading to a more precise final result and improved performance of the recommender system.

Zhang et al. (Zhang, Lin, Lin, and Liu, 2016) has proposed an effective collaborative filtering algorithm based on the users clustering in order to decrease the influence of data scattering. First, a group of users has been introduced to identify the users with various preferences. Then, with respect to the priority of the active user, the nearest neighborhood collection of the user groups is obtained. Furthermore, a new similarity measurement method has been presented for measuring the similarity among the users, having the user priority in focus. This classification and consideration of the users have improved the performance of recommender system.

Lin Goy et al. (Guo and Peng, 2013) has proposed a new method named corrected Cos similarity for the recommender systems by combining the Cos similarity method, Pearson Correlation similarity. Measuring the Cos similarity has a big disadvantage, not considering the difference in the scores of different users. The corrected Cos similarity offsets this problem by subtracting the mean score of users from either user scored that item. The results are indicative of better prediction results compared with that of Cos method and Pearson Correlation Coefficient.

R. Hu et al. (Hu and Pu, 2010) studied the problem of cold start in the collaborative filtering systems. In calculating the traditional similarities of collaborative filtering, this method uses personality characteristics of people, which can present good recommendations for the new users scored to some cases. This method is useful in the recommendations of social networks, in which the personality data of the individuals could be obtained. Studying the results and their comparison with the traditional methods suggests the influential role of this method in the cold start conditions.

4. SIMILARITY CALCULATION

The most crucial factor in the collaborative filtering mechanism is to find the similarities among the users. In this section, the calculation method of similarities in the different users and in different web services has been introduced. Then, the calculation method of similarity in the new collaborative filtering method is explained.

Items

Users

	1	2	…	i	…	M
1	5	3		1	2	
2		2				4
:			5			
u	3	4		2	1	
:					4	
n			3	2		
a	3	5		?	1	

Figure1. Item-user matrix (Sivapalan et al., 2014)

4.1 Collaborative Filtering System

This method is an automatic prediction technique on the user preferences, which is performed by gathering a great deal of information from many users in a collaborative way (Kleinberg and Sandler, 2003). This method proposes items to the users, which have been liked by the similar users (Sivapalan et al., 2014).
Collaborative filtering systems maintain a matrix known as an item-user matrix as a profile of the users. As shown in Figure. 1 which this matrix shows how much interested in the registered items, each element $C(u, i)$ of this matrix indicates the evaluation made by the user u on the item i; if it was void, it means that no evaluation has been made (Kleinberg and Sandler, 2003). Here, the proposed task is to guess that what the user does evaluate on the not-scored item. Generally, the scoring task is applied to all items already not being seen by the user, and then an item with the highest score would be suggested to the user (Burke, 1999). The collaborative filtering algorithms are divided into two categories: memory-based (neighborhood-based) algorithm, which require maintaining all scores, items, and users in the memory, and model-based algorithms, which occasionally produce a summary of the users evaluation patterns in offline mode (Breese, Heckerman, and Kadie, 1998).
The memory-based collaborative filtering algorithms are composed of two kinds: the user-based and item-based collaborative filtering algorithms.

—***User-Based Collaborative Filtering Algorithm***

In this method, a subset of users is selected based on their similarities to the active user, and then predictions about the active user is produced using a weighted combination of the scores given by them.
Many of these methods can be generalized by an algorithm, which a summary of it has been given as follows:

(1) A weight is given to each user, based on the degree of its similarity to the active user.

(2) The intended prediction would be calculated by the degree of resulted similarities(Sivapalan et al., 2014).

The proposed system is composed of M user(s) and N item(s). The relationship between the users and items is shown by a M*N matrix, known as user-item matrix. Each input in this matrix is in $r_{u,i}$ form, which indicates a vector of given scores by the user u to the item i.
Pearson Correlation Coefficient has been introduced in a number of recommender systems to calculate the similarity, as is it easy to be implemented, achieving to high precisions. Its main task is to calculate the similarity weight between the pair-users, which is shown in the Figure2.

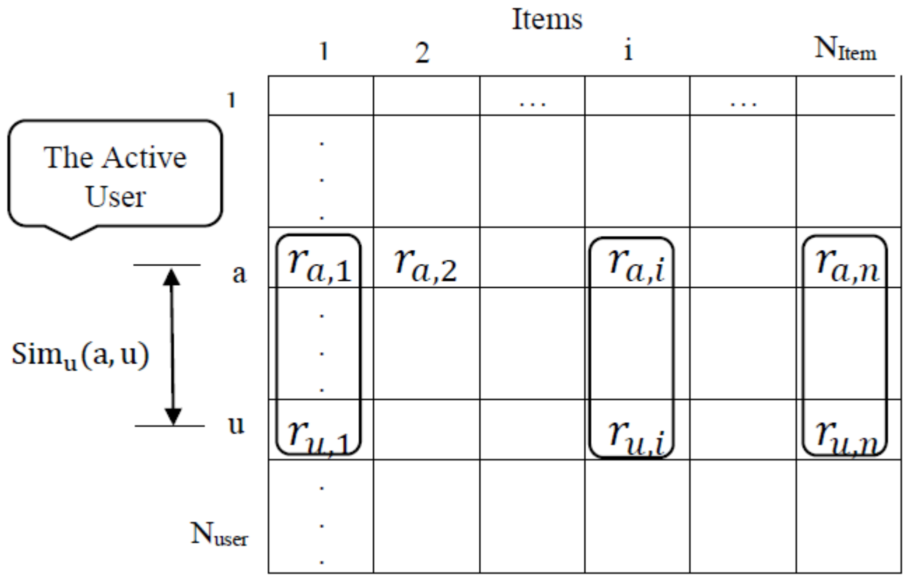

Figure 2.Calculating the degree of similarity between pair-users (Yamashita et al., 2010)

In the user-based collaborative filtering methods, Pearson Correlation Coefficient is obtained from the following equation to calculate the similarities between two a and u users (Zeng et al., 2004):

$$sim(a,u) = \frac{\sum_{i \in I}(r_{a,i} - \bar{r_a})(r_{u,i} - \bar{r_u})}{\sqrt{\sum_{i \in I}(r_{a,i} - \bar{r_a})^2}\sqrt{\sum_{i \in I}(r_{u,i} - \bar{r_u})^2}} \tag{1}$$

in which $I = I_a \cap I_u$ is a subset of scored items by either a and u users. $r_{a,i}$ is the score given to the item i by the user a, and $\bar{r_a}$ and $\bar{r_u}$ are the total mean of the scores given by the a and u users. These two users are similar in the $[-1, 1]$ interval, in which the greater value in that interval indicates the great similarity between a and u users (Zeng et al., 2004). In the second stage, the prediction is usually calculated as a weighted mean of deviation from the neighbor medians, such as (Zeng et al., 2004):
usually calculated as a weighted mean of deviation from the neighbor medians, such as (Zeng et al., 2004):

$$P_{a,i} = \bar{r_a} + \frac{\sum_{u \in k}(r_{u,i} - \bar{r_u}) \times sim(a,u)}{\sum_{u \in k} sim(a,u)} \tag{2}$$

in which $P_{a,i}$ is the prediction made for the active user a on the item i, $sim(a,u)$ is the similarity between the user a and u, and K is a set of similar users.

—***Item-Based Collaborative Filtering Algorithm***

In some cases, due to a higher cost of searching for the user neighbors, the item-based collaborative filtering is used in the item-based collaborative filtering method. On these systems, the similar items are extracted based on the scores given to the items by the users (with respect to item- user scoring matrix columns). In practice, this method responds more quickly in the online systems, generally leading to better suggestions. In other words, while the user-based method makes predictions based on the similarities among the users, the item-based algorithms generate predictions based on the similarities among the users. The prediction for an item should be based on the scores given by the users for the similar goods (Burke, 2000).
In this method, the similarity between i and j items is calculated by Pearson Coefficient as

follows:

$$sim(i,j) = \frac{\sum_{u \in U}(r_{u,i} - \bar{r_i})(r_{u,j} - \bar{r_j})}{\sqrt{\sum_{u \in U}(r_{u,i} - \bar{r_i})^2}\sqrt{\sum_{u \in U}(r_{u,j} - \bar{r_j})^2}} \tag{3}$$

in which $Sim(i,j)$ is the similarity between item i and j. $U = U_i \cap U_j$ is a subset of users scored to either i and j. $\bar{r_i}$ is the mean scores of ith item among the users, and $r_{a,i}$ is the score given to the item i by the user a (Chen et al., 2014).

$$p_{a,i} = \frac{\sum_{j \in k} r_{a,j} \times sim(i,j)}{\sum_{j \in k} |sim(i,j)|} \tag{4}$$

Now, the prediction about the score of the item i for the user a can be calculated using the weighted average:
in which K is a set of items scored by the user a which are very similar to the item i (Sivapalan et al., 2014).

4.2 The Calculation of the Similarity in the New Proposed Method

As mentioned in the previous section, in the user-based collaborative filtering methods, Pearson Correlation Coefficient (PCC) for calculating the similarity between two service users a and u is obtained from the following relationship (Chen et al., 2014):

$$sim(a,u) = \frac{\sum_{i \in I}(r_{a,i} - \bar{r_a})(r_{u,i} - \bar{r_u})}{\sqrt{\sum_{i \in I}(r_{a,i} - \bar{r_a})^2}\sqrt{\sum_{i \in I}(r_{u,i} - \bar{r_u})^2}} \tag{5}$$

in which $I = I_a \cap I_u$ is a subset of items scored by two a and u users. $r_{a,i}$ is the score given to the item i by the user a and $\bar{r_a}$ and $\bar{r_u}$ are the averages of total scores given by the a and u users, respectively. These two users are similar in $[-1,1]$, in which the greater number represents the greater similarity between two a and u users.
Lately, the model of Shilling attacks has been identified for the partnership filtering system and their effectiveness has been studied. Lam and Riedl found that the item-based CF algorithm was much less user-initiated than the CF algorithm, and they suggest that new methods should be used to evaluate and detect shilling attacks against recommended systems[16]. Since Item-Based CF method are less affected by attacks compare to user-based CF, we use the combination of both item-based and user-based CFs in our proposed method to minimize the malicious users affects in accuracy of predicting QoS. Also in calculating the similarity of user-based Pearson Correlation Coefficient, all items are calculated equivalent to each other, while the item similarities can be studied from different aspects. In the proposed method, which is New Pearson Correlation Coefficient (NPCC), the similarity rate of item-based collaborative filtering method (QoS of web services) and median value of the ranks in the target item (QoS of web services) has been used to improve the similarities between the users. In other words, we combine Pearson Correlation Coefficient with the above-mentioned items, which is calculated as follows:

$$sim(a,u)^i = \frac{\sum_{j=1}^{I} Isim(i,j)^2 \times |r_{medi} \times (r_{a,i} - \bar{r_a})|}{\sqrt{\sum_{j=1}^{I}(Isim(i,j) \times r_{medi} \times (r_{a,i} - \bar{r_a}))^2}} \times \frac{|r_{medi} \times (r_{u,i} - \bar{r_u})|}{\sqrt{\sum_{j=1}^{I}(Isim(i,j) \times r_{medi} \times (r_{u,i} - \bar{r_u}))^2}} \tag{6}$$

in which $sim(a,u)$,i is the similarity between the user a and the user u, which recommend item i. $Sim(i,j)$ is the similarity between item i and j. r_{medi} is a median value of the ranks in the target item. What we mean by the target item is the one on which a prediction is made.
In this function, predicting the rank of an item, we consider the similarity and median value of the target item, such that a neighbor belonging to an item can be found that increases the prediction precision.
In Eq (6), $Isim(i,j)$ represents the item similarities, calculated as follows (Chen et al., 2014):

$$Isim(i,j) = \frac{\sum_{a=1}^{n}(r_{a,j} - \bar{r}_i)(r_{a,j} - \bar{r}_j)}{\sqrt{\sum_{a=1}^{n}(r_{a,i} - \bar{r}_i)^2} \times \sqrt{\sum_{a=1}^{n}(r_{a,j} - \bar{r}_j)^2}} \tag{7}$$

in which n is the number of users. $r_{a,i}$ and $r_{a,j}$ represent the given scores to item i and item j by the user a, respectively. $\bar{r}_a$ and $\bar{r}_j$ are the average scores of item i and item j, respectively.
In Eq (6), r_{medi} is the median value of the score given to the target item i, calculated as follows:

$$r_{medi} = \frac{r_{maxi} + r_{mini}}{2} \tag{8}$$

in which r_{maxi} is the maximum score given to the item i, and r_{mini} is the minimum score given to it.

5. PREDICTION CALCULATION

When the similarities between the users is calculated in the item-user matrix, we use the matrix obtained from the similarity to predict the QoS values of the active user. In this step, the QoS values of the web service are calculated using the user-based collaborative filtering by the following equation (Chen et al., 2014):

$$p_{a,i} = \bar{r}_a + \frac{\sum_{u\in k}(r_{u,i} - \bar{r}_u) \times sim(a,u)}{\sum_{u\in k} sim(a,u)} \tag{9}$$

in which $p_{a,i}$ is the prediction made for the active user a about the QoS of the service web i, and $sim(a,u)$ is the similarity between the users a and u. $\bar{r}_a$ and $\bar{r}_u$are the total average scores given by the users a and u, respectively, and $r_{a,i}$ is the score given to the item i by the user a. K is a set of users, which their similarity with the active user has been calculated.

The recommendation system can be explained when an active service user researches for Web services in a Web service discovery system or the system is recommending Web services to an active user. The process of predicting the QoS values for the web services is completed as shown in Figure 3.

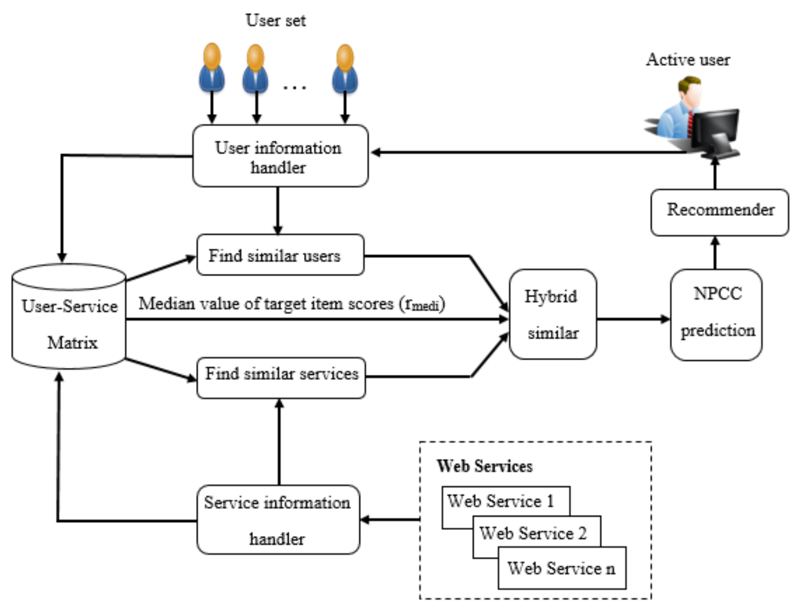

Figure 3.Recommender system

- ✓ User information handler: Finding the information of a user.
- ✓ Service information handler: Finding the information of Web services.
- ✓ Find similar users: This level finds similar service users who are similar to the active user with a pearson correlation coefficient.
- ✓ Find similar services: This level finds similar web services for a target web service by a Pearson Correlation Coefficient.
- ✓ r_{medi} : r_{medi} is the median value of the score given to the target item i.
- ✓ Hybrid similar: The hybrid similar are obtained by combining the user based similar , the service based similar and r_{medi}.
- ✓ NPCC prediction: In this section, using the hybrid similarity from above, we compute the prediction using the NPCC method.
- ✓ Recommender: This module employs the predict QoS values to recommend optimal web services to the active user.

6. IMPLEMENTATION AND TEST

In this section, the simulation of the proposed method has been studied in detail. The proposed method has been compared with Pearson Correlation Coefficient (PCC) method and COS method. The Matlab Software has been used for simulation.

6.1 Dataset

A dataset is a 10020 matrix composed of 100 users and 20 items (the QoS values of the web service), which a subset of values of the dataset is composed of 339 users and 5825 web services in the real world [2], which the ranks given to him are the response time of web services. This dataset is the biggest QoS dataset for the web services, which has been collected by Z. Zheng. et al. (Chen et al., 2014) in order to further investigate the prediction precision of QoS values

[2]www.wsdream.com

of the web services. 150 computers in 24 countries were used to monitor and collect QoS data in the selected web services. Approximately 1.5 million web services were called, and the test results were collected. The results were collected in one matrix, in which each matrix input is a vector composed of response times of web services. This dataset not only has been employed for studying the QoS values of the web service, it can also be used for other QoS research subjects, such as service combination, tolerability of errors in the web services, and etc.

6.2 Evaluation of the Obtained Results

To study the function of the prediction, we compare NPCC [3] method with PCC [4] and COS [5] method.
When the simulation was performed, the results of predicting QoS values have been obtained for all three methods. 30 elements of the predicted elements in all three methods have randomly been selected to show the precisions of the selected results. Table 1 shows numerical results and the real value of the dataset. The prediction results of NPCC method are much nearer to the real value, indicating the better prediction of NPCC method. In Figure 4, the values of the above-mentioned prediction methods and the real value of the user-item matrix has been shown in a diagram.

record	**real value**	**NPCC**	**PCC**	**Cos**
1	0.8040	0.8328	0.8541	0.9107
2	0.3370	0.4136	0.4327	0.4705
3	1.1960	1.2705	1.4028	1.5044
4	0.4560	0.5193	0.5235	0.5675
5	0.9210	0.8519	0.7656	0.6991
6	0.5550	0.5800	0.5941	0.6221
7	0.2240	0.2577	0.2977	0.1565
8	0.8110	0.8351	0.8567	0.9127
9	0.2560	0.2667	0.3303	0.1943
10	0.2660	0.2762	0.3243	0.1802
11	0.9930	1.0187	1.0526	1.1597
12	0.9800	0.9545	0.8838	0.8056
13	0.4270	0.4516	0.4775	0.4782
14	0.3200	0.3124	0.2999	0.1808
15	0.3400	0.3487	0.3531	0.2322
16	0.8330	0.8388	0.8660	0.8818
17	0.5820	0.5887	0.5966	0.6171
18	0.4850	0.4779	0.5120	0.5246
19	0.7060	0.7142	0.7349	0.7520
20	0.4380	0.4314	0.4493	0.4543
21	0.5540	0.5556	0.5404	0.5713
22	0.4670	0.4638	0.4956	0.3947
23	0.3340	0.3351	0.3211	0.2147
24	0.3200	0.3240	0.3426	0.2768
25	0.8969	0.8976	0.9264	0.9419
26	0.4790	0.4776	0.5026	0.5038
27	0.5450	0.5467	0.6009	0.6016
28	1.2470	1.2463	1.4063	1.4702
29	1.2250	1.2245	1.3762	1.4648
30	1.3630	1.3629	1.4352	1.5461

Table I: The prediction results of QoS values in the service web

[3] New Pearson Correlation Coefficient
[4] Pearson Correlation Coefficient
[5] Cosine

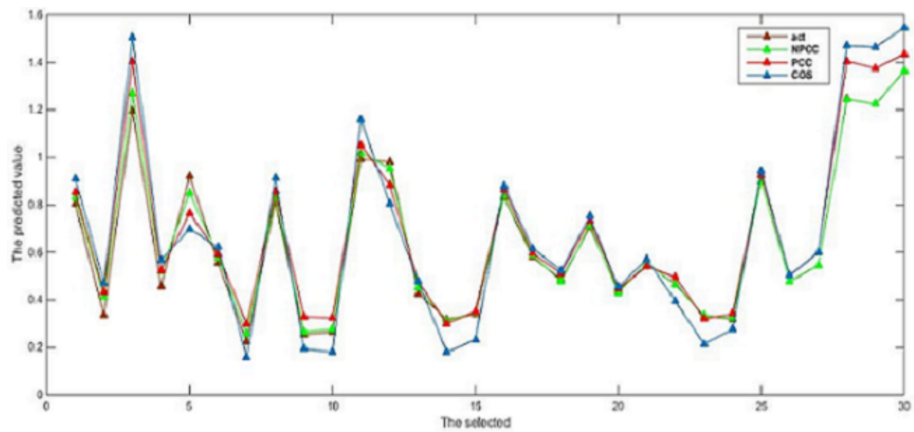

Figure 4.Diagrams of prediction values of the methods

With respect to the table and diagram, it can be concluded that the results of New Pearson Correlation Coefficient (NPCC) method are much nearer to the real value, compared with other methods, in some sections reaching even to a difference of .0001.

6.3 Evaluation of the prediction precision

When each prediction method was evaluated, it is necessary to evaluate and study the capabilities and abilities of the methods in order to select the best method on that basis.
The most commonly used evaluation measures in the recommender systems are MAE [6] and RMSE [7].

—***Mean Absolut Error (MAE)***
This method obtains the mean absolute error of the difference between predicted scores and the real scores, which is equal to a rank predicted by the system given by the user u to the item i minus the rank given by the user u to the item i, calculated as follows:

$$MAE = \frac{\sum_{u,i} |p_{u,i} - r_{u,i}|}{N} \tag{10}$$

—***Root Mean Square Error (RMSE)***

$$RMSE = \sqrt{\frac{\sum_{u,i} (p_{u,i} - \bar{r}_{u,i})^2}{N}} \tag{11}$$

in which $p_{u,i}$ is the predicted score for the user u to the item i, and $r_{u,i}$ is the real score given to the item i by the user u. N is the number of predictions (Sivapalan et al., 2014).
The obtained results have been shown in Table.2. The greater the density of user-item, the better results would be presented. The lower values indicate better result.

According to the table, the MAE and RMSE values are smaller in NPCC method, compared with other methods, and as the number of data increased, this value decreased further. When

[6]Mean Absolut Error
[7]Root Mean Square Error

Table II: The evaluation results of MAE and RMSE

Evaluation criterion	Methods	N (The number of predictions)					
		5	10	15	20	25	30
MAE	COS	0.1764	0.1266	0.1260	0.1045	0.1038	0.0955
	PCC	0.1151	0.0867	0.0737	0.0610	0.0597	0.0531
	NPCC	0.0625	0.416	0.0339	0.0271	0.0221	0.0186
RMSE	COS	0.1929	0.1472	0.1434	0.1357	0.1270	0.1165
	PCC	0.1289	0.1006	0.0883	0.0775	0.0774	0.0700
	NPCC	0.0649	0.0486	0.0413	0.0360	0.0322	0.0294

the amount of data is 5, MAE= 0.0625 and RMSE=0.0649 in the NPCC method. As the number of data increases and reaches 30 data, finally MAE=0.0186 and RMSE=0.024, indicating that the greater the data, the better result will be obtained, and NPCC method has lower error value than other methods, and as a result, has higher measuring precision. For better representation, the results obtained from MAE and RMSE are shown in the Figure 5 and Figure 6, respectively.

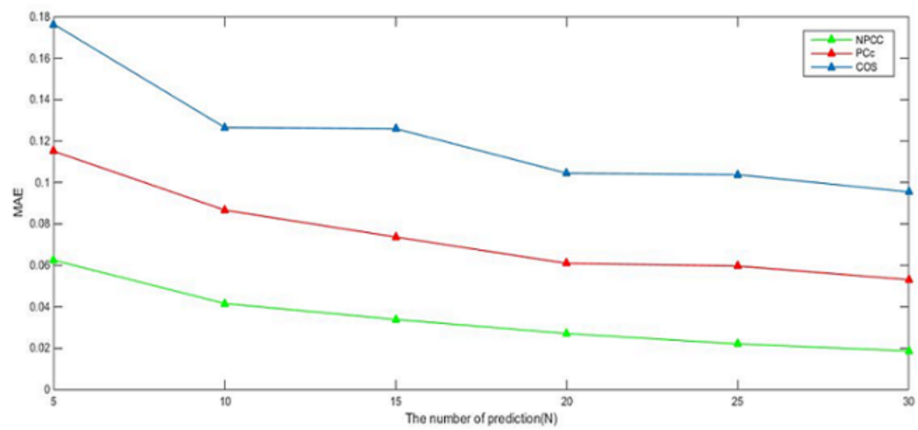

Figure 5.The obtained MAE results

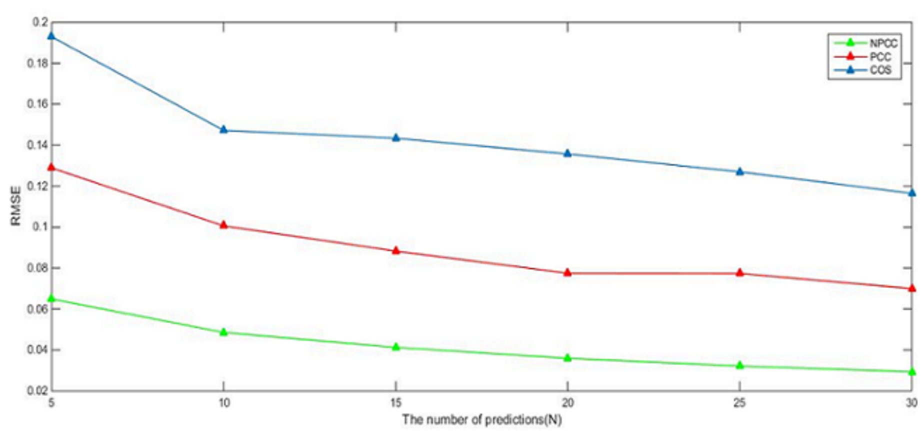

Figure 6.The obtained RMSE results

As the obtained value gets closer to zero in the diagrams, the measurement error becomes smaller. The proposed method constantly obtains smaller values of MAE and RMSE, which indicates better prediction precision. Also, as the amount of data increases from 5 to 30, the values of MAE and RMSE becomes smaller, indicating the improvement in the prediction precision by representing the greater QoS values.

7. CONCLUSION

As the number of web services increases in the World Wide Web, the recommendations of the effective web services become more significant. The recommender systems are widely used. Improvement in the function of recommender system is highly important. The calculation method of similarity in Pearson Correlation Coefficient has not been able to respond all requests of the recommender systems. So, there is a need to find more valuable information in a huge amount of information.

In this paper, a new collaborative filtering method known as NPCC has been presented for predicting the QoS values of web services. In this method, a combination of user-based collaborative filtering methods and the degree of item similarities (QoS values of web services) has been presented. Items were studied from two aspects. At first, the similarities of the target item with other items were obtained by the similarity degree of item-based collaborative filtering method, which has resulted in having more precise neighbors for every user-item. In addition, the score value of the median in the target item has been used in calculating the similarity. Therefore, the similarity of target item and median value of the target item have been used as the item weight. The experimental results show that this method gives full information about the items, improving the function of recommender systems.

References

Breese, J. S., Heckerman, D., and Kadie, C. 1998. Empirical analysis of predictive algorithms for collaborative filtering. *Proc. 14th Conf. Uncertain. Artif. Intell. 461,* 8, 4352.

Burke, R. 1999. Integrating knowledge-based and collaborative-filtering recommender systems. 6972.

Burke, R. 2000. Knowledge-based recommender systems. *Encycl. Libr. Inf. Syst. 69,* 32, 175186.

Chen, X., Zheng, Z., and Lyu, M. R. 2014. Qos-aware web service recommendation via collaborative filtering. *Web Serv. Found. 9781461475*, 563588.

Guo, L. and Peng, Q. K. 2013. Combinative similarity computing measure for collaborative filtering. *Appl. Mech. Mater. 347350*, 29192925.

Herlocker, J. and Konstan, J. 1999. An algorithmic framework for performing collaborative filtering. *Proc. 22nd* , 8.

Hu, R. and Pu, P. 2010. Using personality information in collaborative filtering for new users. *2nd ACM RecSys10 Work. Recomm. Syst. Soc. Web*, 1724.

Kleinberg, J. M. and Sandler, M. 2003. Convergent algorithms for collaborative filtering. *Conf. Electron. Commer. (EC 03)*, 110.

MENDONA, N. C., SILVA, C. F., MAIA, I. A. N. G., RODRIGUES, M. A. F., and VALENTE, M. T. O. 2008. A loosely coupled aspect language for soa applications. *Int. J. Softw. Eng. Knowl. Eng. 18*, 243262.

Puri, A. and Bhonsle, M. A survey of web service recommendation techniques based on qos values. *4,* 12, 498501.

Sivapalan, S., Sadeghian, A., Rahnama, H., and Madni, A. M. 2014. Recommender systems in e-commerce. *2014 World Autom. Congr.*, 179184.

Xia, S., Chen, S., and Wang, Z. 2015. An hybrid similarity function for neighbor selection in collaborative filtering. *8,* 6, 243252.

Yamashita, A., Kawamura, H., and Suzuki, K. 2010. Similarity computation method for collaborative filtering based on optimization. *14,* 6, 654655.

Zeng, L. Z., Benatallah, B., a H. H. Ngu, Dumas, M., Kalagnanam, J., and Chang, H. 2004. Qos-aware middleware for web services composition (html). *IEEE Trans. 30*, 139.

Zhang, J., Lin, Y., Lin, M., and Liu, J. 2016. An effective collaborative filtering algorithm based on user preference clustering. *Appl. Intell.*.

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