IJARCCE

ISSN (Online) 2278-1021
ISSN (Print) 2319 5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 4, Issue 12, December 2015

A Survey of Web Service Recommendation Techniques based on QoS values

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Abstract: Web service recommendation has become a hot yet fundamental research topic in service computing. The most popular technique is the Collaborative Filtering (CF) based on a QoS values. With increasing presence and adoption of Web services on the World Wide Web, Quality-of-Service (QoS) is becoming important for describing nonfunctional characteristics of Web services. Several approaches to web service selection and recommendation via collaborative filtering have been studied, so here we are going to do survey of these techniques with pros and cons of techniques. Also based on these reviews we are going to propose a new technique to predict web service selection based on known and unknown QoS values which we explain in our future work.

Keywords: Web Service, Service Computing, Collaborative filtering, QoS values.

I. INTRODUCTION

Web services are software components designed to support interoperable machine-to-machine interaction over a network. The increasing presence and adoption of Web services on the World Wide Web demand effective recommendation and selection techniques, which recommend the optimal Web services to service users from a large number of available Web services. With the number increasing of Web services, Quality-of-Service (QoS) is usually employed for describing nonfunctional characteristics of Web services [11]. Among different QoS properties of Web services, some properties are user independent and have identical values for different users (e.g., price, popularity, availability, etc.). The values of the user independent QoS properties are usually offered by service providers or by third-party registries (e.g., UDDI). On the other hand, some QoS properties are user dependent and have different values for different users (e.g., response time, invocation failure rate, etc.). Client-side Web service evaluation requires real-world Web service invocations and encounters the following drawbacks:

- First, real-world Web service invocations impose costs for the service users and consume resources of the service providers. Some Web service invocations may even be charged.
- Second, there may exist too many Web service candidates to be evaluated and some suitable Web services may not be discovered and included in the evaluation list by the service users.
- Finally, most service users are not experts on Web service evaluation and the common time-to-market constraints limit an in-depth evaluation of the target Web services.

However, without sufficient client-side evaluation, accurate values of the user-dependent QoS properties cannot be obtained. Optimal Web service selection and recommendation are thus difficult to achieve.

So in this paper, in Section II we studied basics of collaborative filtering, in Section III we did survey of previous research with their techniques, finally paper ends with proposed solution and conclusion.

II. COLLABORATIVE FILTERING METHODS

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. Collaborative Filtering was firstly proposed by Rich [10] and has been widely used in service recommendation systems. 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.

Collaborative Filtering algorithm applies two processes:

a) Prediction is a numerical value which expressing the predicted likeliness of web services those does not access by particular user. This predicted value is in same scale as opinion values provided by same user [6].

b) Recommendation is a list of N items that the active user will like the most. This recommended list must be on web services those are not already access by the active

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user. This interface of Collaborative filtering algorithm is called Top-N recommendation [6]. Collaborative filtering process is shown in below figure 1.

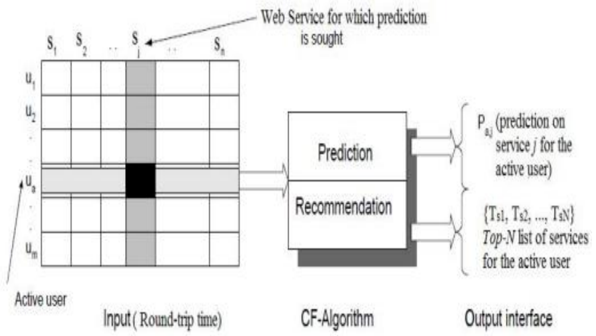

Fig 1: Collaborative Filtering Process

There are two types of Collaborative Filtering algorithms:
1. Model Based Collaborative Filtering
2. Memory Based Collaborative Filtering

2.1 Model Based Collaborative Filtering
Model-based algorithms use the collection of QoS to learn a model, which is then used to make QoS predictions. Model based CF algorithms include Bayesian models (probabilistic) and clustering models [2]. Model-based CF approaches provide a predefined model to fit the observed QoS data, and then the trained model can be used to predict the unknown QoS values. Matrix factorization is one of the most popular model-based CF approaches, which was first introduced to address the QoS prediction problem in [7]. Matrix factorization model handles the sparsity problem well and usually achieves better performance than neighbourhood-based approaches.

2.2 Memory Based Collaborative Filtering
Memory-based algorithms make predictions by operating on data (users, services and QoS data) stored in memory. They can be classified into Nearest Neighbour algorithms and Top-N recommendation algorithms. Nearest neighbour algorithms are the most commonly used Memory based CF algorithms. Users similar to the current user with respect to preferences are called as neighbours. This type of CF approaches use the observed QoS data to compute the similarity values between users or services, and further leverage them for QoS prediction. Top-N recommendation is to recommend a set of N top-ranked web services, those will be of interest to a certain user. Top-N recommendation techniques analyse the user-service matrix to correlate different users or services and use them to compute the recommendations.

III.RELATED WORK

1. Predicting QoS values of Web services based on History:
Z. Zheng, H. Ma, M. R. Lyu, and I. King [3] present a collaborative filtering approach for predicting QoS values of Web services and making Web service recommendation by taking advantages of past usage experiences of service users. They first proposed a user collaborative mechanism for past Web service QoS information collection from different service users. Then, based on the collected QoS data, a collaborative filtering approach is designed to predict Web service QoS values.

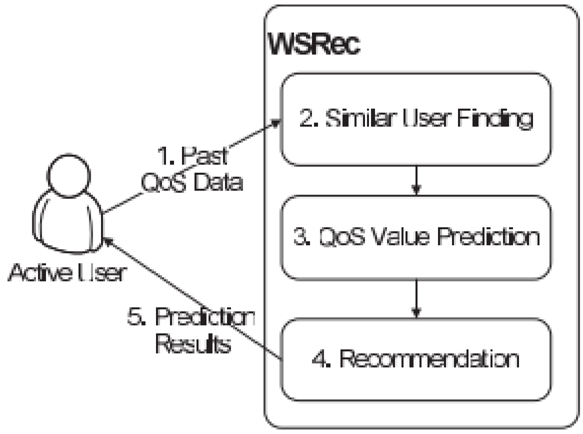

Fig 2: Procedure of QoS Value Prediction

They proposed a Web service QoS value prediction approach by combining the traditional user-based and item-based collaborative filtering methods. Their approach requires no Web service invocations and can help service users discover suitable Web services by analyzing QoS information from similar users.
In their Web service evaluations reported in paper, to reduce the effect of the Web service invocations to the real-world Web services, they only selected one operation from a Web service for making evaluations and employ the performance of this operation to present the performance of the Web service.

2. Web service recommendation based on location aware Qos:
Previous approaches fail to consider the QoS variance according to user's locations; and previous recommender systems are all black boxes providing limited information on the performance of the service candidates. So that X. Chen, Z. Zheng, X. Liu, Z. Huang, and H. Sun [4] proposed a novel collaborative filtering algorithm designed for large-scale web service recommendation. First, they combined the model-based and memory based CF algorithms for web service recommendation, which significantly improves the recommendation accuracy and time complexity compared with previous service recommendation algorithms. . Second, they design a visually rich interface to browse the recommended web services, which enables a better understanding of the service performance. Their algorithm employs the characteristic of QoS by clustering users into different regions. Based on the region feature, a refined nearest-neighbor algorithm is proposed to generate QoS prediction. The final service recommendations are put on a map to reveal the underlying structure of QoS space and help users accept the recommendations.

Similarly, M. Tang, Y. Jiang, J. Liu, and X. Liu [6] proposed a method of location aware collaborative filtering to recommend Web services to users by incorporating locations of both users and services.

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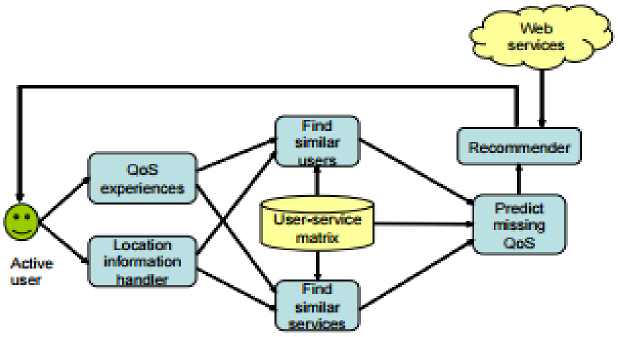

Fig 3: Location-Aware Collaborative Filtering

Different from existing user-based collaborative filtering for finding similar users for a target user, instead of searching entire set of users, they concentrate on users physically near to the target user. Similarly, they also modify existing service similarity measurement of collaborative filtering by employing service location information. After finding similar users and services, they use the similarity measurement to predict missing QoS values based on a hybrid collaborative filtering technique. Web service candidates with the top QoS values are recommended to users.

In the Location aware method, they first acquire historical QoS data and the location information of the active user. A location information handler deals with the location information of both the active user and the target service whose QoS values are missing to the active user. The user-service matrix records every user's QoS experiences on Web services he invoked. To find similar users, user similarity measurement will be computed based on the historical QoS data of the users who are located close to the active user, determined by the location information handler. Likewise, services similarity measurement is computed based on the QoS records of the services which are located close to the target service, also determined by the location information handler. After finding similar users and similar services for the active user and target service respectively, both user-based CF and item-based CF algorithm are used to predict the missing QoS values of the target service.

For building an efficient region model, X. Chen, X. Liu, Z. Huang, and H. Sun [8] proposed Region-KNN, a novel hybrid collaborative filtering algorithm that is designed for large scale web service recommendation. Different from other approaches, this method employs the characteristics of QoS by building an efficient region model. Based on this model, web service recommendations will be generated quickly by using modified memory-based collaborative filtering algorithm. Their algorithm was first cluster users into several regions based on their physical locations and historical QoS similarities. Then region-sensitive services are identified. After that, modified nearest neighbor based approach is used to automatically predict the QoS of the candidate web services for an active user by leveraging historical QoS information gathered from users of highly correlated regions. Based on the prediction, the service with the best predicted QoS will be recommended to the active user.

3. Web Service Recommendation Methods Based on Personalized Collaborative Filtering

There have been several methods of Web service selection and recommendation based on collaborative filtering, but seldom have they considered personalized influence of users and services. That why Y. Jiang, J. Liu, M. Tang, and X. Liu [5] present an effective personalized collaborative filtering method for Web service recommendation. A key component of Web service recommendation techniques is computation of similarity measurement of Web services. Different from the Pearson Correlation Coefficient (PCC) similarity measurement, they take into account the personalized influence of services when computing similarity measurement between users and personalized influence of services. Based on the similarity measurement model of Web services, they develop an effective Personalized Hybrid Collaborative Filtering (PHCF) technique by integrating personalized user-based algorithm and personalized item-based algorithm.

Similarly, L. Shao, J. Zhang, Y. Wei, J. Zhao, B. Xie, and H. Mei [9] being aware of different QoS experiences of consumers, they proposed a collaborative filtering based approach to making similarity mining and prediction from consumer's experiences.

4. Web service recommendation based on Unknown Web Service QoS Values:

Quality-of-service-based (QoS) service selection is an important issue of service-oriented computing. A common premise of previous research is that the QoS values of services to target users are supposed to be all known. However, many of QoS values are unknown in reality. So to understand unknown QoS, J. Wu, L. Chen, Y. Feng, Z. Zheng, M. C. Zhou, and Z. Wu [7] presents a neighborhood based collaborative filtering approach to predict such unknown values for QoS-based selection. Compared with existing methods, the proposed method has three new features:

1) The adjusted-cosine-based similarity calculation to remove the impact of different QoS scale;

2) A data smoothing process to improve prediction accuracy; and

3) A similarity fusion approach to handle the data sparsity problem. In addition, a two-phase neighbor selection strategy is proposed to improve its scalability.

Similarly, You Ma, Shangguang Wang, Patrick C.K. Hung, Ching-Hsien Hsu, Qibo Sun, and Fangchun Yang [1] proposed a Highly Accurate Prediction Algorithm (HAPA) for Unknown Web Service QoS Values. To determine some important characteristics of objective QoS datasets that has never been found before. They proposed a prediction algorithm to realize these characteristics, allowing the unknown QoS values to be predicted accurately.

HAPA is a CF-based algorithm, i.e., it concretely consists of user-based and item-based HAPAs. Each type of HAPA can make predictions, however they always used the combination of the two HAPAs to make predictions more accurate.

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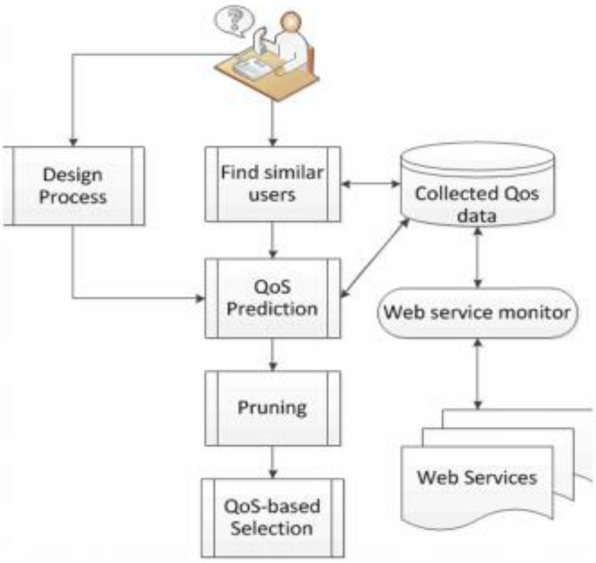

Fig 4: Architecture of CF-based service selection

For user-based CF methods, PCC uses the following equation to calculate the similarity between two user's u and v based on the Web services they commonly invoke:

$$sim(u,v) = \frac{\sum_{i \in I}(r_{u,i} - \overline{r_u})(r_{v,i} - \overline{r_v})}{\sqrt{\sum_{i \in I}(r_{u,i} - \overline{r_u})^2}\sqrt{\sum_{i \in I}(r_{v,i} - \overline{r_v})^2}}$$

where $I = I_u \cap I_v$ is the subset of Web service previously invoked by both user u and v. ,rui is the QoS value of Web service i observed by user u, and u r represents the aver-age QoS value of different Web services observed by user u. Similarly, for item-based CF, the PCC between two service items is calculated as:

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

where $U = U_i \cap U_j$ is the subset of users who have previously invoked both Web services i and j, and ri represents the average QoS value of Web service i observed by different users.

IV. CONCLUSIONS AND FUTURE WORK

This paper has aimed to give the overview of web service recommendation system using collaborative filtering and gives brief explanation on its types and filtering procedure that is QoS prediction and recommendation. QoS Prediction method has combined user-based and item-based algorithm to predict the unknown QoS values of services and then recommend Web services with optimal QoS to the active user. Similarity calculation of users or services is based on historical invocation information of services or users. The development in Collaborative Filtering will improve accuracy of QoS predicted for users and will give more accurate recommendations suitable for user.

As future work, based on survey no author works on privacy concerned about user data, so it will be interesting to see privacy preserving framework for QoS based Web service recommendation.

ACKNOWLEDGMENT

We would like to thank all the authors of different research papers referred during writing this paper. It was very knowledge gaining and helpful for the further research to be done in future.

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DOI 10.17148/IJARCCE.2015.412142