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# A Privacy-Preserving QoS Prediction Framework for Web Service Recommendation

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**Abstract** - Web service recommendation has become a hot topic even in basic research in IT. The most popular technique is the collaborative filtering (CF) on the basis of a quality of service value. With the increasing presence and adoption of web services over the World Wide Web, the quality of service (QoS) is becoming more important to the description Nonfunctional characteristics of Web services. Several approaches for the selection of Web services and recommendation via collaborative filtering were studied; here we are going to investigate these techniques with the pros and cons of Techniques. Also based on these comments, we will propose a new technique for predicting the Web service selection based on known quality of service values and unknown we explain in our future work.

**Key Words:** Web Service, Service Computing, Collaborative filtering, QoS values, Web service recommendation; QoS prediction; collaborative filtering; privacy preservation ...

#### 1.INTRODUCTION

Web services are software components to support interoperable machine-to-machine interaction over a network. The increasing presence and acceptance of Web services on the World Wide Web demand effective recommendation and selection techniques that recommend the optimum web service users from a variety of available web services. With the number of Web services to increase Quality of Service (QoS) [1] is generally used to describe non-functional properties of Web services. Among the different QoS properties of Web services, some features are user independent and have identical values for different users (for example, price, popularity, availability, etc.). The values of the user independency of QoS properties are typically offered by service providers or third-party registers (for example, UDDI). On the other hand some QoS features users are dependent and have different values for different users (for example, response time, Invocation failure rate, etc.). Client-side Web service evaluation requires real web service calls and encounters the following drawbacks:

1) First, real Web service invocations impose costs for service users and consume the resources of the service provider. Some web service calls can also be charged.

- 2) Secondly, it can exist on many Web service candidate analyzed and some appropriate web services in the evaluation list may not be detected and recorded by the service user.
- 3) Finally, most service users are not experts in web service evaluation and the common time-to-market constraints limiting an in-depth review of the target web service.

However, without sufficient client-side evaluation, exact values of the user-specific OoS properties cannot be obtained. Optimal Web service selection and recommendation are so difficult to achieve.

### 2. RECOMMENDER SYSTEM

User needs a special system which can understand their interests and suggest them the best usable services. In this case, Recommender systems can help users with the most suitable items to their interests, have been considered as one of the best solutions. Based on the functionality, the recommender systems can be classified as collaborative filtering, content based filtering, Hybrid models[2]. Recommender systems can help consumers and the most valuable items by calculating the similarities among other consumers with collaborative filtering algorithms.

### 2.1 Collaborative Filtering Methods

The process of identification of similar users, related Web services and recommend what similar users like is called collaborative filtering. The Web services for the user are based on the previous Web service history. A user can hardly recall all the services that the QoS (i.e. round-trip time RTT) represents, values of services that the user has not called are unknown. Therefore, and accurate Web service QoS forecast is very necessary for service user providers. Based on the predicted OoS values the desired service selection can be made. Collaborative Filtering[3] was initially proposed by Rich and has been widely used in service recommendation systems. In Web service recommendation, the primary question of the CF is to find a group of similar users, a group of similar services and user-service-matrix on the QoS value of services that is build by users. The user service matrix is actually very sparse in practice. Based on such a sparse matrix, the prediction accuracy of OoS values of services will decrease considerably. So we initially expected the QoS

values of the matrix of the search for historical QoS data for similar user or similar services lacking and recommend Web services at the optimal QoS values to the active user.

Collaborative Filtering algorithm uses two processes:

- a) Prediction process[3][4] where a numerical value expressing the predicted probability of web services that cannot be upheld certain users. This predicted value is in the same scale as opinion by the same user supplied values.
- b) Recommendation process[3] where a list of N items that the active users like the most is recommended. This recommended list has those users who do not already have access to Web services. This interface of collaborative filtering algorithm Top N recommendation [13] is called Collaborative filtering process and is as shown in the following figure 1.

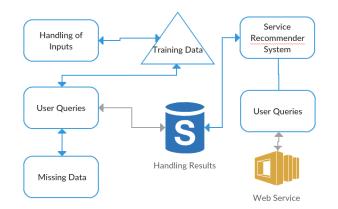


Fig 1. Web service recommendation process

It is impractical for every user to actively measure QoS values due to the expensive overhead of invoking a large number of services. To address this issue, collaborative QoS prediction has recently been proposed, and becomes a key step to QoS-based Web service recommendation [3], [4], [5]. Specifically, two types of CF approaches have been studied for QoS prediction of Web services[5] in recent literature. There are two types of collaborative filtering algorithms:

- 1. Model Based Collaborative Filtering
- 2. Memory Based Collaborative Filtering

### 2.1.1 Model-Based Collaborative Filtering

It involves building a model based on the dataset of ratings. In other words, we extract some information from the dataset, and use that as a "model" to make recommendations[5] without having to use the complete dataset every time. This approach potentially offers the

benefits of both speed and scalability. Using model-based algorithms we can study the collection of QoS, a model which is then used for QoS predictions. Model-based CF algorithms include Bayesian models (probabilistic) and clustering models [6]. Model-based CF technique [6] deliver a predefined model adjust the observed QoS data, and then the trained model can be used to predict the unknown QoS values. Matrix factorization[7] is one of the most popular model-based CF approaches that were first introduced to address the QoS prediction problem. Matrix factorization model [7] treats the problem well sparsely and generally achieved better performance than neighborhood-based approaches. Typical examples include user-based approaches (e.g., UPCC [8]) that leverage the QoS information of similar users for prediction.

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### 2.1.2 Memory Based Collaborative Filtering

Memory-based algorithms approach the collaborative filtering problem by using the entire database. As described by Breese et. al [9], it tries to find users that are similar to the active user (i.e. the users we want to make predictions for), and uses their preferences to predict ratings for the active user. Memory-based algorithms to make predictions stored in memory through the use of data (users, services and QoS data). They can be classified in nearest neighbor algorithms and top-N recommendation algorithms. Neighbor algorithms are the most commonly used memory based CF algorithms. Users similar to the current user in terms of preferences are called neighbors. This type of CF approaches use the observed QoS data to calculate the similarity values between users or services and use them further for QoS forecasts. Top-N recommendation is to recommend a number of N top Web services, this will be to a specific user of interest. Analyze Top N recommendation[10] techniques to correlate the user service matrix different users or services and use them to calculate the recommendations.

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### 3. RELATED WORK

# 3.1. QoS aware Web service recommendation History:

As the number of Web services available on the Internet increases quickly, service consumers pay more attention to QoS instead of functionality than before. QoS mainly consists of non-functional attributes such as response time, throughput, availability, etc. It has been widely used in

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Volume: 04 Issue: 02 | Feb -2017 www.irjet.net p-ISSN: 2395-0072

web service selection [11], [12] (Wang, Wang et al. 2013), service composition (Feng, Ngan et al. 2013), service recommendation (Cao, Wu et al. 2013; Jiang, Liu et al. 2011) and other popular topics in the field of Services Computing. In this section, we present the related work of efficient QoSaware Web service [12] recommendation.

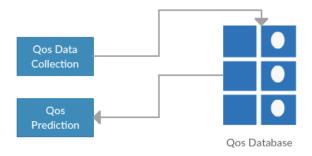


Fig2. Web Service QoS Prediction

They suggested that a Web service QoS value prediction approach by the traditional user-based combination and item-based collaborative filtering method. Their approach does not require Web service calls and help by analyzing QoS information of similar users Service users discover appropriate Web services. In its Web service[12] evaluations in paper reports, to reduce the effect of Web service calls to the real web services, they selected only one operation from a web service make for evaluations and use the power of this operation to the performance by presenting the Web service.

### 3.2. Web service recommendation based on location aware Qos:

Existing approaches fail QoS variance according to user locations to consider; and former recommender systems are all black boxes provide only limited information about the performance of the service candidates. Thus X. Chen, Z. Zheng, X. Liu, Z. Huang, H. and Sun [13], [13] proposed designed a novel collaborative filtering algorithm for largescale Web service recommendation on location aware QoS. First, it combines the model-based and memory-based CF algorithms for Web service recommendation, clearly showing the recommendation accuracy and time complexity improved compared to earlier service recommendation algorithms. Second, they create a visually appealing interface to browse the recommended web services, which allows a better understanding of the service performance. Your algorithm uses the property of QoS of users in different regions clustering. Based on the feature region a refined nearest neighbor algorithm is proposed to generate QoS forecasts. The final service recommendations are on a map by putting the underlying structure of QoS space to show and help users who accept recommendations.

Similarly, M. Tang, Y. Jiang, J. Liu and X. Liu [6] proposed a method for location aware Collaborative Filtering Web services for users to recommend sites of both users and services

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Unlike existing user-based collaborative filtering to find similar users for a target user, rather than searching for group of users, they focus on the user physically close to the target. Similarly, they also change existing service similarity measurement of collaborative filtering which is used by service location information based on a hybrid collaborative filtering technology. After finding similar users and services they use the similarity measure to predict missing QoS values. Web service candidate with the top QoS values are recommended to users. In place consciously method they acquire first historical QoS data and the location information of the active user. A location information handler deals with the location information of active users and the target service, the QoS values are missing for the active user. The user service matrix records every QoS experience the user's web services he has called. To similar users, user similarity measurement are based on the historical QoS data of the user that is calculated, which are in the active user nearby, determined by the location information handler. Likewise Services similarity measurement is calculated based on the QoS records of the services that are close to the target service, also determined by the location information handler. Similar users and related services for the active user and target service or CF algorithm and item-based are used for both user-based forecasting and finding the missing QoS values of the target service.

## 3.3. Web Service Recommendation Methods Based on Personalized Collaborative Filtering

There were different methods of selecting Web services and recommendation based on collaborative filtering, but rarely do they take into account personal influence of users and services. Therefore Y. Jiang, J. Liu, Tang, X. Liu [14] provided a method of collaborative personalized recommendation effective filtering [18] for Web service. A significant portion of these techniques is the calculation of the measure of the similarity of web services. Unlike the Pearson correlation coefficient (PCC) similarity measure, they consider the personal impact of services where between users and the personal impact of the measure of calculated similarity of services. Based on the model of similarity measure Web services, they develop a custom hybrid effective collaborative filtering technology (HICP) for integrating algorithm based on custom user and custom algorithm based item.

Similarly, L. Shao, J. Zhang, Y. Wei, J. Zhao, B. Xie and Mei H. [15] being aware of different experiences of consumers quality of service, they hit a collaborative approach to filtering based on mining similarity decision and forecasting of consumer experiences.

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Page 388

**Volume: 04 Issue: 02 | Feb -2017** www.irjet.net p-ISSN: 2395-0072

# 4. FRAMEWORK OF QOS-AWARE WEB SERVICE RECOMMENDATION

In this section, an online service searching scenario to show the research problem of this paper. The basic idea of this approach is that users closely located with each other are more likely to have similar service experience than those who live far away from each other. We employ the idea of user-collaboration in our web service recommender system. The more QoS information the user contributes, the more accurate service recommendations the user can obtain, since more user characteristics can be analyzed from the user contributed information. Based on the collected QoS records, our recommendation approach is designed as a two-phase process. In the first phase, we divide the users into different regions based on their physical locations and historical QoS experience[15] on web services. In the second phase, we find similar users for the current user and make QoS prediction for the unused services. Services with the best predicted QoS will be recommended to the current user.

# 4.1. Location Information Representation, Acquisition and Processing

This section discusses how to represent, acquire, and process location information of both Web services and service users, which lays a necessary foundation for implementing location-aware Web service recommendation method.

### **4.1.1. Location Representation:**

We represent a user's location as a [IP Address], [Country], [IP No.], [AS], [Latitude], [Longitude]. Typically, a country has many ASs and an AS is within one country only. The Internet is composed of thousands of ASs that interconnected with each other.

However, users located in the same AS are not always geographically close, and vice versa. Therefore, even if two users are located in the same city, they may seem to be at different ASs. This explains why we have chosen, AS instead of other geographic positions, such as latitude and longitude, to represent a user's location.

#### 4.1.2. Location Information:

Acquisition fetch the location information of both Web services and service users can be easily done. Based on the users' IP addresses are already known, to obtain full location in-formation of a user, we only need to identify both the AS and the country in which he is located based on IP address. A number of services and databases are available for this purpose (e.g. the Who is lookup service2). In this work, we accomplished the IP to AS mapping and IP to country mapping using the GeoLite Autonomous System Number

# **4.1.3. Similarity Computation and Similar Neighbor Selection**

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Here we have defined notations for the convenience of describing our method and algorithms. We implemented a weighted PCC for computing similarity between both users and Web services, which takes personal QoS characteristics [16] into consideration. Finally, author has discussed incorporating locations of both users and Web services into the similar neighbor selection.

### 4.1.4. Similar Neighbor Selection:

This selection is a very important step of CF. In conventional type of user-based CF, the Top-N similar neighbor selection algorithm is used invariably [16]. It selects N users that are most similar to the active user as neighbors. Similarly, the Top-N similar neighbor selection algorithm can be employed to select N Web services that are most similar to the target Web service. Traditional Top-N algorithms ignore this problem and still choose the top N most ones. Because of the resulting neighbors are not actually similar to the target user (service), doing this will impair the prediction accuracy. Therefore, abandoning those neighbors from the top N similar neighbor set is better if the similarity is not greater than zero. Secondly, as previously mentioned, Web service users may happen to perceive similar QoS values on a few Web services.

Considering the location-relatedness of Web service QoS [5], authors have incorporated the locations of users and Web services into similar neighbor selection.

### 4.2. User-Based QoS Value Prediction:

Authors presented a user-based location-aware CF method, named as ULACF[16]. Traditional user-based CF[17] methods usually adopted for finding value predictions. This equation, however, may be inaccurate for Web service QoS value prediction. As Web service QoS factors such as response time and throughput, which are objective parameters and their values, vary largely. Therefore, predicting QoS values based on the average QoS[17][18][19] values perceived by the active user (i.e., r (u)) is flawed. Intuitively, given two users that have the same estimated similarity degree to the target user, the user nearer to the target user should be placed more confidence in QoS prediction than the other.

### 5. CONCLUSION

The assembly of the various QoS properties is significant for the accomplishment of web service technology. Due to the increasing popularity of Web services technology and the latency of dynamic service selection and integration, several service providers now provide parallel services. QoS is a modified factor to discriminate functionally similar Web

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services. To make it more problematic understanding is the progression of hiding unique data with arbitrary characters or data. The Web service recommendation helps users find a mandatory service has become important topic in the calculation of the service.

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