LOCATION-AWARE AND PERSONALIZED COLLABORATIVE FILTERING FOR WEB SERVICE RECOMMENDATION WITH RATING

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Abstract-- As the number of web services with similar functionality increases, the service users usually depend on web recommendation systems. Now a days the service users pay more importance on non functional properties which are also known as Quality of Service (QoS) while finding and selecting appropriate web services. The Collaborative filtering approach predicts the QoS values of the web services effectively. Existing recommendation systems rarely consider the personalized influence of the users and services in determining the similarity between users and services. The proposed system is a ranking oriented hybrid approach which integrates user-based and item-based QoS predictions. Many of the non-functional properties depends on the user and the service location. The system thus employs the location information of users and services in selecting similar neighbors for the target user and service and thereby making personalized service recommendation for service users.

Index terms:- Web services, Collaborative filtering, Location-aware, QoS prediction, Service recommendation.

I. INTRODUCTION

Web service has been emerged as a promising technique to support inter-operable machine-to-machine interaction which provides a method of communication between electronic devices over a network. As the number of web services with similar functionality has increased rapidly over the internet the web service discovery is not a challenging task but selection and recommendation are becoming more important.

The Optimality of a web service depends on its performance and performance is measured through Quality of Service i.e.QoS.QoS is the set of non functional properties[1] of a web service which includes response time,price,failure rate and so on. Recommendation system initially searches for the list of web services those having similar functionality, which the user requested and finally the optimal web services are recommended to users. Collaborative filtering is widely employed in web service recommendation.Existing QoS prediction[2],[3] methods rarely finds the similarity of users,services and location of users into consideration.
The proposed method uses both the location of users and web services on selecting similar neighbors[4] for the target user or service.

II. SYSTEM MODEL

In this section we consider the existing system design and the proposed system.

2.1 EXISTING SYSTEM

Location-Aware and Personalized Collaborative Filtering for Web Service Recommendation existing Quos prediction methods seldom consider personalized influence of users and services when measuring the similarity between users and between services However, existing Web service QoS prediction methods seldom took this observation into consideration. We conducted an experiment to evaluate the prediction time of our method, and compare it with some existing.

2.1.1 Existing System Algorithms

Collaborative filtering is one of the most popular recommendation techniques, which has been widely used in many recommender systems. In this section, we give a brief survey of CF algorithms, and summarize recent work on CF-based Web service recommendation.

Problem Identified:

- It is impractical for a user to acquire QoS information by invoking all of the service candidates. And some QoS properties (e.g., reputation and reliability) are difficult to be evaluated, since they require both long observation duration and a large number of invocations. These challenges call for more effective approaches to acquire service QoS information.
- Previous CF-based Web service recommendation methods have rarely taken into account the peculiar characteristics of Web service QoS when making QoS predictions.
- QoS attributes of Web services such as response time and throughput highly depend on the underlying network conditions, which, however, are usually ignored by the previous work.

2.2 PROPOSED SYSTEM

We proposed an enhanced measurement for computing QoS similarity between different users and between different services. The measurement takes into

account the personalized deviation of Web services' QoS and users' QoS experiences, in order to improve the accuracy of similarity computation.

Although several CF-based Web service QoS prediction methods have been proposed in recent years, the performance still needs significant improvement.we propose a location-aware personalized CF method for Web service recommendation.

The proposed method leverages both locations of users and Web services when selecting similar neighbors for the target user or service. To evaluate the performance of our proposed method, we conduct a set of comprehensive experiments using a real-world Web service dataset. Based on the above enhanced similarity measurement, we proposed a location-aware CF-based Web service QoS prediction method for service recommendation. We conducted a set of comprehensive experiments employing a real-world Web service dataset, which demonstrated that the proposed Web service QoS prediction method significantly outperforms previous well-known methods.

Benefits:

- Our location-aware QoS prediction method has a solid basis, because of the strong relation between the locations of users (or Web services) and the Web services' QoS perceived by the users.
- We conducted an experiment to evaluate the impact of data sparseness on the prediction coverage, in which, our proposed methods (including ULACF, ILACF and HLACF) were compared with the traditional CF methods such as UPCC and IPCC. We find that, our methods can always achieve nearly 100% prediction coverage, when the matrix density varies from 5% to 30%. By contrast, the traditional CF methods have significantly lower prediction coverage, especially when K is small.
- Achieves aiming at improving the QoS prediction performance, we take into account the personal QoS characteristics of both Web services and users to compute similarity between them.

III. DESIGN CONSTRUCTION

This Section consists of the following module design are to be explained in this section.
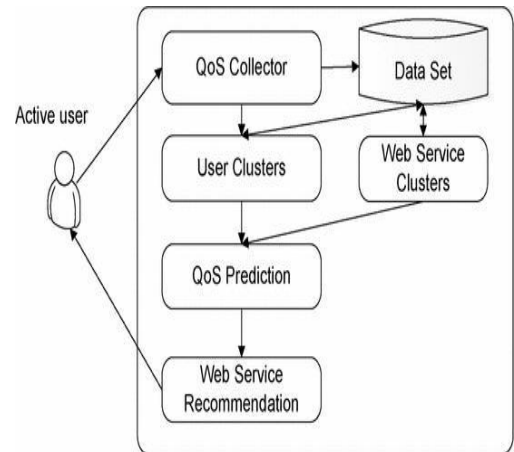**3.1 SYSTEM ARCHITECTURE**

Fig-1: Overview of our Web service recommendation model

3.2 RECOMMENDATION SYSTEM MODULE DESCRIPTION:

3.2.1 Web services

CF-based Web service recommendation aims to predict missing QoS (Quality-of-Service) values of Web services. With the prevalence of Service-Oriented Architecture (SOA), more and more Internet applications are constructed by composing Web services. As a consequence, number of Web services has increased rapidly over the last decade.
Collaborative Filtering (CF) is widely employed to rec-ommend high quality Web services to service users. Based on the fact that a service user may only have in-voked a small number of Web services, CF-based Web service recommendation technique focuses on predicting missing QoS values of Web services for the user.

3.2.2 Collaborative Filtering (CF)

Collaborative filtering is a method of making automatic predictions (filtering) about the interests of a user by collecting preferences or taste information from many users (collaborating)
CF techniques can be generally decomposed into two categories: model-based and memory-based [5],[6]. Memory-based CF is also named neighborhood-based CF. Depending on whether user neighborhood or item neighborhood is considered, neighborhood-based CF can further be classified into user-based and item based.

For example, using the temporal context, a travel recommender system would provide a vacation recommendation in winter very different from the one provided in summer. They demonstrated that incorporating contextual information in essence would improve both the effectiveness and the efficiency of a recommender system.
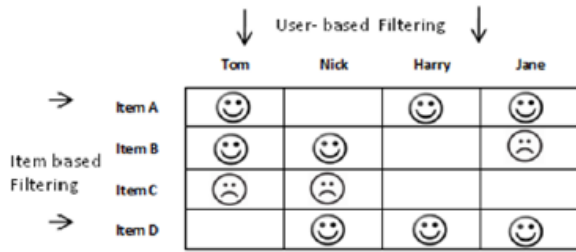
Fig-2: Compare user-based and item-based filtering.

3.2.3 Web Service Recommendation

Various recommendation techniques have recently been applied to Web service recommendation, such as the content- based link prediction-based. Their argued that, for every pair of ac-tive user and target Web service, both the QoS experience of the users similar to the active user and the QoS values of the services similar to the target service can be em-ployed for QoS prediction. However, these previous ap-proaches failed to exploit the characteristics of QoS in the similarity computation. Based on the traditional CF approaches, several en-hanced methods have been proposed to improve the pre-diction accuracy. This is probable if the Web services are deployed in a high performance Cloud environment.

If the QoS is good enough (as in this instance), a small variation of QoS values over all users is likely to be ob-served. Some Web services may have a very poor QoS for all users.

3.3.4 Incorporating QoS Variation into User and Service Similarity Measurement

Previous QoS prediction methods assume that the co-invoked Web services have equal contribution weights when computing similarity between two users. We argue that the personalized characteristics (e.g., QoS variation) of both Web services and users should be incorporated into measuring the similarity among users and services. Web service QoS factors, such as response time, avail-ability and reliability, are usually user-dependent. From different Web services, we can derive different personal-ized characteristics, based on their QoS values, as perceived by a variety of users. Some Web services may have a very good QoS for all users.

For example, the availabil-ity is always 100%. This is probable if the Web services are deployed in a high performance Cloud environment. If the QoS is good enough (as in this instance), a small variation of QoS values over all users is likely to be ob-served. Some Web services may have a very poor QoS for all users. For example, the availability is always below 50%. This is probable if the Web services are deployed in a network environment with poor performance and bandwidth.

These Web services are also likely to have small variation of QoS values over different users. Many other Web services may have a relatively large variation of QoS over different users. These Web services are considered to be user-sensitive.The following example explains why Web services

with different QoS variations could contribute differently when computing the similarity between service users.

3.4.5 Incorporating Locations of Users and Services into Similar Neighbor Selection

Web services are deployed on the Internet. Thus, QoS of Web services (such as response time, reliability and throughput) is highly dependent on the performance of the underlying network [33]. If the network between a target user and a target Web service is of high performance, the probability that the user will observe high QoS on the tar-get service will increase. There are several factors affecting the network performance between the target user and the target service. The most important factors include network distance and network bandwidth, which are highly relevant to locations of the target user and the target service. When the user and the service are located at different networks which are far away from each other on the Internet, network performance is likely to be poor due to both the transfer delay and the limited bandwidth of links between different networks.

In contrast, when the user and the Web service are located in the same network, the user is more likely to observe high network performance.

User location information handler: This module obtains location information of a user including the network and the country according to the user's IP address. It also provides support for efficient user-querying based on location.

Service location information handler: This handler acquires additional location information of Web services according to either their URLs or IP addresses. The location information includes the network and the country in which the Web service are located. It also provides functionalities for supporting efficient locationbased Web service query.

Find similar users: This module finds users who are similar to the active user by considering both the users' QoS experiences and locations. For accurate user similarity measurement and scalable similar user selection, we propose a weighted user-based PCC via exploring QoS variation of Web services and incorporate user locations into similar user selection.

Find similar services: In contrast to finding similar users, this module finds similar Web services for a target service, considering both QoS of Web services as well as service locations. A weighted service-based PCC for measuring similarity between services is proposed.

User-based QoS prediction: After a certain number of similar users are identified for the active user, this function aggregates the QoS values they perceived on target Web services, and predicts the missing QoS values for the active user.

Service-based QoS prediction: After a certain number of similar services are identified for a target Web service, this function aggregates their QoS values to predict the missing QoS values for the active user

Hybrid QoS prediction: This function combines the userbased QoS prediction and the service-based QoS

prediction results, making final QoS predictions. The cold-start problem and data-sparsity problem in QoS predictions are also addressed in this module.

Recommender: After predicting missing QoS values for all candidate Web services, this function recommends Web services with optimal QoS to the active user.

3.3.6 Location Information Representation, Acquisition, And Processing.

This section discusses how to represent, acquire, and pro-cess location information of both Web services and ser-vice users, which lays a necessary foundation for imple-menting our location-aware Web service recommendation method.

Location Representation :

We represent a user's location as a triple (IPu, ASNu, CountryIDu), where IPu denotes the IP address of the user, ASNu denotes the ID of the Autonomous System (AS)1 that IPu belongs to, and CountryIDu denotes the ID of the country that IPu belongs to. Typically, a country has many ASs and an AS is within one country only. The Internet is composed of thousands of ASs that inter-connected with each other.

Generally speaking, intra-AS traffic is much better than inter-AS traffic regarding transmission performance, such as re-sponse time. Also, traffic between neighboring ASs is better than that between distant ASs. Therefore, the Inter-net AS-level topology has been widely used to measure the distance between Internet users. Note that users located in the same AS are not always geographically close, and vice versa. For example, two users located in the same city may be within different ASs. Therefore, even if two users are located in the same city, they may look distant on the Internet if they are within different ASs.

Location Information:

Acquisition Acquiring the location information of both Web services and service users can be easily done. Because 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 according to his IP address.

A number of services and databases are available for this purpose (e.g. the Whois lookup service2). In this work, we accomplished the IP to AS mapping and IP to country mapping using the GeoLite Autonomous System Number Database3. The database is updated every month, ensuring that neither the IP to AS mapping nor the IP to country mapping will be out-of-date.

3.3.7 Similarity Computation And Similar Neighbor Selection

In this section, we first formally define notations for the convenience of describing our method and algorithms. We then present a weighted PCC for computing similarity between both users and Web services, which takes their personal QoS characteristics into consideration. Finally, we discuss incorporating locations of both users and Web services into the similar neighbor selection.

Similar Neighbor Selection :

Similar neighbor selection is a very important step of CF. Selecting the neighbors right similar to the active user is necessary for accurate missing value prediction. In conventional user-based CF, the Top-K similar neighbor selection algorithm is often employed [7]. It selects K users that are most similar to the active user as his/her neighbors. Similarly, the Top-K similar neighbor selection algorithm can be employed to select K Web services that are most similar to the target Web service.

There are several problems involved, however, when applying the Top-K similar neighbor selection algorithm to Web service recommendation. Firstly, in practice, some service users have either few similar users or no similar users due to the data sparsity. Traditional Top-K algorithms ignore this problem and still choose the top K most ones. Because the resulting neighbors are not actually similar to the target user (service), doing this will impair the prediction accuracy. Therefore, removing those neighbors from the top K similar neighbor set is better if the similarity is no more than 0. Secondly, as previously mentioned, Web service users may happen to perceive similar QoS values on a few Web services. But they are not really similar.

Considering the location-relatedness of Web service QoS, we incorporate the locations of both users and Web services into similar neighbor selection.

User-based QoS Value Prediction

In this subsection, we present a user-based location-aware CF method, named as ULACF. Traditional user-based CF methods usually adopt for missing value predictions. This equation, however, may be inaccurate for Web service QoS value prediction for the following reasons. Web service QoS factors such as response time and throughput, which are objective parameters and their values vary largely.

In contrast, user ratings used by traditional recommender systems are subjective and their values are relatively fixed. Therefore, predicting QoS values based on the average QoS values perceived by the active user (i.e., r (u)) is flawed. Moreover,

$$\hat{r}_u(u,i) = \overline{r}(u) + \frac{\sum_{v \in N(u)} Sim(u,v) \times (r(v,i) - \overline{r}(v))}{\sum_{v \in N(u)} Sim(u,v)}$$

(1)

Eq. (1) given two users that have the same estimated similarity degree to the target user, the user closer to the target user should be placed more confidence in QoS prediction than the other.

Item-based QoS Value Prediction

In this subsection, we present an item-based locationaware CF method, named as ILACF. Based on the similar consideration as ULACF's, we use Eq. to compute the

predicted QoS value for a service based on the QoS values of its similar services .

Integrating QoS Predictions

Due to the sparsity of the user-item matrix, to make the missing value prediction as accurate as possible, it's better to fully explore the information of similar users as well as similar services. Therefore, we develop a hybrid location-aware CF, named as HLACF, which integrated the user-based QoS prediction with the item-based QoS prediction. The following four cases will be considered in integrating QoS predictions.

IV.   PERFORMANCE EVALUATION

The proportion of a user's (service's) top-K similar neighbors that are located in the same AS or country as the user (service):
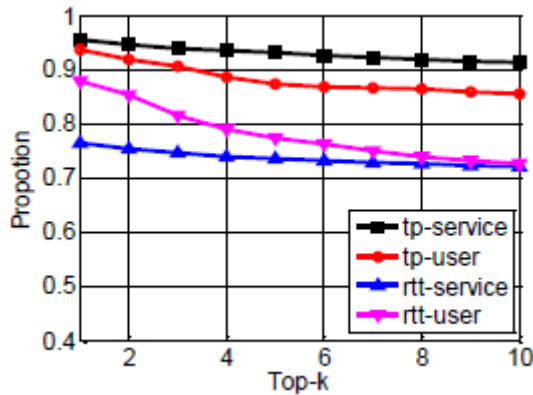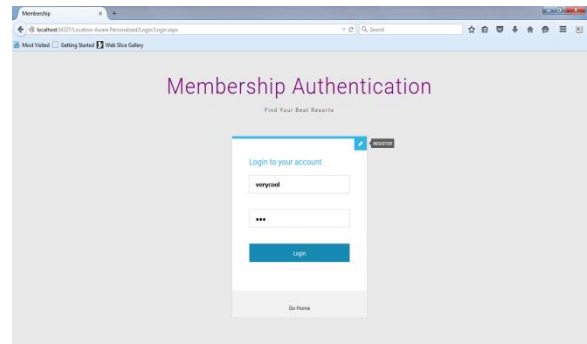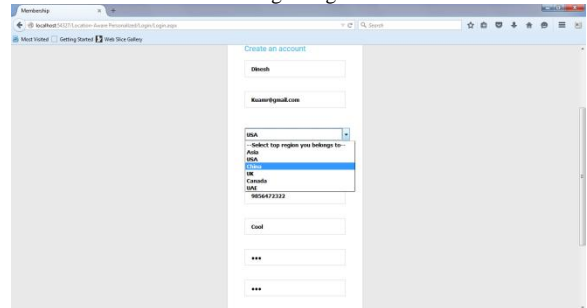

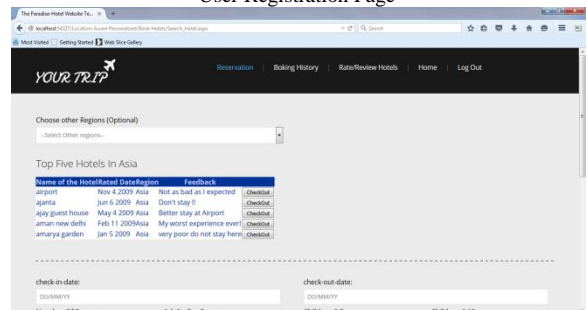(a) regarding country
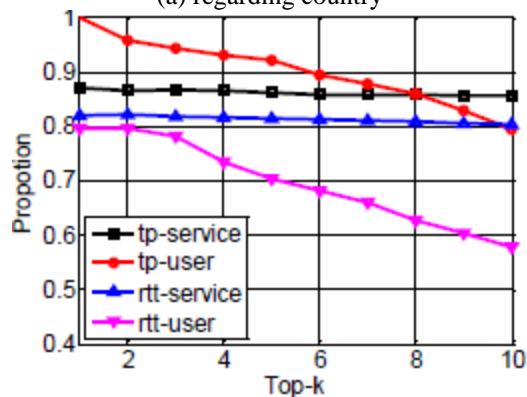
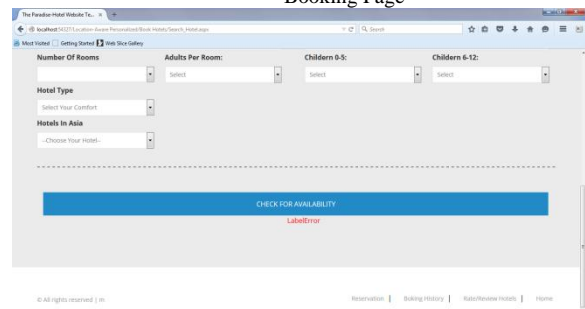(b) regarding AS

V.   SIMULATION RESULT

Login Page

User Registration Page

Booking Page

User Availability Checking

VI.   CONCLUSION

This paper presents an innovative QoS-aware Web service recommendation approach .The basic idea is to predict Web services QoS values and recommend the best one for active users based on historical Web service QoS records. In order to better recommend Web services to users from amount of services with identical functions, this paper proposed a Web service recommendation approach based on collaborative filtering.

In this paper, recommendation approach considered the correlation between QoS records and users" physical locations

by using IP addresses, which has achieved good prediction performance and makes the QoS prediction more confident for Web service recommendation.

Feature Work: In the future, we will take more detailed location in-formation into consideration for QoS prediction, such as the Internet's AS topology. We will also consider incorpo-rating the time factor into QoS prediction, and plan to obtain bigger datasets for evaluating our methods.

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