Web Services Recommendation and Visualization for Custom-Made QoS

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Abstract**—** Web services are integrated software components for the support of interoperable machine to machine interaction over a network.Some previous problems are1) earlier approaches are not succeed to consider the QoS variation according to users'locations; and 2) earlier recommender systems are all black boxes it just takes input from user and provide different services that provide incomplete or limited information on the performance of the service applicant.In this system we provide novel collaboration filtering based web services recommender system to helps users select services with best QoS performance. Our approach employs the characteristic of QoS and achieves considerable improvement on commendation accuracy.We present exact web services location in an interactive visualization map. Interaction is provide through SOM based interaction visualization techniques.

Keywords**—***Service, recommendation, QoS, collaborative filtering, self-organizing map, visualization*

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I. INTRODUCTION

Webservices are software components designed to support interoperable interaction of machine to machine over a network, usually the Internet. Web services employs interface description using WSDL (Web Services Description Language) and exchanging structured information using SOAP (Simple Object Access Protocol). Benefiting from the cross-language and cross-platform characteristics, Web services have been widely employed by both enterprises and developers for building services oriented applications. The adoption of Web services as a delivery model in business has fostered a paradigm shift from the development of monolithic applications to the dynamic set-up of business processes.

When developing services-oriented applications, developers studies all requirements and then design the business process according to requirements, and then try to find and reuse existing services to build the process. Currently like Google Developers (*developers.google.com*), Yahoo! Pipes (*pipes.yahoo.com*), programmable Web (*programmableweb.com*), etc are many developers explore services through these public sites. However, none of them provide location-based QoS information for users. Some Web services are only available in EU, thus software employing these services cannot be shipped to other countries.

Since selecting high quality Web services among a large number of candidates is a non-trivial task, some developers choose to implement their own services instead of using publicly available ones, which incurs additional overhead in both time and resource. Using inappropriate services, on the other hand, may add potential risk to the business process. Therefore, effective approaches to services selection and commendation are in an urgent need, which can help services reduce users risk and deliver high-quality business procedure.

Quality-of-Services (QoS) is widely employed to represent the non-functional characteristics of Web services and has been considered as the key factor in services selection [33]. QoS is a set of properties including reputation, throughput, response time, availability, etc.

Among these QoS properties, values of some properties (e.g., response time, user-observed availability, etc.) need to be measured at the client-side [26]. It is not practical to acquire such QoS information from services providers, since these QoS values are susceptible to the uncertain Internet environment and user background (e.g., user network state, user location etc.). Therefore, different users may observe moderately different QoS values of the same Web services.

In other words, QoS values evaluated by one user cannot be employed directly by another for services selection. It is also not practical for users to obtain QoS information by evaluating all services candidates by themselves, since conducting real world Web services invocations is resource-consuming and time consuming. Moreover, some QoS properties (e.g., reliability) are not easy to be evaluated as long-time inspection is necessary.

To attack this challenge, to attack this challenge, this system investigates custom-made QoS value prediction for services users by employing the available past user experiences of Web services from different users. Our approach requires no additional Web services invocations. Based on the predicted QoS values of Web services, custom-made QoS-aware Web services commendations can be produced to help users select the optimal services among the functionally equivalent ones. From a large number of real-world servicesQoS data composed from dissimilar locations, we find that the user-observed

Web servicesQoS performance has strong correlation to the locations of users. Google Transparency Report1 has comparable observation on Google services. To enhance the prediction accuracy, we propose a location-aware Web services recommender which employs both Web servicesQoS values and user locations for making custom-made QoS prediction Web services recommender system share their past usage experience of Web services, and in return, the system provides custom-made services commendations to them. Web services recommender system first gather user observed QoS records of different Web services and then groups users who have similar QoS observations together to generate commendations. The main contributions of this work are two-fold:

• First, we propose a new location-aware Web services commendation approach, which significantly improves the commendation accuracy and time complexity compared with existing services commendation algorithms.

• Second, we conduct comprehensive experiments to evaluate our approach by employing a real-world Web servicesQoS data set. More than 1.7 million real world Web servicesQoS records from more than 20 countries are engaged in our experiments. Whole analysis on the impact of the algorithm parameters is also provided.

The rest of this paper is organized as follows: Section 2 reviews related work of collaborative filtering and Web services commendation. Section 3 presents the system architecture. Section 4 describes the proposed Web services commendation algorithm. Section 5 shows our extensive experiment results, employing QoS values of real-world Web services, and Section 6 concludes the paper.

II. Existing System

A number of earlier works has applied collaborative filtering (CF) to web service commendation [3][6]. These CF-based web service recommender systems works by collecting user observed QoS records of different web services and matching together users who share the same information requirements or same experiences. Users of a CF system share their judgments and opinions on web services, and in return, the system provides useful custom-made commendations. There is some drawback of existing system,

I] it is fail to identify the QoS variation with user's physical location.

II] Online time complexity of memory based CF commendation for tens of thousands user in real time.

III] Current recommender system is all black boxes, providing list of ranked web services with no simplicity into the reasoning behind the commendation system.

Shao et al. proposed a user-based CF algorithm to predict QoS values. Zheng et al. combined the user based and item-based CF algorithm to recommend web services. However, since neither of the two approaches recognized the different characteristic between web service QoS and user ratings, the prediction precision of these methods was not good enough.

Zheng et al. proposed a neighborhood-integrated matrix factorization approach for

making custom-made QoS value prediction. The approach fuses the neighborhood-based and model-based collaborative filtering approaches to achieve higher prediction accuracy. But the neighbors are defined as the users who have related QoS records.

Zhang et al. also used the matrix factorization method, and propose a model-based

approach, for time-aware custom-made QoS value prediction. Peng et al. made a further step by modeling more time-effect features, and achieved better prediction precision.

Chen et al. [2] proposed a location-aware QoS prediction method. It uses thefeature of QoS by clustering users into dissimilar regions. Based on the region feature, a nearest-neighbor algorithm is proposed to generate QoS prediction. However, this technique just made a good start for location-aware QoS prediction, and there is enough space for the upgrading of prediction precision.

III. A Stimulating Scenario

In this section, we present an online service searching

Scenario to show the explore problem of this paper. As Fig. 1

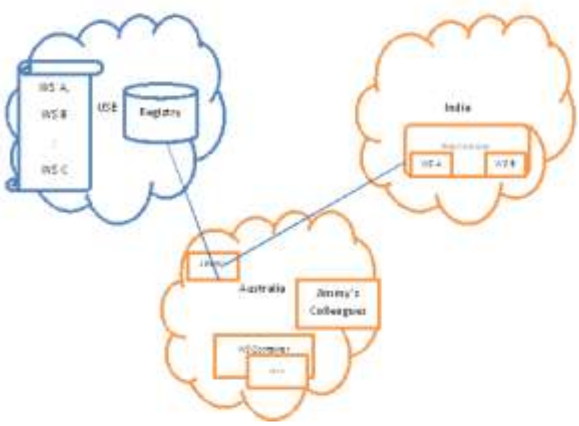

Fig 1. Jimour's Situational Problem

depicts, jimour is a software engineer working in Australia. He needs an email justification service to filter emails. After searching a service registry located in USE, he gets a list of Recommendedservices in ascending order of the service average response time. jimour tries the first two services provided by a Indian company and discovers that the response time is much higher than his hope. He then realizes that the service ranking is based on the assessment Conducted by the registry in USE, and the response time of the same service may vary greatly due to the different user background such as user location, user network state, etc.

Jimour then turns to her colleagues in India for suggestion. They suggest her try service k provided by a local company though ranked lower in the previous commendation list.

After trying it, Jimour thinks that service k has a good performance and meets her requirements. The problem that Jimour faces is to find a service that meets both nonfunctional and functional requirements. The current way of finding a suitable web service is rather inefficient, since Jimour needs to try the recommended services one by one. To address this challenge, we propose a more precise approach to service commendation with consideration of the region factor. Moreover, we try tomake available a more informative and user-friendly interface for browsing the commendation results rather than a ranked list. By this way, users are able to know more about the overall performance of the recommended services, and thus trust the commendations.

The basic thought of our approach is that users closelysituated with each other are more likely to have relatedservice experience than those who exist far away from eachother. Motivated by the achievement of Web 2.0 websites that Emphasize information sharing interface, and collaboration, we employ the thought of user-collaboration in our web service recommender system. Users are encouraged to share their experimental web serviceQoS Performance with others in our recommenderscheme. The more QoS information the user donate, the more precise service commendations the user can get,since more user features can be analyzed from the user donate information. Based on the composed QoS records, our commendation Approach is designed as a two-step method. In the first step, we divide the users into dissimilar regions based on their physical locations and past QoS experience on web services. In the second step, we find out similar users for the existing user and create QoS prediction for the unused services. Services with the best predicted QoS will be recommended to the current user.

IV. THE COMMENDATION APPROACH

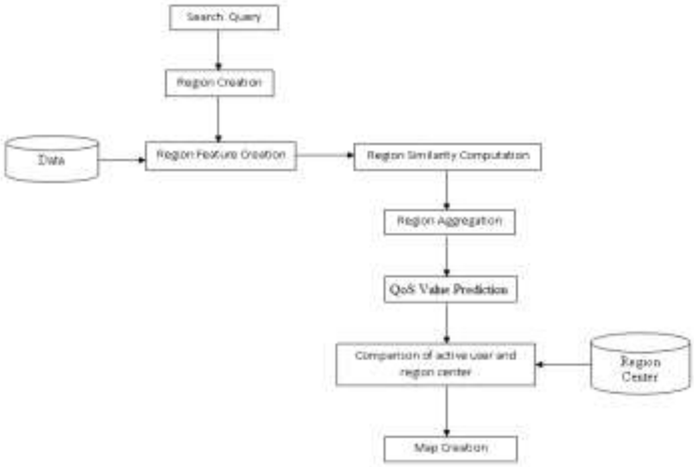

Fig 2- System Architecture

The commendation approach is designed as a two-phase process. In the first step, it divides the users into different regions based on their physical locations and historical QoS experience on web services. In the second step, systems find similar users for the current user and make QoS prediction for the unused services. Services with the most excellent predicted QoS will be recommended to the current user.

Step 1.Region Creation

In this,our center of attention on the QoS Properties that are prone to change and can be easily obtained and objectively calculated by each and every users, such as availability and response time . To simplify the explanation of our approach, we use response time (also called round-trip time (RTT)) to explain our approach.

We assume that there are n users and m services. The correlation between users and services is denoted by an

$n \times m$ matrix R. Each entry $R_{i;j}$of the matrix represents the

RTT of servicej observed by user i and $\perp$ is the symbol of

no RTT value. Each user i ($i \in \{1; 2; \dots; n\}$)is associatedwith a row vector $R_i$representing his/her observed RTTvalues on different web services. The user $a(a \in \{1,2, \dots .n\}$)is called the active user or current user if he/she has provided some RTT records and needs service commendations.

In web service recommender system, users typically provide QoS values on a small number of web services. Here a region is nothing but a group of users who are closely located with each other and likely to have similar QoS profiles. Each user is a member of exactly one region. Regions require tobe internally coherent, but clearly separate from each other. The region formation phase is designed as a three-step process.

Step 1.1. Region Feature Extraction

In the first step, put the users with similar IP addresses into a small region and extract region features.

We can define Region center as the median vector of all the RTT vectors connected with the region users. the median RTT value is the element i of center of serviceiobserved by users from the region. Median separates higher half of a sample from the lower half.

To differentiate services with not fixed performance to different regions and regard them as region-sensitive services, which is another important region characteristic as well the region center.The set of non-zero RTT's of service s, $R_{.s}=\{R_{1,s},R_{2,s},\ldots,R_{k,s}\}$,1<=k<=n, collected from users of all regions is a sample from the population of service s response time. To estimate the mean μ and the standard deviation σ of the population, we use two robust measures: median and median absolute deviation (MAD) . MAD is defined as the median of the absolute deviations from the sample's median

$$MAD=median_i\,(|R_{i,s}-median_j(R_{j,s})|)\ldots\ldots(1)$$

Where, i=1,…..k, j=1,…..,k

Based on the median and MAD, the two estimators can be calculated by

$$\hat{\mu}=median_i(R_{i,S})\, i=1,\ldots,k, \quad \ldots\ldots(2)$$

$$\hat{\sigma}= MAD_i(R_{i,S})\, i=1,\ldots.k. \quad \ldots\ldots(3)$$

Step 1.2. Region Similarity Computation

In the second step, calculate the similarity between different regions. In first step we have to calculate similarity of two regions M and N it is calculated by the similarity of their region centers m and n. we are use pearson correlation coefficient (PCC) to find the similarity

$$sim(m,n) = \frac{\sum_{s\in S(n)\cap S(m)}(R_{m,n}-\bar{R}_m)\cdot(R_{n,s}-\bar{R}_n)}{\sqrt{\sum_{s\in S(n)\cap S(m)}(R_{m,s}-\bar{R}_m)^2}\cdot\sqrt{\sum_{s\in S(n)\cap S(m)}(R_{n,s}-\bar{R}_n)^2}}\ldots\ldots(4)$$

Where,

1. $s(n)\cap s(m)$ is the set of coinvokedservices by users from region *M* and *N*

2. $R_{m,s}$is the RTT vale of service s provided by region center m.

3.$\bar{R}_m$ and R_n represent the average RTT of all the services of center m and n.

But PCC considers the RTT difference of coinvokedservices between regions. But there are possibility is that two regions that are not similar,but there is few coinvokedservices with similar RTTs.

To improve accuracy of prediction can be improved if we add a correlation significance weighting factor.we use the following adjusted PCC equation to measure the similarity between two region.

$$sim'(m,n) = \frac{|S(m)\cap S(n)|}{|S(m)\cup S(n)|}\, Sim(m,n)\ldots\ldots(5)$$

Step 1.3. Region Aggregation

In the last step, aggregate highly correlated regions to form a certain number of large regions.

Step 2: QoS Value Prediction

After the step of region aggregation next step is QoS value Prediction, lots of users are clustered into a certain number of regions based on their past QoS and physical locations similarities. The service experience of users in a region is represented by the region center. With the compressed searching neighbors, making predictions and QoS data for an active user can be computed rapidly.

In this approach, similarity between the active user and users of a region is computed by the similarity between the active user and the region center.

V. COMMENDATION VISUALIZATION

QoS space visualization is more than a picture or method of computing. It makes over the information of high dimensional QoS data into a visual form enabling service users to understand, browse, and observe the information. The QoS map by two steps: dimension decrease step and map creation step.

In the first step that is dimension decrease step we create a 2D representation of the high-dimensional QoS space by using self-organizing map (SOM), and each web service is mapped to a unique 2D coordinates.

In the second step that is and map creation step we create a geographic-like QoS map based on the SOM training results.

The direct approach to web serviceQoS map is to assign each web service a distinct portion of the 2D display area, and put services with similar QoS performance next to each other. The System provides a personalized map for browsing the commendation results. The map explicitly shows the QoS relationships of the recommended web services as well as the underlying structure of the QoS space by using map metaphor such as spatial arrangement, dots, and areas.

VI. CONCLUSION AND FEATURE SCOPE

In this paper, we have presented a new approach to custom-made web service commendation and visualization.from previous work, our algorithm employs the characteristic of QoS by clustering users into different regions. Based on the region feature, a efficient allocation algorithm is proposed to generate QoS prediction. The final service commendations are put on a map to disclose the underlying arrangement of QoS space and help users admit the commendations. Experimental results show that our Approach considerably improves the prediction precision than the existing methods.

In this paper, our commendation approach consideredthe correlation between users' physical locations by using IP addresses and QoS records, which has accomplished excellent Prediction performance. In some cases, however, users in the same physical locations may observe unusual QoS performance of the same web service. Besides the user physical location, we will examine more background information that influence the client-side QoS performance, such as the workload of the servers, network state, and the behavior that users carry out with web services (e.g., web services are used alone or in composition). More examination on the distribution of RTT and the relationship between different QoS properties such as RTT and availability will be conducted in our web service search engine project ServiceXchange.

For the visualization of the commendation results, weplan to include more user interactions such as searching web services on the QoS map, zooming in and zooming out. Graphic map like google map will be combined to help users navigate their similar users and web service supplier on the map.

Our future work also contains investigating the relationship between different QoS Properties, and detecting malicious users with incorrect QoS information. User approval rate of the commendation is a key Indicator of the effectiveness of the recommender system. We will collect more user feedbacks of the commendation to help improve the prediction precision of our web service commendation algorithm.

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