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RESEARCH ARTICLE

Web Amenities Commendation and Visualization for Custom-made QoS

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ABSTRACT- Web amenities are integrated software components for the support of interoperable machine to machine interaction over a network. Some previous problems are 1) 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 amenities that provide incomplete or limited information on the performance of the amenity applicant. In this system I have provide novel collaboration filtering based web amenities recommender system to helps users select amenities with best QoS performance. My approach employs the characteristic of QoS and achieves considerable improvement on commendation accuracy. I present exact web amenities location in an interactive visualization map. Interaction is providing through SOM based interaction visualization techniques.

Keywords - Amenities, Commendation, QoS, Collaboration _ltering, self-organizing map, Visualization

I. INTRODUCTION

Web amenities are software components designed to support interoperable interaction of machine to machine over a network, usually the Internet. Web amenities employs interface description using WSDL (Web Amenities Description Language) and exchanging structured information using SOAP (Simple Object Access Protocol). Benefiting from the cross-language and cross-platform characteristics, Web amenities have been widely employed by both enterprises and developers for building amenities oriented applications. The adoption of Web amenities 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 amenities-oriented applications, developers studies all requirements and then design the business process according to requirements, and then try to find and reuse existing amenities 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 amenities through these public sites. However, none of them provide location-based QoS information for users. Some Web amenities are only available in EU, thus software employing these amenities cannot be shipped to other countries. Since selecting high quality Web amenities among a large number of candidates is a non-trivial task, some developers choose to implement their own amenities instead of using publicly available ones, which incurs additional overhead in both time and resource. Using inappropriate amenities, on the other hand, may add potential risk to the business process. Therefore, effective approaches to amenities selection and commendation are in an urgent need, which can help amenities reduce users risk and deliver high-quality business procedure.

Quality-of-Services (QoS) is widely employed to represent the non-functional characteristics of Web amenities and has been considered as the key factor in amenities 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 amenities 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 amenities. In other words, QoS values evaluated by one user cannot be employed directly by another for amenities selection. It is also not practical for users to obtain QoS information by evaluating all amenities candidates by themselves, since conducting real world Web amenities 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, this system investigates custom-made QoS value prediction for amenities users by employing the available past user experiences of Web amenities from different users. Our approach requires no additional Web amenities invocations. Based on the predicted QoS values of Web amenities, custom-made QoS-aware Web amenities commendations can be produced to help users select the optimal amenities among the functionally equivalent ones. From a large number of real world amenities QoS data composed from dissimilar locations, we find that the user-observed Web amenities QoS performance has strong correlation to the locations of users. Google Transparency Report1 has comparable observation on Google amenities. To enhance the prediction accuracy, we propose a location-aware Web amenities recommender which employs both Web amenities QoS values and user locations for making custom-made QoS prediction Web amenities recommender system share their past usage experience of Web amenities, and in return, the system provides custom-made amenities commendations to them. Web amenities recommender system first gather user observed QoS records of different Web amenities 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 amenities commendation approach, which significantly improves the commendation accuracy and time complexity compared with existing amenities commendation algorithms.

Second, we conduct comprehensive experiments to evaluate our approach by employing a realworld Web amenities QoS data set. More than 1.7 million real world Web amenities QoS 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 amenities commendation. Section 3 presents the system architecture. Section 4 describe the proposed Web amenities commendation algorithm. Section 5 shows our extensive experiment results, employing QoS values of real-world Web amenities, and Section 6 concludes the paper.

II. EXISTING SYSTEM

A number of earlier works has applied collaborative filtering (CF) to web amenity commendation [3][6]. These CF-based web amenity recommender systems works by collecting user observed QoS records of different web amenities 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 amenities, 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 users 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 amenities 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 amenities. 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. Butthe 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 the feature 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 amenity searching scenario to show the explore problem of this paper.

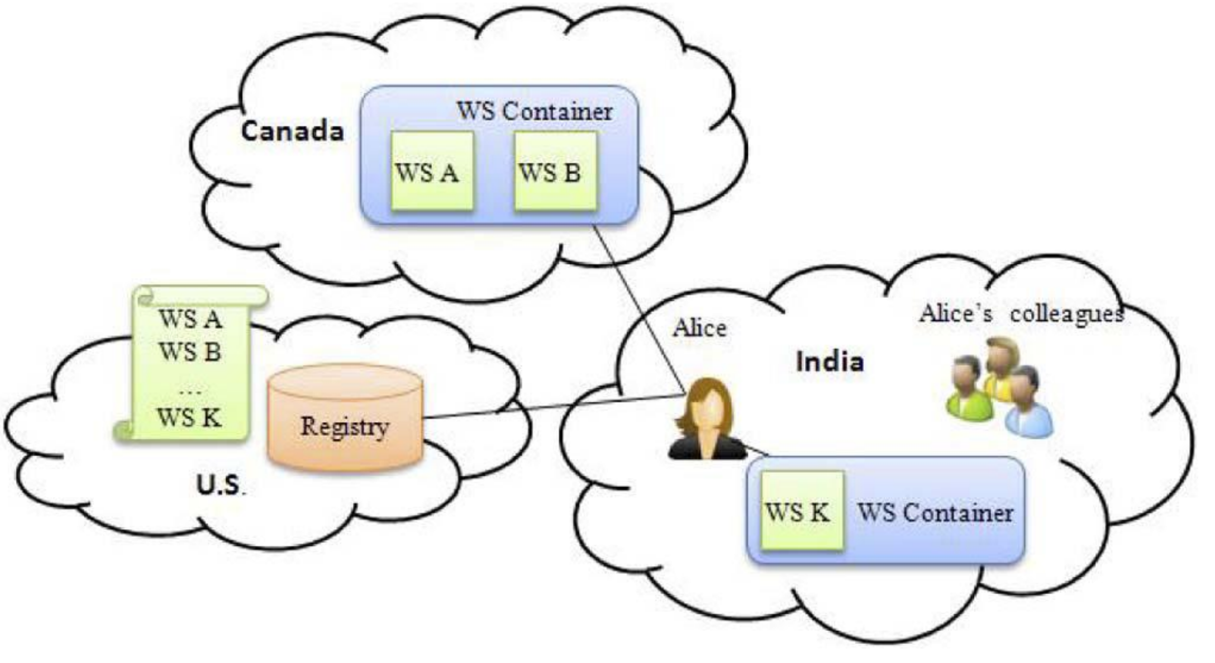


Figure 1: Alice Situational Problem

As Fig. 1 depicts, alice is a software engineer working in Australia. He needs an email justification amenity to filter emails. After searching a amenity registry located in USE, he gets a list of Recommended amenities in ascending order of the amenity average response time. alice tries the first two amenities provided by a Indian company and discovers that the response time is much higher than his hope. He then realizes that the amenity ranking is based on the assessment Conducted by the registry in USE, and the response time of the same amenity may vary greatly due to the different user background such as user location, user network state, etc. Alice then turns to her colleagues in India for suggestion. They suggest her try amenity k provided by a local company though ranked lower in the previous commendation list. After trying it, Alice thinks that amenity k has a good performance and meets her requirements. The problem that Alice faces is to find a amenity that meets both nonfunctional and functional requirements. The current way of finding a suitable web amenity is rather inefficient, since Alice needs to try the recommended amenities one by one. To address this challenge, we propose a more precise approach to amenity commendation with consideration of the region factor. Moreover, we try to make 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 amenities, and thus trust the commendations. The basic thought of our approach is that users closely situated with each other are more likely to have related amenity experience than those who exist far away from each other. 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 amenity recommender system. Users are Encouraged to share their experimental web amenity QoS Performance with others in our recommender scheme. The more QoS information the user donate, the more precise amenity 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 amenities. In the second step, we find out similar users for the existing user and create QoS prediction for the unused amenities. Amenities with the best predicted QoS will be recommended to the current user.

IV. THE COMMENDATION APPROACH

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 amenities. In the second step, systems find similar users for the current user and make QoS prediction for the unused amenities. Amenities with the most excellent predicted QoS will be recommended to the current user.

Step 1. Region Creation

In this, my 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 amenities. The correlation between users and amenities is denoted by an n_m matrix R. Each entry *Ri,j* of the matrix represents the RTT of amenity j observed by user i and *?* is the symbol of no RTT value. Each user i (i ϵ 1; 2; ...; n)is associated with a row vector *Ri* representing his/her observed RTT values on different web amenities. The user a(a ϵ 1,2,.n)is called the active user or current user if he/she has provided some RTT records and needs amenity commendations. In web amenity recommender system, users typically provide QoS values on a small number of web amenities. 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 to be 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 amenity i observed by users from the region. Median separates higher half of a sample from the lower half. To differentiate amenities 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 RTTs of amenity collected from users of all regions is a sample from the population of service s response time.

s,*Rs* = *f R*1,*s* , *R*2,*s*, ..., *Rk,s g* ,1 <=k<=n,

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 samples median

MAD = *mediani*(*jRi,s* □ *mediani*.(*Ri,s*)*j*) (1)

Where, i=1,..k, j=1,..,k

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

μ = *mediani*(*Ri,s*)*i* = 1, ..., *k* (2)

σ = *MADi*(*Ri,s*)*i* = 1, ..., *k* (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

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

Where, 1. s(n) \ s(m) is the set of coinvoked amenities by users from region M and N 2. *Rm, s* is the RTT vale of services provided by region center m. 3.*Rm* and *Rn* represent the average RTT of all the amenities of center m and n. But PCC considers the RTT difference of coinvoked amenities between regions. But there are possibility is that two regions that are not similar, but there is few coinvoked amenities 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.

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

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 amenity 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.

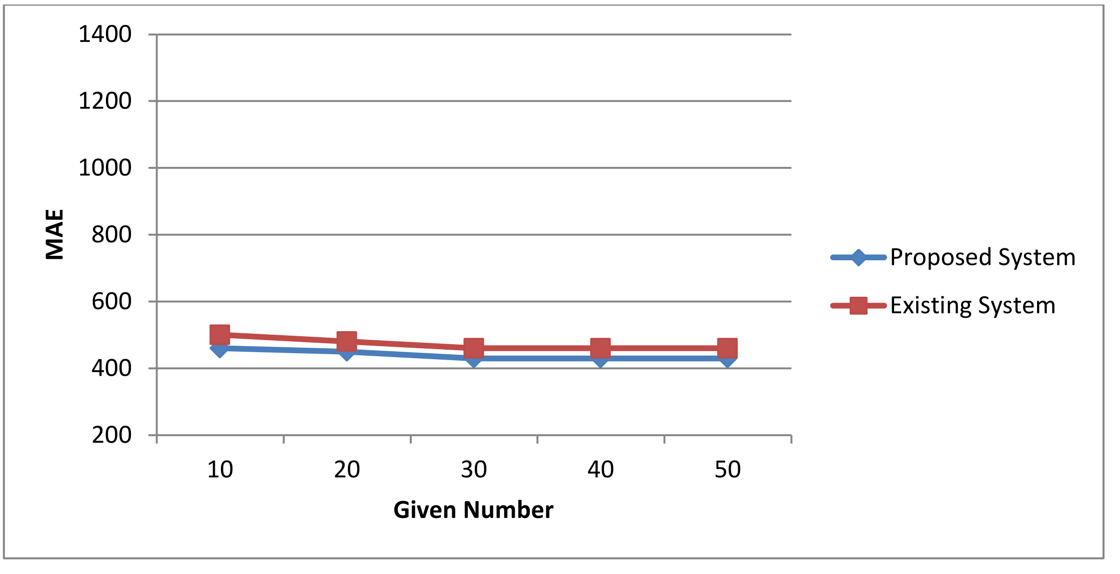
V. COMMENDATION VISUALIZATION

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 amenity 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 amenity 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 amenity QoS map is to assign each web amenity a distinct portion of the 2D display area, and put amenities 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 amenities as well as the underlying structure of the QoS space by using map metaphor such as spatial arrangement, dots, and areas.

VI. RESULTS

We examine the impact from two aspects: the density of training matrix and the number of QoS values given by active users (given number). We divide the experiment into two parts and use 10 times 10- fold cross-validation to assess the prediction results and report the average MAE.



Given Number	Proposed System	Existing System
10	460	500
20	450	480
30	430	460
40	430	460
50	430	460

MAE:

We use Mean Absolute Error (MAE), the well-known statistical accuracy metric, to measure the prediction accuracy. MAE is the average absolute deviation of predictions to the ground truth data. For all test services and test users

$$MAE = \frac{\sum_{u,s} |R_{u,s} - \hat{R}_{u,s}|}{L},$$

where Ru;s denotes the actual RTT of web service s observed by user u; ^Ru;s denotes the predicted RTT value, and L denotes the number of predicted values. Smaller MAE indicates better prediction accuracy.

VII. CONCLUSION

In this proposed system, I have presented an innovative approach to web service recommendation and visualization. Different from previous work, my algorithm employs the characteristic of QoS by clustering users into different regions. The final service recommendations are put on a map to reveal the underlying structure of QoS space and help users accept the recommendations. Experimental results show that my approach significantly improves the prediction accuracy than the existing methods. My recommendation approach considered the correlation between QoS records and users physical locations by using GPS location, which has achieved good prediction performance. In some cases, however, users in the same physical locations may observe different QoS performance of the same web service.

Besides the user physical location, I will investigate more contextual information that influences the client-side QoS performance, such as the workload of the servers, network conditions, and the activities that users carry out with web services (e.g., web services are used alone or in composition) and also I will try to implement to observe client side QoS for more accurate prediction.

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