Personalized Web Service Recommender System

(Clustering using Location and Quality-of-Service Information)

Sai Alekhya E
Department of Computer Science & Engineering
Bharat Institute of Engineering & Technology
Ibrahimpatnam, RangaReddy District (501 510) ***E-mail*****:**
saialekhya.e@gmail.com

Y J Nickhil Benjamin
Department of Computer Science & Engineering
Bharat Institute of Engineering & Technology
Ibrahimpatnam, RangaReddy District (501 510) ***E-mail*****:**
nickhil.benjamen@gmail.com

B Sai Prasanna
Department of Computer Science & Engineering
Bharat Institute of Engineering & Technology
Ibrahimpatnam, RangaReddy District (501 510)
E-mail**: sai.prasanna746@gmail.com**

M Manoj Kumar
Department of Computer Science & Engineering
Bharat Institute of Engineering & Technology
Ibrahimpatnam, RangaReddy District (501 510) ***E-mail*****:**
manojm044@gmail.com

ABSTRACT

Web Services Are Integrated Software Components For The Support Of Interoperable Machine-To-Machine Interaction Over A Network. The Number Of Publicly Available Web Services Is Steadily Increasing On The Internet. This Increase In Availability Makes It Hard For A User To Select An Accurate Web Service Among A Large Amount Of Available Services. An Inappropriate Service Selection May Cause Many Problems. In This Paper, We Propose A Novel Collaborative Filtering-Based Web Service Recommender System To Help The Users Select Services With Optimal Quality-Of-Service (Qos) Performance. This Recommender System Employs Location Information And Qos Values To Cluster Users And Services, And Make Personalized Service Recommendation For Users Based On The Clustering Results. Compared With Existing Service Recommendation Methods, Our Approach Achieves Considerable Improvement On The Recommendation Accuracy.

Index Terms—Web Service Recommendation, Quality Of Service (Qos), Collaborative Filtering.

I. Introduction

Web services are software components designed to support interoperable machine-to-machine interaction over a network, usually the Internet. Web service employs Web Service Description Language (WSDL) for interface description and Simple Object Access Protocol (SOAP) for exchanging structured information. Benefiting from the cross-language and cross-platform characteristics, Web services have been widely employed by both enterprises and individual developers for building service oriented applications. When developing service-oriented applications, developers first design the business process according to the requirements, and then try to find and re-use the existing services to build the process. Currently, public sites like Google Developers (developers.google.com), Yahoo! Pipes (pipes.yahoo.com), programmable Web (programmableweb.com), etc are used by developers to search services. However, none of them provide location-based QoS information for users. Such information is quite important for software deployment. Some Web services are only available in European Union (EU), thus the softwares employing these services cannot be shipped to other countries. Without knowledge of these things, deployment of serviceoriented software can be at great risk.

Since selecting a high quality Web service among a large number of candidates is a significant task, some developers choose to implement their own services, instead of using the publicly available ones, which incurs additional overhead, in both time and resource. Using an inappropriate service, on the other hand, may add potential risk to the process. Therefore, effective approaches to service selection and recommendation are in an urgent need, which can help service users reduce risk and deliver high-quality business processes. Quality-ofService (QoS) is widely employed to represent the nonfunctional characteristics of Web services and has been considered as the key factor in service selection [12]. QoS is defined as a set of properties including response time, throughput, availability, reputation, 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 [9]. Practically, it is not possible to acquire such QoS information from service providers, since these QoS values are susceptible to the uncertain user location, user network condition, etc. Therefore, different users may observe quite different QoS values of the same Web service. In other words, QoS values evaluated by one user cannot be employed directly by another user for service selection. It is also impractical for users to acquire QoS information by evaluating all service candidates by themselves, since conducting real world Web service invocations is time consuming and resource-consuming.

To answer this challenge, this paper investigates personalized QoS value prediction for service users by employing the available past users' experiences of Web services from different users. No additional Web service invocations are required in this approach. Based on the predicted QoS values of Web services, personalized QoS-aware Web service recommendations can be produced to help users select the optimal service among the functionally equivalent ones. From a large number of real-world service QoS data collected from different locations, we find that the user observed Web service QoS performance has strong correlation to the locations of users. To enhance the prediction accuracy, we propose a location-aware Web service recommender system, which employs both Web service QoS values and user locations for making personalized QoS prediction. Users of this system share their past usage experience of Web services, and in return, the system provides personalized service recommendations to them. The location-aware Web service recommender system first collects user observed QoS records of different Web services and then groups users who have similar QoS observations together to generate recommendations. Location information is also considered when clustering users and services. The main contribution of this work is, we propose a novel location-aware Web service recommendation approach, which significantly improves the recommendation accuracy and time complexity compared with existing service recommendation algorithms.

II. Collaborative Filtering

Collaborative Filtering (CF) is widely employed in commercial recommender systems, such as Netflix and Amazon.com. The basic idea of CF is to predict and recommend potential favorite items for a particular user employing rating data collected from other users. CF is based on processing the user-item matrix. Breese et al. [3] divided the CF algorithms into two broad classes: memory based algorithms and model-based algorithms. The most analyzed examples of memory-based collaborative filtering include user-based approaches, item-based approaches and their fusion. User-based approaches predict the ratings of users based on the ratings of their similar users, and item-based approaches predict the ratings of users based on the information of item similarity. Memory-based algorithms are easy to implement, require little or no training cost at all, and can easily take ratings of new users into account. However, memory based algorithms do not scale well to a large number of users and items due to the high computation complexity. Model-based CF algorithms learn a model from the rating data using statistical and machine learning techniques. Examples include clustering models, latent semantic models, latent factor models, and so on. These algorithms can quickly generate recommendations and achieve good online performance. However, these models must be rebuilt when new users or items are added to the system.

III. System Architecture

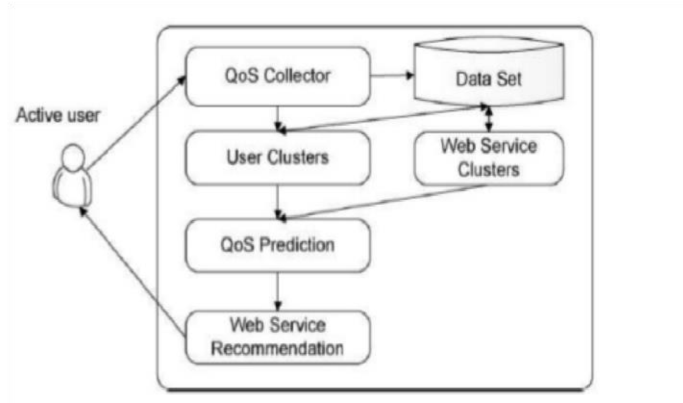

Fig. shows the architecture of our recommender system, which includes the following procedures:

- Web service users log on to system and share observed Web service QoS records with other users. In this paper, users who have submitted Web service QoS records to Location-aware Web Service recommender System are called training users. If a training user requires Web service recommendation, then the user becomes an active user. QoS values of training users will be employed to make personalized recommendation for the active user.
- The recommender System clusters training users into different regions according to their physical locations and past Web service usage experiences.
- Location-aware Web Service recommender System clusters functionally similar Web services based on their QoS similarities.
- Also it maps the active user to a user region based on historical QoS and user location.
- The recommender system predicts QoS values of candidate Web services for the active user and recommend the best one.
- The active user receives the predicted QoS values of Web services as well as the recommendation results, which can be employed to assist decision making.

IV. Service Selection and Recommendation

Service selection and recommendation have been extensively studied to facilitate Web service composition in recent years. Alrifai and Risse [1] propose a method to meet users' end-toend QoS requirements employing integer programming (MIP) to find the optimal decomposition of global QoS constraints into local constraints. Barakat et al. [2] model the quality dependencies among services and proposes a Web service selection method for Web service composition. El Hadadd et al. [4] propose a selection method considering both the transactional properties and QoS characteristics of a Web service. Hwang et al. [5] use finite state machine to model the permitted invocation sequences of Web service operations, and propose two strategies to select Web services that are likely to successfully complete the execution of a given sequence of operations. Kang et al. [6] propose AWSR system to recommend services based on users' historical functional interests and QoS preferences. Wang et al. [10] present a Web service selection method by QoS prediction with mixed integer program. Zheng et al. [37] provide a QoS-based ranking system for cloud service selection. Zhu et al. [14] employ clustering techniques to their QoS monitoring agents and provide Web service recommendations based on the distance between each user and their agents. A certain amount of work has been done to apply CF to Web service recommendation. Shao et al. [8] employ a user-based CF algorithm to predict QoS values. Combinations of different types of CF algorithms are also engaged in Web service recommendation. Zheng et al. [13] combine user-based and item-based CF algorithms to recommend Web services. Meanwhile, several tasks employ location information to use a region-based CF algorithm to make Web service recommendation. To help users know more about Web service performance, they also propose a visualization method showing recommendation results on a map. Lo et al. [11] employ the user location in a matrix factorization model to predict QoS values. Different from existing work, this paper interprets Web service QoS information from both user's perspective and Web service's perspective. Clustering technique and location information are employed to achieve more accurate recommendation result and better online performance.

V. METHODOLOGY

Values of some QoS properties, such as response time, on the same Web service vary from user to user. Research finds that some QoS properties highly relate to the physical locations of users. For example, the response time of a service observed by closely located users usually fluctuates mildly around a certain value. On the other hand, the response time observed by users who are far away from each other sometimes varies significantly. Based on this finding, our recommendation algorithm takes location information into consideration to improve the recommendation accuracy. Our recommendation algorithm is designed as a three-phase process, i.e., 1) user region creation, 2) service region creation, and 3) QoS prediction & recommendation.

Phase 1: User Region Creation---In this phase, users will be clustered into different regions according to their locations and historical QoS records. At the beginning, we retrieve users' approximate locations by their IP addresses. The location information reveals a user's country, city, latitude/longitude, ISP and domain name. Then users from the same city will be grouped together to form initial regions. These small regions will be aggregated into large ones with a bottom-up hierarchical clustering method [7]. The clustering method has two parts: initialization and aggregation. In the initialization part, we select non-sensitive user regions for aggregation, and compute the similarity between each region pair. To aggregate regions:

1. Select the most similar region pair, merge the two regions to regioni if their similarity exceeds the similarity threshold, otherwise stop this region aggregation process. To merge the two regions,

a. Compute the sensitivity and region center of this newly merged region regioni. Remove this region from aggregation process if it becomes a sensitive one.

b. Remove similarities between regionj and other existing regions.

c. Update similarities between regioni and other existing regions.

2. Repeat the above step. Threshold _u is a tunable parameter that can be adjusted to trade off accuracy for time and space requirements.

Phase 2: Service Region Creation

Normally, each user only uses a limited amount of Web services. Compared with the large number of services available on the Internet, the number of services with user submitted QoS records is relatively small. Thus, it is difficult to find similar users, and predicting missing QoS values only from user's perspective is not enough. Clustering Web services can help our location-aware Web Service Recommender System find potentially similar services. Different from retrieving user location from an IP address, the recommender system directly clusters Web services based on their QoS similarity. To enhance user interaction and to minimize delay, service providers will route user requests to different servers according to user locations or application types. Usually the server that processes requests is different from the one that responds to the users. Thus, retrieving a service location from an IP address does not prove much value. In location-aware Web Service Recommender System, Web services are aggregated with a bottom-up hierarchical clustering algorithm. The similarity between two clusters is defined as the similarity of their centers. Each Web service is regarded as a cluster at the outset. The algorithm aggregates the pairs of the most similar clusters until none of the pairs' similarities exceeds threshold _w. Phase 3: Personalized QoS Prediction

The first two phases aggregate users and Web services into a certain number of clusters based on their respective similarities. QoS predictions can be generated from both service regions and user regions. With the compressed QoS data, searching neighbors and making Web service QoS predictions for an active user can be computed faster than conventional methods.

Phase 4: Web Service Recommendation

Web service QoS prediction is used in different ways in location-aware Web Service Recommender System to facilitate Web service recommendation. First, when a user searches Web services using this recommender system, predicted QoS values will be shown next to each candidate service, and the one with the best predicted value will be highlighted in the search result for the active user. It will be easier for the active user to decide which one to have a try. Moreover, this system selects the best performing services (services with the best submitted QoS) and services with the best predicted QoS from the whole service repository for the active user so that he/she can quickly find potential valuable ones instead of checking the service one by one.

VI. CONCLUSION

This paper presents a Personalized QoS-aware Web service recommendation approach. The basic idea is to predict Web service QoS values and recommend the best one for active users based on historical Web service QoS records. We combine prediction results generated from service regions and user regions, which achieves better results than existing approaches. We also find that the combination result is much better than the result from any single method, either the prediction generated from user regions or the one generated from Web service regions. This is because these two methods analyze the problem from different aspects and the combination of them counteracts the error of individual methods.

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