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Recommender System for Web Services Employing QoS Values and Physical Location

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***Abstract*— Recommendation of Web service is the popular area of research in the field of IT. Collaborative filtering (CF) is one of the popular method of web service recommendation which is based on a Quality of Service (QoS) parameters of the service. Web services are nothing but a software component which are designed to perform machine to machine communication over the network. The QoS of web service is essential factor which is taken into consideration while selecting the appropriate web service. Previously a number of studies or methods were conducted for choosing web services and making their recommendation by performing collaborative filtering; here we are going to examine these methods with their advantages and limitations. And also based on this study we are proposing a new technique for web service recommendation which is based on past experience of user regarding QOS of web service and their location.**

Keywords: - *Web Service, Service Computing, Collaborative filtering, QoS values, Web service recommendation, QoS prediction, collaborative filtering, privacy preservation.*

I INTRODUCTION

Web services are software components to support interoperable machine-to-machine interaction over a network. The increasing acceptance of web services in large organization demands efficient recommendation and selection techniques for optimum web service amongst the variety of available services on internet. Web services have been extensively employed by both individual developers and enterprises for building service-oriented applications. While considering the QoS properties of Web services, some features of web services are user independent and having equal values for different users (e. g Availability, price, popularity etc.)The values of the user independency of QoS properties are typically offered by service providers or third-party registers (for example, UDDI). In another case some QoS features for users are reliant and have dissimilar values for different users (for example, Invocation failure rate, response time, etc.).

Client-side Web service evaluation requires real web service calls and encounters the following drawbacks: First, real Web service invocations enforce costs for service users and utilize the resources of the service provider.

It can exist on many Web service candidate analyzed and some suitable web services in the assessment list may not be detected and observed by the service user.

1. Finally, in web service evaluation not all the users are expert.

However, without adequate client-side evaluation, accurate values of the user-specific QoS properties cannot be obtained. Hence optimal Web service selection and recommendation are not easy to accomplish.

II RECOMMENDER SYSTEM

Large organization and individual user requires a particular system which can understand the interests of user and recommend them the best utilizable services. So according to their functionality recommender systems can be classified as content based filtering, collaborative filtering, ,Hybrid models[2].Recommender systems can help users by selecting most valuable items by calculating the similarities among other users with the help of collaborative filtering algorithms.

2.1 Collaborative Filtering Methods

Collaborative filtering is nothing but an identification of similar users, related web services and recommend them. Collaborative filtering is generally employed in commercial recommender systems like as Amazon.com and Netflix. The Web services suggestion for the user is based on the prior knowledge of web service history. Therefore, and accurate Web service QoS prediction is required for service user providers. On the basis of predicted QoS values the preferred service selection can be completed. Collaborative Filtering [3] was firstly proposed by Rich and has been extensively used in service recommendation systems.

Collaborative Filtering algorithm uses two processes:

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.

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.

It is not practical for each user to dynamically determine QoS values due to the exclusive overhead of invoking a huge number of services.

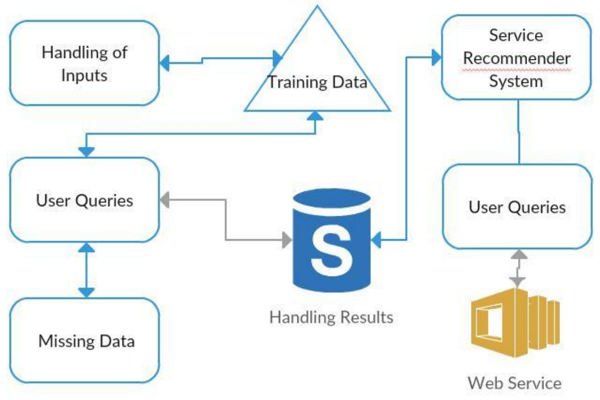

Figure 1: Web service recommendation process

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:

2.1.1 Model-Based Collaborative Filtering

On the basis of ratings of dataset a models is built in this technique. In other words, we take out some useful information from the dataset, and consider that model to make recommendations [5] without using the whole dataset every time. With the help of this approach ones can potentially offers advantage of both speed and scalability. With the help of model-based algorithms we can learn and understand the collection of QoS, a model which is then used for QoS predictions. Model-based CF algorithms consist of Bayesian models (probabilistic) and clustering models [6]. Model-based CF technique [6] deliver a predefined model by studying previous Qos parameters, and then the trained model can be used to predict the unknown QoS values. To address the QoS prediction problem matrix factorization [7] is one of the most popular model-based CF approaches that were first introduced. 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.

2.1.2 Memory Based Collaborative Filtering

In memory-based algorithms approach the collaborative filtering is perform by considering the complete database. As described by Breese et. al [9], It finds the users those who are similar to active user (i.e. the users we want to make predictions for) and it uses their preferences to forecast ratings for the current user. For making predictions memory-based algorithms uses the data (users, services and QoS data)stored in memory. They can be categorized in to nearest neighbor algorithms and top-N recommendation algorithms. This type of model for CF approaches use the experiential QoS data to compute the similarity values between users or services and use them further for QoS recommendation. 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 dissimilar users or services and use them to calculate the recommendations.

III RELATED WORK

3.1. QoS aware Web service recommendation

Due to the vast availability of web services on internet users firstly pays their attention to QoS instead of functionality than before. Web service QoS mostly contains non-functional attributes such as availability, security, response time and throughput, etc. It has been widely used in 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 QoS-aware Web service [12] recommendation.

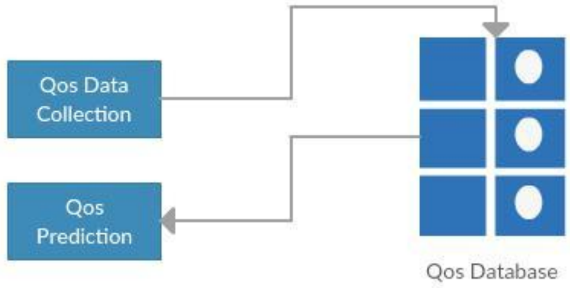

Figure 2: Web Service QoS Prediction

By studying user-based combination and item-based collaborative filtering method Web service QoS value prediction can be done. 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 because of QoS discrepancy according location of user to consider; and former recommender systems are all black boxes offers only partial 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 large-scale Web service recommendation on location aware QoS. It firstly combines the memory-based and model-based and CF algorithms for Web service recommendation, So this method clearly showing the recommendation accurateness and time complexity improved as compared to previous 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. This algorithm uses the property of QoS of users in distinct regions clustering. Based on the feature region a refined nearest neighbor algorithm is proposed to generate QoS forecasts.

The concluding service recommendations are on a map by putting the underlying structure of QoS space to show and help users who accept recommendations. 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. Missing QoS values are find after finding similar users and services.

3.3. Web Service Recommendation Methods Based on Personalized Collaborative Filtering

There were number of techniques are available for selecting web services and recommendation on the basis of collaborative filtering, but not often do they take into account personal influence of users and services. Therefore Y. Jiang, J. Liu, Tang, X. Liu [14] proposed a technique of collaborative personalized recommendation effective filtering for Web service. A major piece of this method is the computation of the measure of the similarity of web services. Unlike the Pearson correlation coefficient (PCC) similarity measure, they consider the individual impact of services where among users and the individual impact of the measure of calculated likeness of services. On the basis of similarity measure of web services, they build up a custom hybrid efficient 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. being aware of different experiences of consumers QoS, they strike a collaborative approach to filtering based on mining matching decision and forecasting of consumer experiences.

IV FRAMEWORK OF QOS-AWARE WEB SERVICE RECOMMENDATION

The basic proposal of this scheme is that, the users those who are closely located with each other are more likely to have similar service experience than those who live far away from each other. Here we are employing the idea of user-collaboration in our web service recommender system.Our recommendation technique is designed as a two-phase process which is based on the collected QoS records. In the first step user are grouped according to their physical location and previous experience of web service QoS. In the second step, we search for similar users for the active user and make QoS prediction for the unused services. And finally service with best predicted QoS will be recommended to active user.

4.1. Location Information Representation, Acquisition and Processing

In this section we are going to discuss how to represent, acquire, and process location information of service users and web service which leaves an essential base for employing location-aware Web service recommendation method.

4.1.1. Location Representation:

User's location can be represented as a [IP Address], [Country], [IP No.], [AS], [Latitude], [Longitude]. Normally, a country has many ASs and an AS is within one country only. Ass is connected with each other and internet is composed of different number off Ass.

However, it is not always true that users located in the same AS are always geographically close, and vice versa. Therefore, it possible that even if two users are located in the same city, they may seem to be at different ASs. So this is the main reason behind choosing AS instead of other geographic positions instead of latitude and longitude for representing user's location.

4.1.2. Location Information:

Within the phase of acquisition we can fetch the location information of both Web services and service users. By using user's IP address it is possible to obtain his full location information, the things which we only needs are only to identify both the AS and the country in which he is located based on IP address. There are number of services and databases are presented 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

Here we have defined notations for the convenience of describing our method and algorithms. For computing similarity between both users and Web services we implemented weighted PCC algorithm, which takes personal QoS characteristics 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 section is a very important step of CF. In conventional type of user-based CF, the Top-N similar neighbor selection algorithm is used always . It selects the first N users as neighbors those who are most similar to the active user. Similarly, the Top-N similar neighbor selection algorithm can be useful to select top N Web services that are most similar to the web service for which we want to find recommendation. Old-fashioned 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 degrade the prediction accuracy. Therefore, leaving 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 notice similar QoS parameters on a few Web services.By taking location-relatedness of Web service QoS into consideration [5], authors have combined the user's location and Web services into similar neighbor selection.

4.2. User-Based QoS Value Prediction:

Authors offered a user-based location-aware CF method, named as ULACF. Traditional user-based CF methods usually adopted for finding value predictions. This equation, however, may be incorrect for Web service QoS value prediction. Web service QoS factors such as response time and throughput are the objective parameters and their values are not constant. Therefore, predicting QoS values based on the average QoS values perceived by the active user is not sufficient which gives faulty result. Intuitively, given two users that have the same estimated similarity degree to the target user, the user who is nearer to the target user should be placed more confidence in QoS prediction than the other.

V CONCLUSION

The association of the various QoS properties is important for the achievement of web service recommendation. Due to the increasing demand of Web services and the latency of dynamic service selection and integration, some service providers now provide parallel services. QoS is one of the modified factor to differentiate functionally similar Web services. The basic idea behind this work is to predict web service QoS values and recommend the best web service to active user best on past QoS records of web service. In this work we combine prediction results generated from user region and service region which gives better results than existing techniques. We also noticed that combination result is much better than the result from either one method of prediction from user region or the one generated from service region. Our future work includes the correlation between different QoS properties and detecting the users those who are contain inaccurate QoS information.

REFERENCES

[1] Jianxun Liu, Mingdong Tang, Member, IEEE, Zibin Zheng, Member, IEEE, Xiaoqing (Frank) Liu, Member, IEEE, Saixia Lyu, "Location-Aware and Personalized Collaborative Filtering for Web Service Recommendation", IEEE Transactions on services computing, manuscript Val X , No XX, 2015

[2] W. Zhang, H. Sun, X. Liu, and X. Guo, "Temporal QoS-aware web service recommendation via non-negative tensor factorization," in Proc. of the 23rd International World Wide Web Conference (WWW), 2014, pp. 585–596.

[3] X. Chen, Z. Zheng, Q. Yu, and M. R. Lyu, "Web service recommendation via exploiting location and QoS information," IEEE Trans. Parallel Distrib. Syst., vol. 25, no. 7, pp. 1913–1924, 2014.

[4] X. Chen, Z. Zheng, X. Liu, Z. Huang, and H. Sun, ''Personalized QoS-Aware Web Service Recommendation and Visualization,'' IEEE Trans. Serv. Comput., vol. 6, no. 1, pp. 35-47R1st Quart., 2013.

[5] R. Salakhutdinov and A. Mnih, "Probabilistic matrix Factorization," in Proc. of the 21st Annual Conference on Neural Information Processing Systems (NIPS), 2007.

[6] M. Tang, Y. Jiang, J. Liu, X. F. Liu: Location-Aware Collaborative Filtering for QoS-Based Service Recommendation. in Proc. 10th International Conference on Web Services, Hawaii, USA, June 2012, pp.202-209

[7] S. Wang, Q. Sun, and F. Yang, ''Towards Web Service Selection Based on QoS Estimation,'' Int'l J. Web Grid Serv., vol. 6, no. 4, pp. 424-443, Nov. 2012.

[8] G. Kang, J. Liu, M. Tang, X. F. Liu, K. K. Fletcher. "Web Service Selection for Resolving Conflicting Service Requests". Proceedings of International Conference on Web Services. IEEE Computer Society, pp. 387-394, 2011.

[9] Breese, J. S., Heckerman, D., Kadie, C. (1998). Empirical analysis of predictive algorithms for collaborative filtering, Proceedings of the 14 th Conference on Uncertainty in Artificial Intelligence (UAI 1998), Madison, Wisconsin, USA, July 24-26, 1998, 43-52.

[10] Y. Zhang, Z. Zheng, M. R. Lyu, "WSExpress: a QoS-aware search engine for Web services", in Proc. 8th IEEE International Conference on Web Services, Miami, FL, USA, July, 2010, pp.83-90

[11] M. Alrifai, and T. Risse, "Combining Global Optimization with Local Selection for Efficient QoS-aware Service Composition," in Proc. of the International World Wide Web Conference, Apr. 2009, pp. 881- 890.

[12] X. Su and T. M. Khoshgoftaar, "A survey of collaborative filtering techniques," Adv. Artificial Intelligence, vol.2009, 2009.

[13] Z. Zheng, H. Ma, M.R. Lyu, and I. King. "WSRec:A Collaborative Filtering Base Web Service Recommendation System," in Proc. 7th

[14] International. Conference on Web Services, Los Angeles, CA, USA, pp.437- 444, 2009.