Web Service Recommender System with Location and QoS Prediction Framework

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Abstract: Web service recommendation has become a hot topic even in basic research in IT. The most popular technique is the collaborative filtering (CF) on the basis of a quality of service value. With the increasing presence and adoption of web services over the World Wide Web, the quality of service (QoS) is becoming more important to the description Non-functional characteristics of Web services. Several approaches for the selection of Web services and recommendation via collaborative filtering were studied; here we are going to investigate these techniques with the pros and cons of Techniques. Also based on these comments, we will propose a new technique for predicting the Web service selection based on known quality of service values and unknown we explain in our future work.

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 presence and acceptance of Web services on the World Wide Web demand effective recommendation and selection techniques that recommend the optimum web service users from a variety of available web services. With the number of Web services to increase Quality of Service (QoS) [1] is generally used to describe non-functional properties of Web services. Among the different QoS properties of Web services, some features are user independent and have identical values for different users (for example, price, popularity, availability, etc.). The values of the user independency of QoS properties are typically offered by service providers or third-party registers (for example, UDDI). On the other hand some QoS features users are dependent and have different values for different users (for example, response time, Invocation failure rate, etc.). Client-side Web service evaluation requires real web service calls and encounters the following drawbacks:

1) First, real Web service invocations impose costs for service users and consume the resources of the service provider. Some web service calls can also be charged.

2) Secondly, it can exist on many Web service candidate analyzed and some appropriate web services in the evaluation list may not be detected and recorded by the service user.

3) Finally, most service users are not experts in web service evaluation and the common time-to-market constraints limiting an in-depth review of the target web service.

However, without sufficient client-side evaluation, exact values of the user-specific QoS properties cannot be obtained. Optimal Web service selection and recommendation are so difficult to achieve.

II. LITERATURE SURVEY

A. Recommender system

User needs a special system which can understand their interests and suggest them the best usable services. The recommender systems can be classified as collaborative filtering, content based filtering, Hybrid models[2]..

a) Collaborative Filtering Methods

The process of identification of similar users, related Web services and recommend what similar users like is called collaborative filtering. Collaborative Filtering[3] was initially proposed by Rich and has been widely used in service recommendation systems. In Web service recommendation, the primary question of the CF is to find a group of similar users, a group of similar services and user-service-matrix on the QoS value of services that is build by users. Collaborative Filtering algorithm uses two processes:

1) 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.

2) 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.

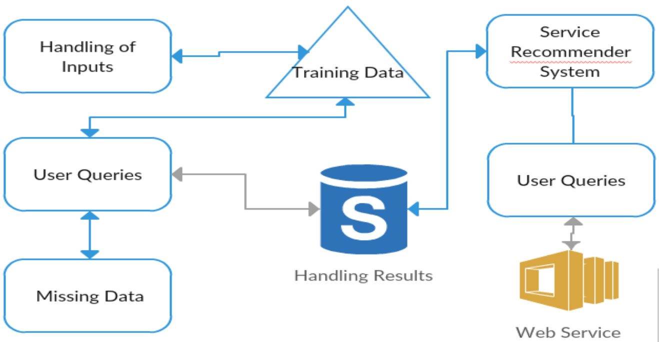

Fig 1. Web service recommendation process

It is impractical for every user to actively measure QoS values due to the expensive overhead of invoking a large number of services. 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:

1. Model-Based Collaborative Filtering

It involves building a model based on the dataset of ratings. In other words, we extract some information from the dataset, and use that as a "model" to make recommendations[5] without having to use the complete dataset every time. is one of the most popular model-based CF approaches that were first introduced to address the QoS prediction problem. 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. Memory Based Collaborative Filtering

Memory-based algorithms approach the collaborative filtering problem by using the entire database. As described by Breese et. al [9], it tries to find users that are similar to the active user (i.e. the users we want to make predictions forTop-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 different users or services and use them to calculate the recommendations.

B. QoS aware Web service recommendation History

As the number of Web services available on the Internet increases quickly, service consumers pay more attention to QoS instead of functionality than before. 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.

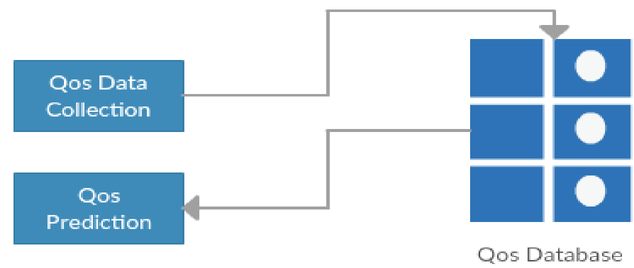

Fig2. Web Service QoS Prediction

They suggested that a Web service QoS value prediction approach by the traditional user-based combination and item-based collaborative filtering method.

C. Web service recommendation based on location aware Qos

Existing approaches fail QoS variance according to user locations to consider; and former recommender systems are all black boxes provide only limited 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. The final service recommendations are on a map by putting the underlying structure of QoS space to show and help users who accept recommendations.
Similarly, M. Tang, Y. Jiang, J. Liu and X. Liu [6] proposed a method for location aware Collaborative Filtering Web services for users to recommend sites of both users and services.

D. Web Service Recommendation Methods Based on Personalized Collaborative Filtering

There were different methods of selecting Web services and recommendation based on collaborative filtering, but rarely do they take into account personal influence of users and services. Therefore Y. Jiang, J. Liu, Tang, X. Liu [14] provided a method of collaborative personalized recommendation effective filtering [18] for Web service.

Similarly, L. Shao, J. Zhang, Y. Wei, J. Zhao, B. Xie and Mei H. [15] being aware of different experiences of consumers quality of service, they hit a collaborative approach to filtering based on mining similarity decision and forecasting of consumer experiences.

III. System Architecture

The explosion of web services on the internet brings new challenges in service discovery and selection. Particularly, the demand for efficient quality of service evaluation is becoming urgently strong. To address this issue, we define a formal privacy preserving formal location-based prediction framework which allows an efficient global optimization scheme and then exploit different baseline estimate components to improve prediction performance.

With respect to the collaborative QoS prediction, the commonly used methods are neighborhood based collaborative filtering and matrix factorization. The advantages of location based CF are simplicity, justifiability and efficiency. By the same token, users of cloud services certainly hope to get reasonable explanation for the QoS predictions provided by a service recommendation system.

Web application such as social networking sites and self-publishing sites encourage users to share their knowledge and learn from others. It employs the idea of user collaboration and provides a platform for users to share observed Web service QoS values and search web services. This system will generate personalized service recommendations based on the user shared QoS values. The more QoS records user contribute, the more accurate the recommendations will be, since more information can be mined from the user contributed values. The following Fig are shows System Architecture.

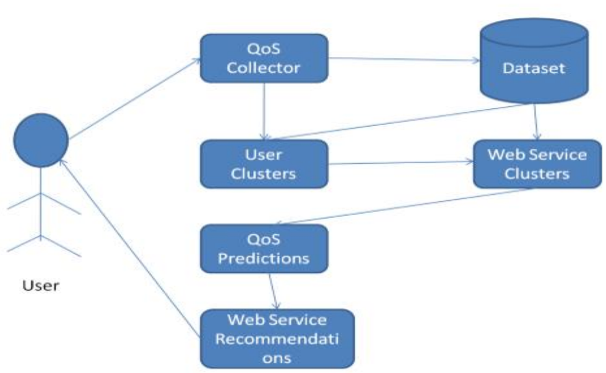

Fig. 3 System Architecture

Web service user log on to the system and share observed Web Service QoS values with other users. Web service QoS records are called training users. If a training user requires Web Service Recommendation then the user becomes and active user. Hence the user becomes an active user. QoS values of the training users are kept in the encrypted format so as to keep user data private. QoS values of the training users will be employed to make personalized recommendation for the active user. The system clusters training users into different regions according to their physical locations and past web service usage experiences. It also clusters functionally similar web services based on their QoS similarities. Then 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 recommends the best one.

When the user logs into the system, he becomes an active user if he is asking for the recommendations. The active user's location is found out from the IP address. The IP address provides information about a user's country, city etc. the system has a dataset which contains encrypted QoS values shared by training users. The dataset which contains the user data is passed for collaborative filtering. QoS predictions are made from these aggregations, through which recommendations are generated for the active user. For example, there are four users U1, U2, U3, U4 in our system and U1 is requesting for recommendations.

IV. FRAMEWORK OF QOS-AWARE WEB SERVICE RECOMMENDATION

In this section, an online service searching scenario to show the research problem of this paper. The basic idea of this approach is that users closely located with each other are more likely to have similar service experience than those who live far away from each other. We employ the idea of user-collaboration in our web service recommender system. The more QoS information the user contributes, the more accurate service recommendations the user can obtain, since more user characteristics can be analyzed from the user contributed information. Based on the collected QoS records, our recommendation approach is designed as a two-phase process. In the first phase, we divide the users into different regions based on their physical locations and historical QoS experience[15] on web services. In the second phase, we find similar users for the current user and make QoS prediction for the unused services. Services with the best predicted QoS will be recommended to the current user.

A. Location Information Representation, Acquisition and Processing

This section discusses how to represent, acquire, and process location information of both Web services and service users, which lays a necessary foundation for implementing location-aware Web service recommendation method.

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a) Location Representation

We represent a user's location as a [IP Address], [Country], [IP No.], [AS], [Latitude], [Longitude]. 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.

However, users located in the same AS are not always geographically close, and vice versa. Therefore, even if two users are located in the same city, they may seem to be at different ASs. This explains why we have chosen, AS instead of other geographic positions, such as latitude and longitude, to represent a user's location.

b) Location Information

Acquisition fetch the location information of both Web services and service users can be easily done. Based on 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 based on IP address. A number of services and databases are available 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 Num

c) Similarity Computation and Similar Neighbor Selection

Here we have defined notations for the convenience of describing our method and algorithms. We implemented a weighted PCC for computing similarity between both users and Web services, which takes personal QoS characteristics [16] into consideration. Finally, author has discussed incorporating locations of both users and Web services into the similar neighbor selection.

d) Similar Neighbor Selection:

This selection is a very important step of CF. In conventional type of user-based CF, the Top-N similar neighbor selection algorithm is used invariably [16]. It selects N users that are most similar to the active user as neighbors. Similarly, the Top-N similar neighbor selection algorithm can be employed to select N Web services that are most similar to the target Web service. Traditional 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 impair the prediction accuracy. Therefore, abandoning 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 perceive similar QoS values on a few Web services.

B. *User-Based QoS Value Prediction:*

Authors presented a user-based location-aware CF method, named as ULACF[16]. Traditional user-based CF[17] methods usually adopted for finding value predictions. This equation, however, may be inaccurate for Web service QoS value prediction. As Web service QoS factors such as response time and throughput, which are objective parameters and their values, vary large. Therefore, predicting QoS values based on the average QoS values perceived by the active user (i.e., r (u)) is flawed. Intuitively, given two users that have the same estimated similarity degree to the target user, the user nearer to the target user should be placed more confidence in QoS prediction than the other.

C. *Item-Based QoS Value Prediction:*

Author says, an item-based location aware CF method [17][18][19].

V. RESULT ANALYSIS

A. *Result 1*

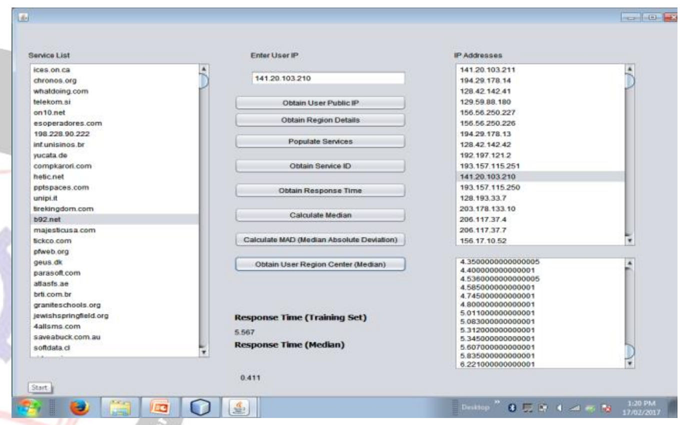

Fig: 4 Obtain MAD and User Region Center Form

Figure 1 shows the homepage the implementation which contains the list of all IP addresses specified in the dataset.

Result 2:

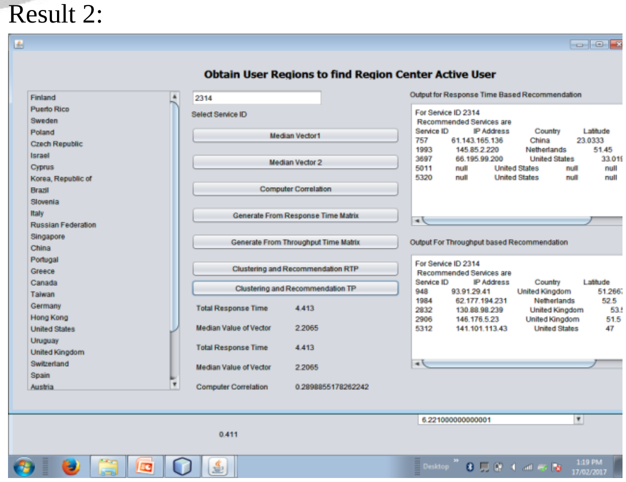

Figure 5 Recommendation Form

Figure 5 shows the form for computing correlation and recommendations for the asked service. Here user has to enter the service ID of the service for which he/she wants the recommendation.

B. Performance Analysis

The comparison of prediction time of web service recommendation with previous methods such as IPCC, UPCC, WSRec, LORec and Region-KNN is done in this experiment.

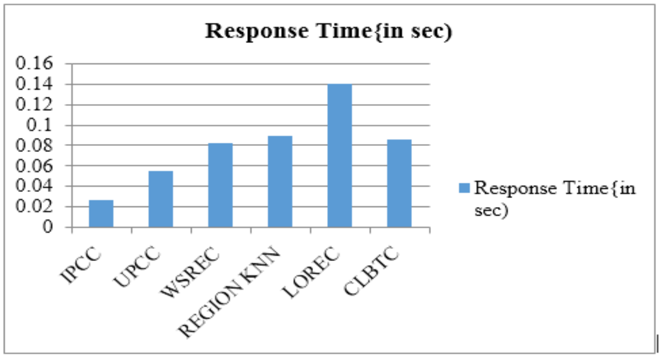

Fig: 6 Response Time Comparison of Various Algorithms

The comparison for response time required is shown below in Figure 3 in graphical format. As shown in above figure, the response time of proposed system is compared with different algorithms like IPCC(which employed only item based similarity computation), UPCC(which involved only user based comparisons) and other methods like WSRec, Region-KNN, LoREC.

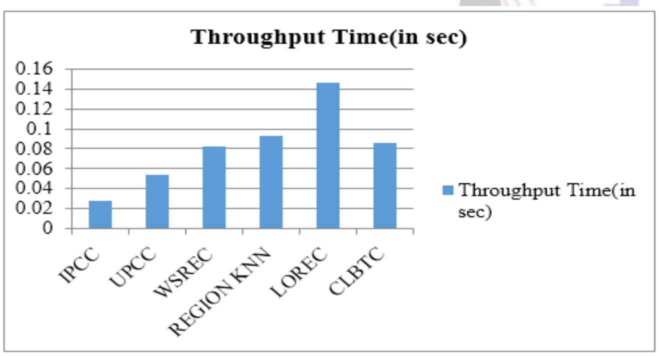

Figure 7 Throughput Time Comparisons of Various Algorithms

As shown in figure 7, we have compared different methods for prediction time of throughput with our proposed techniques. It takes about 0.0855 sec to fetch the most similar items based upon the throughput from the file which contains the computed similarity coefficients of all pairs of services.

VI. CONCLUSION

The assembly of the various QoS properties is significant for the accomplishment of web service technology. Due to the increasing popularity of Web services technology and the latency of dynamic service selection and integration, several service providers now provide parallel services. QoS is a modified factor to discriminate functionally similar Web services. To make it more problematic understanding is the progression of hiding unique data with arbitrary characters or data. The Web service recommendation helps users find a mandatory service has become important topic in the calculation of the service.

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 Based Web Service Recommendation System*," in Proc. 7th International Conference on Web Services, Los Angeles, CA, USA, pp. 437- 444, 2009.

[14] 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.

[15] Shao. L., Zhang, J., Wei, Y., Zhao, J., Xie, B., Mei, H. (2007). *Personalized QoS prediction for web services via collaborative filtering*, Proceedings of the 14th IEEE International Conference on Web Services (ICWS 2007), Salt Lake City, Utah, USA, July 9-13, 2007, 439-446.

[16] T. Yu, Y. Zhang, and K.-J. Lin, "*Efficient algorithms for web services selection with end-to-end QoS constraints*," ACM Transactions on Web, 1(1):6, 2007.

[17] G. Xue, C. Lin, Q. Yang, W. Xi, H. Zeng, Y. Yu, and Z. Chen,‘‘*Scalable Collaborative Filtering Using Cluster-Based Smoothing*,’’in Proc. 28th Int’l ACM SIGIR Conf. Res. Dev. Inf. Retrieval,2005, pp. 114-121.

[18]K. Karta, ‘‘*An Investigation on Personalized Collaborative Filtering for Web Service Selection*,’’ Honours Programme Thesis, Univ. Western Australia, Brisbane, Old., Australia, 2005.

[19] Z. Zheng, H. Ma, M. R. Lyu, and I. King "*QoS-Aware Web Service Recommendation by Collaborative Filtering*", IEEE Trans. on Services Computing, 2011, vol.4, no.2, pp.140-152.

