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Location-Aware Web Service Recommendation Using Personalized Collaborative Filtering

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ABSTRACT

The Served Method concern both locations of users and Web services when applying similar neighbors for the target user or service, Collaborative Filtering (CF) is worth employed for making Web service recommendation. CF-based Web service recommendation aims to predict missing Quality-of-Service (QoS) values of Web services. Although several CF-based Web service QoS probable Methods have been Served in recent years, the performance still needs significant improvement. Firstly, existing QoS probable Methods seldom consider personalized influence of users and services when measuring the similarity between users and between services. Secondly, Web service QoS factors, such as response time and throughput, usually depends on the locations of Web services and users. However, existing Web service QoS probable Methods seldom took this observation into assumption. In this Project, we propose a location-aware predicated CF Method for Web service recommendation. The Served Method concern both locations of users and Web services when applying similar neighbors for the target user or service. The Method also includes an enhanced similarity measurement for users and Web services, by assuming into account the personalized influence of them. To evaluate the performance of our Served Method, we conduct a set of extensive experiments using a real-world Web service dataset. The experimental results indicate that our Method improves the QoS probable accuracy and computational efficiency significantly, compared to previous CF-based Methods.

Keywords: **Collaborative filtering, Big Data, Qos Service, Recommendation**

I. INTRODUCTION

Web Services have been widely accepted over the internet, they have been employed by individual developers and companies for building services through this application. As the abundance of web services have increased, designing an effective method for recommendation and selection of web services has gained importance. In order to predict Web Services for a user, user preferences, user Diverse Information and web service properties should be considered, like Quality-of-Service (QoS) which has been considered as a major factor in service selection. QoS includes response time, price, correctness, etc. Among these properties some values like response time, etc.. Some QoS factors like reliability needs to be calculated by observing for long period of time. For the recommendation system it becomes difficult to get QoS data for all the services due to huge number of web services. These problems are overcome by giving personalized predictions to the user based on past user experiences or the feedback data. And the users can select the service which gives them optimal performance.

The growth of the Internet has made it much more difficult to effectively extract useful information from all the available online information. The overwhelming amount of data necessitates mechanisms for efficient information filtering. One of the techniques used for dealing with this problem is called collaborative filtering (CF). The motivation for collaborative filtering comes from the idea that people often get the best recommendations from someone with similar tastes to themselves. Collaborative filtering is a technique used by the recommender systems to make predictions and recommend potential favorite items to a user by finding similar users to that user , CF is based on user-item matrix. The underlying assumption of the collaborative filtering approach is that if a person A has the same opinion as a person B on an issue, A is more likely to have B's opinion on a different issue x than to have the opinion on x of a person chosen randomly [6]. Breese et al. [7] divide the CF algorithms into two broad classes memory based algorithms and model-based algorithms. Memory based collaborative filtering includes user-based approaches, item-based approaches and their fusion. User-based approaches predict the ratings of users based on the ratings of other similar users, and item-based approaches predict the ratings of users based on the similarity of the item. Memory-based algorithms are easy to implement, require little or no training cost, and can easily take ratings of new users into account but do not scale well to a large number of users and items due to the high computation complexity.

II. LITERATURE SURVEY

X. Chen et al. say that effective QoS based recommendation is becoming more and more important and previous Methods have failed to consider QoS variance according to the user's Diverse Data and also provide limited data on the performance of service candidates. This Project proposes a new collaborative filtering algorithm designed for large scale Web Services. The recommendation Method makes use of region-based CF algorithm and consists of two phase Method. The first phase, the users are divided into various regions based on their physical Diverse Data and previous QoS experience on Web Services. In the second phase, when a user is requesting Web Services, it finds similar users for the current user and makes probable for Web Services which have the best predicted QoS values for the unused services.[1]

J. Yin et al. Stresses that QoS values are important and propose a new collaborative QoS probable framework. Let us assume that there are m users and n Web Services, and they contribute to an m x n web service QoS matrix R, and each entry $r_{u,i}$ represents a QoS value recording the specific usage data of web service i executed by user u and predicts missing QoS values of Web Services by using the concept of localization and matrix factorization. This Method assumes that users nearby share similar web service invocation experience and makes of matrix factorization framework for predicting missing QoS values.[3]

J. Zhu et al. propose a new clustering-based QoS probable framework, in which various Landmarks (computers) are deployed in the internet to monitor QoS data of the available Web Services by invoking these services at regular intervals and then cluster the computers based on the QoS data that has been obtained. It then clusters these small groups into a large existing cluster, and try to form hierarchy of clusters, this is done by measuring the latency between the landmark and the cluster, from this QoS probable are made from the QoS data that has been gained from the landmarks.[8]

G. Kang et al. propose a Web Services recommendation Method which recommends Web Services to a user based on the user's history. The system measures the similarity between the user's functional interests and web services and based on the similarity in the functional and non-functional characteristics Active Web Service Recommendation System, ranks the services so that a list is generated which has top recommendations for the user.[9]

Z. Zheng et al. present a collaborative filtering Method for predicting QoS values of Web Services. It proposes a protocol called Web Service Recommendation (WSRec) which makes use of user-collaborative mechanism for collecting Web Services QoS data from various users, and based on the collected QoS data, probable are made using the collaborative filtering Method. WSRec is a centralized server which consists of web service QoS data for various Web Services contributed by service users and makes recommendations for the user requesting a web service.[10]

J.E. Haddad et al. address the issue of recommending Web Services by considering into account transactional properties like compensable or not, QoS characteristics, and also the functional requirements of Web Services according to the requirements of the user. The web service composition can be viewed as a three stage Method. In the first step, the user submits a query that he/she wants a composite web service to satisfy. In the second step, Web Services that satisfy the user requirements will be displayed to the user and the user can select from those results or they could be automatically decided by the system. The third step is executing the selected WS component. This Project has focused on designing a composite web service by designing an algorithm which integrates QoS and transactional properties that will ensure proper execution. In this, mainly five QoS criteria (execution price, execution duration, reputation, successful execution rate, and availability) have been used and a local QoS-driven service selection related to these criteria has been chosen. In this Project, risk notion has been calculated for each of the scenarios or based on the user preferences, if some user prefers minimum price then it calculates the risk for a particular web service and recommends those web service which has potentially low risk. So probable's are given based on analysis of risk to the user.[11]

L. Shao et al. propose that non-functional properties such as quality of service (QoS), should be taken into assumption when making recommendations to the customers. But there are a lot of Web Services that can be found on the internet for which we do not have any idea about its QoS factors, for such Web Services for which the user does not have any idea about, probable's are made on the quality of such unknown Web Services. This Project makes use of the concept of similarity mining through collaborative filtering for making probable to the users from other consumer experiences.[12]

III. PROBLEM STATEMENT AND PROPOSED SYSTEM

A. Problem Statement

Various from the existing Method, which suffer from low probable accuracy, we design an effective CF algorithm for web service recommendation with the assumption of the region factor. We design a Diverse Data-aware QoS based Web services recommendation Method, in which we gain the QoS data and give personalized results to the user's. We use the Method of filtering the results obtained from collaborative filtering (CF) technique based on the user's Diverse Data which significantly improves the recommendation accuracy by predicting and recommending potential favorite items for a user.

B. Proposed System

We perform a new location aware-aware service ranking algorithm to find the optimal top-k Web services based on a

Served extensive ranking measure. We propose a new service recommendation Method by assuming location aware into assumption. We integrate the functional relevance, QoS utility, and location aware features of Web services for recommending well diversified top-k services to users. We compare our Served algorithm with three diversified ranking Methods in graph domain again with the location aware, score, and the overall ranking measurement as evaluation metrics. We propose a new Web service recommendation Method incorporating a user's potential QoS preferences and location aware feature of user interests on Web services. We propose a new service recommendation Method by assuming location aware into assumption. We integrate the functional relevance, QoS utility, and location aware features of Web services for recommending well diversified top-k services to users. By using this algorithm author can do following things.

a. We perform a new location aware-aware service ranking algorithm to find the optimal top-k Web services based on a Served extensive ranking measure.
b. We survey the re-lasted work on service recommendation in these three cat-goriest, and on location aware-based ranking algorithms.
c. There are two algorithms based on this framework: the Grasshopper algorithm and the manifold rank with stop points algorithm.
d. The above diversified ranking algorithms neither are scalable to large graphs due to the time or memory re-quirements, nor are intuitive and reasonable diversified ranking measures.

C. Contribution

This recommender system aims at making the recommendations efficient to the user, by giving recommendations to users based on Diverse Information and QoS feedback, as studies have shown that users in a particular region experience difference in QoS for the same service accessed from a different region [1].

IV. MATHEMATICAL MODEL

To make the measurement of user similarity for each criteria using cosine formula as follows

$$s(u,v)=\cos(\vec{R}(u,*),\vec{R}(v,*))=\frac{\vec{R}(u,*)\bullet\vec{R}(v,*)}{\left\|\vec{R}(u,*)\right\| * \left\|\vec{R}(v,*)\right\|}$$

The algorithm of user similarity measurement (Sim) using the cosine formula can be written as follows

Input: Ratings matrix R (u,i)
Output: Similarity (u1, u2, criterion)

```
Set First User and Second User (u1, u2)
For criterion = 1 to 5
Index  = 1
For doc = 1 to N
If (R(u1,doc) ≠ 0 AND R(u2,doc) ≠ 0)
Begin
Vector_u1[Index] = R(u1,doc)
Vector_u2[Index] = R(u2,doc)
Index = Index + 1
End Begin
End For
Sim(u1,u2,criterion) = cos(vec_u1,vec_u2)
End For
```

There were five user-neighborhood matrices, so five values of user similarity were obtained as follows

a. Sim1(u,v) : user similarity u and v based on U-ranking criteria.
b. Sim2(u,v) : user similarity u and v based on Admission criteria.
c. Sim3(u,v) : user similarity u and v based on Accreditation criteria.
d. Sim4(u,v) : user similarity u and v based on Location criteria.
e. Simu(u,v) : user similarity u and v based on Courses criteria.

Meanwhile, the measurement of user similarity using the concept of multidimensional distance can be explained in three steps as follows.

The first step is to calculate distance between two users for each document that was co-rated. The more the documents that were co-rated, the more the values of multidimensional distance. For example, the multi ratings of users u were (r1,r2,r3,r4,ru) and the multi ratings of users were (r'1,r'2,r'3,r'4,r'u), so the multidimensional distance between the users u and v for one document was written as d(u,v) calculated by using the Manhattan formula as follows

$$d(u,v)=|r_1-r_1'||r_2-r_2'|+|r_3-r_3'|+|r_4-r_4'|+|r_u-r_u'|$$

The second step is to calculate the multidimensional distance between two users based on members D(u, v) that is a set of document co-rated by the users u and v. The multidimensional distance, written by dtotal(u,v), was an average of all d(u,v) shown as follows

$$d_{total}(u,v)=\frac{1}{|D(u,v)|}\sum d(u,v)$$

The third step is to converse the multidimensional distance value gained from the second step to be the similarity value. A relation between multidimensional distance and similarity was stated by with the formula as follows

$$s(u,v)=\frac{1}{1+d_{total}(u,v)}$$

The algorithm of user similarity measurement by using the concept of multidimensional distance can be written as follows

Input: Ratings matrix R(u,i)
Output: Similarity (u1,u2)

```
Set First User and Second User (u1, u2)
Index = 1
For doc = 1 to N
If (R(u1,doc) ≠ 0 AND R(u2,doc) ≠ 0)
Begin
Vector_u1[index] = R(u1,doc)
Vector_u2[index] = R(u2,doc)
Index = Index + 1
End Begin
End For
Distance(u1,u2) = 0
```

```
For i = 1 to N
d_rating[i] = 0
 For j = 1 to 5
 d[j] = abs(vector_u1[j] - vector_u2[j])
 d_rating[i] = d_rating[i] + d[j]
 End For
 Distance(u1,u2) = Distance(u1,u2)+d_rating[i]
 End For
 Distance (u1,u2) = Distance(u1,u2)/N
 Similarity (u1,u2) = 1/(1+Distance(u1,u2))
```

V. EXPERIMENT AND ANALYSIS

A. Error Accuracy

We compare the accuracy of different approaches by introducing two error types. Type error refer to the situation when matched data is classified as unmatched one, and Type error refer to unmatched data is classified into matched data. The 25 testing sample data from listed Site is denoted as Trade, The prediction result is listed. Support Vector Machine (SVM) method shows the best overall prediction accuracy level at 100 %. Using the unmatched and unbalanced testing data, Nearest Neighbour (NN) method, shows the best overall prediction accuracy level at 96 % .

Method	Number of sample	error Type	error	Error Accuracy
NN	25	2/25	8%	92%
SVM	25	1/25	4%	96%
CF	25	0/25	0%	100%

1. Error Accuracy Table

B.Classification Accuracy

Classification accuracy is measured using the average of precision and recall (the so-called breakeven point). Precision is the proportion of items placed in the category that are really in the category, and Recall is the proportion of items in the category that are actually placed in the category. Table 1 summarizes micro-averaged breakeven performance for 5 different learning algorithms explored for the 10 most frequent categories as well as the overall score for all 2 categories.

Dataset	NN	SVM	CF
US -Trade	92%	95%	98.22%
UK-Trade	92.8%	94.99%	97.28%
Average Total	92.8%	94.99%	98.50%

2. Classification Accuracy Table

CF were the most accurate method, averaging 98.50% for the 2 most frequent categories and 97.2% over all 2 categories. These results are consistent with results in spite of substantial differences in image pre-preprocessing, term weighting, and parameter selection, suggesting the CF or SVM approach is quite robust and generally applicable for Leaf categorization problems.

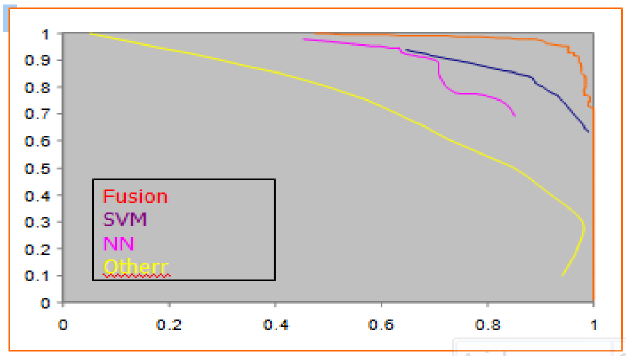

Figure1. ROC Curve

Figure 1 shows a representative Receiver Operating Characteristic (ROC) curve for the category “Downy”. This curve is generated by varying the decision threshold to produce higher precision or higher recall, depending on the task. The advantages of the Fusion can be seen over the entire recall-precision space.

VI. CONCLUSION AND FUTURE WORK

With the increase in the number of web services, developers are facing difficulties in finding appropriate services which fit their requirements. In order to make the developers work easy, we have designed a recommender system. In this project, we are trying to give recommendations to users based on historical QoS records and Diverse Data data of the user, through which the user can select a well suited service. The existing Methods lack Diverse Data based recommendations and also do not provide a platform to the users for giving ratings for a web service. We have overcome this in our project. Our system has various kinds of recommendations where the user can select recommendations based on categories like Personalized, History, Diverse Data and Interest.

Future work includes improving the Web service recommendation in terms of clustering Method, improving the security level, improving the user interaction with our system and making the recommendations more personalized.

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