IMPROVED FRAMEWORK FOR DIVERSIFYING WEB SERVICE RECOMMENDATION RESULTS USING USERS REVIEWS AND USAGE HISTORY

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ABSTRACT

As the increasing web services day by day over the internet, discovery of web services is becoming challenging research problem to be addressed for service computing community. There are number of web service recommendation methods has been proposed so far to solve the problem of web service discovery from the large pool of web services. However the limitation of these methods is that they are producing the similar web services in recommendation lists some times. To address this research problem, the novel improved web service recommendation method is presented in this paper. This approach is mainly dealing to produce the diversity in results of web service recommendation. In this paper, functional interest, QoS preference and diversity features are combined to produce the unique recommendation list of web services to end users. To produce the unique recommendation results, In this paper use proposed diversified web service ranking method which is based on web services functional relevance such as non-functional relevance, historical user interest relevance, potential user interest relevance etc. Additionally to improve the performance, designed new algorithm name as user relevance reviews. This method helps to improve the quality, accuracy of web service recommendation results.

KEYWORDS: QoS,Diversified Web Services, non-functional relevance, historical user interest relevance, potential user interest relevance.

I. INTRODUCTION

Web service recommendation is vital and widely used in many real time applications like e-commerce websites. There is number of web service recommendation solutions presented in order to accurately recommend the web services of user's interest. However the limitation of these methods is that they are producing the similar web services in recommendation lists some times. To address this research problem, novel improved web service recommendation method is proposed in this paper. This approach is mainly dealing to produce the diversity in results of web service recommendation. In this method, functional interest, QoS preference and diversity features are combined to produce the unique recommendation list of web services to end users.[1] In this paper we take care user satisfaction by taking feedback of user about the result and try to give best result user relevance review algorithm. Web services are loosely-coupled software systems designed to support exchange information and use it machine-to-machine interaction over a network. The increasing presence and adoption of Web services call for effective approaches for Web service recommendation and selection, which is a key issue in the field of service computing.

In the presence of multiple Web services with identical or similar functionalities, Quality of Service (QoS) pro-vides non-functional Web service characteristics for the optimal Web service selection. Since the service providers may not be deliver the QoS it declared, and some QoS properties (e.g. Invocation failure-rate, network latency, , etc.) are more related to the locations and network conditions of the service users, Web service evaluation by the service users can obtain more accurate results on whether the demanded[2].

Diversity aware search has been studied in recent years. Most of the existing solutions that support diversity on top-ksearch results consider the ranking of all the search results are given in advance. Based on which, a diversity search algorithm is given to output results based on a scoring function that takes both query relevance and diversity. Other works give algorithms that solve the diversity problem for a special area, i.e.

Graph search, document search, etc. and can hardly be extended to support general top-kdiversity search [4]. Ranking nodes on graphs is fundamental task in information retrieval, data mining, and social network analysis. It has a large number of applications such as ranking web pages, measuring centrality in social networks, as well as enhancing personalized services for web search. Most of existing graph-based ranking algorithms are based on the static distribution of the random walk on graphs, such as the Page Rank algorithm and its variants. The idea of this random walk based ranking algorithms is that the node of a graph with higher rank if there are more high-ranking nodes link to it. This basic idea has become a crucial criteria for bundling ranking algorithms on graphs and also has been successfully use in many applications.

However, as discussed in, the design criteria lead to many nodes found in the top-K ranking list are similar because it only considers the relevance of the nodes. It minimize the ranking effectiveness when the applications need to incorporate diversity into the top-K ranking results. Take Flickr which is a well-known photo shared website, as an example. Flickr users can make friends and join in many interest groups. Consider a retrieval task of finding the top-K relevant users who are related to a given user but are from as many interest groups as possible in the Flickr social network. In general, in this paper use personalized Page Rank algorithms to rank the users, and then find the top-Kusers based on their Page Rank scores. However, the top-K users find by the personalized. [10]

Page Rank typically include many users who are in the same interests group, thereby they cannot meet our objective of diversity. To this end, they need to take the diversity of the top-K ranking list into account for build ranking algorithms. In other words, the ranking algorithms in this case should produce diversified ranking results so as to cover as many groups as possible [5].

Existing recommender systems need to be adjusted for service selection, because of the differences in characteristics and marketplace maturity between software services and products. The characteristics which differentiate the selection of software services compared to the selection of products are rooted in the greater involvement of the service consumer in the delivery of a service [Sampson and Froehle 2006]. Compared with product usage, service episodes are richer and more context sensitive, which puts additional concern on contextual information of services. In terms of marketplace maturity, for example, software service marketplaces and search portals such as ProgrammableWeb1, XMethods2, WebServiceList3 and Seekda4 are currently immature and do not have the wealth of user feedback, reviews and rankings which characterize their mature counterparts focused on products (i.e. PriceRunner5, Ciao6) or conventional services (i.e. TripAdvisor7) [6].

To overcome the problems in the existing algorithms, in this paper, present feedback means user review relevance method. The basic idea of our approach is this method helps to improve the quality, accuracy of web service recommendation results. The performance of this method will be implemented and evaluated against existing method.

II. LITERATURE SURVEY

In this section the various strategies those are conferred to mine high utility item sets effectively are presented.

Zibin Zheng (2009)

In [2], they present WSRec, a Web service recommender system, to attack this crucial problem. WSRec includes a user-contribution mechanism forWeb service QoS information collection and for Webservice QoS value use effectiveand novel hybrid collaborative filtering algorithm prediction. WSRec is implemented byJava language and deployed to the real-world environment. To study the prediction performance, A total number of 21,197 public Web services are derived from the Internet and a largescale real-world experiment is conducted, where more than1.5millions test results are collected from 150 service users from different countries on 100 publicly available Web serviceslocated all over the world.

Chinnu Priya J.V. (2016)

In [11], as the number of web services with same functionality increases,the service users usually depend on web recommendation systems.Now a days the service users pay more importance on nonfunctional properties which are also called as Quality of Service (QoS) while finding and selecting appropriate web services. Collaborative filtering approach predicts the QoS valuesof the web services effectively. Existing recommendation systems infrequently consider the personalized influence of the users and services in determining the similarity between users and services. Theproposed system is a ranking oriented hybrid approach which combine user-based and item-based QoS predictions.

Guosheng Kang (2015)

In [1],they analyze different item-based recommendation generation algorithms They look in to different techniques for computing item-item similarities (e.g. Item-item correlation vs. cosine similarities between item vectors) and different techniques for finding recommendations from them(e.g. Weighted sum vs. regression model). Finally, they experimentally evaluate our results and compare them to the k-nearest neighbor approach.Our experiments suggest that item-based algorithms provide dramatically betterPerformance than user-based algorithms, while at the same time providing betterQuality than the best available user-based algorithms.

Lu Qin (2012)

In [4], Top-k query processing finds a list of k results that have largest scores w.r.t the user given query, with the supposition that all the k results are independent to each other. In practice, some of the top-k results returned can be very similar to each other. As a result some of the top-k results returned are unnecessary. In the literature, diversified top-k search has been studied to return k results that take both score and diversity into consideration. Most existing system solutions on diversified top-K search assume that scores ofall the search results are given, and some works solve the diversity problem on a specific problem and can hardly be expand to general cases. In this paper, they study the diversified top-k search problem. They define a general diversified top-k search problem thatonly considers the similarity of the search results themselves.

Rong-Hua Li (2012)

In [5],in this paper, they propose a new diversified ranking measure on large graphs, which captures both relevance and diversity, and evaluate the diversified ranking problem as a submodular set function maximization problem. Based on the sub modularity of the proposed measure, they develop an efficient greedy algorithm with linear time and space complexity with respect to the graph size to achieve near-optimal diversified ranking. In addition, they present a generalized diversified ranking measure and give a near optimal randomized greedy algorithm with time and space complexity for optimizing it. They evaluate the proposed methods through extensive experiments on five real datasets. The experimental results indicate the effectiveness and efficiency of the proposed algorithm.

Liwei Liu (2010)

In [6], they address these issues by proposing a semantic content-based recommendation approach which study the context of intended service use to provide effective recommendations in conditions of scarce user feedback. The paper contain two experiments based on a realistic set of semantic services. The first experiment indicate how the proposed semantic contentbased approach can produce effective recommendations using semantic reasoning over the service specifications by comparing it with three other approaches. The second experiment demonstrates the effectiveness of the proposed context analysis mechanism by comparing the performance of both plain versions and context aware of our semantic content-based approach, benchmarked against user-performed selection informed by context.

Neil Hurley (2011)

In [7], article they assert that the motivation of diversity research is toincrease the probability of retrieving unusual or novel items which are relevant to the user and introducea methodology to determine their performance in terms of novel item retrieval. Moreover, noting that the retrieval of a set of items matching a user query is a common problem across many applications of informationretrieval, they evaluate the trade-off between diversity and matching quality as a binary optimization problem, with an input control parameter allowing explicit tuning of this trade-off. They study solution methods to the optimization problem and demonstrate the importance of the control parameter in obtaining desiredsystem performance. The methods are find for collaborative recommendation using two datasets andcase-based recommendation using a synthetic dataset constructed from the public-domain Travel dataset

Mr.A.Avinash (2016)

In [8],nowa days the service users pay more importance on nonfunctional properties which are also known as Quality of Service (QoS) while finding and selecting appropriate web services. Collaborative filtering effectivelypredicts the QoS values for the web services. Existing recommendation systems rarely consider the personalized influence of the users and services in evaluate the similarity between users and services.

The proposed system is a ranking oriented hybrid approach which integrates user-based and item-based QoS predictions. Many of the non-functional properties depend on the service location and user. The system thus employs the location information of users and services in selecting similar neighbors for the service target user and thereby making personalized service recommendation for service users

III. PROPOSED APPROACH FRAMEWORK AND DESIGN

PROBLEM DEFINITION

Since from last decade, development of web services is growing very fast as it is playing the significant role in applications like enterprise application integration, e-commerce etc. As the increasing web services day by day over the internet, discovery of web services is becoming challenging research problem to be addressed for service computing community. There are number of web service recommendation methods has been proposed so far to solve the problem of web service discovery from the large pool of web services. Web service recommendation helps to satisfy the user's needs. The current web service recommendation methods are focusing on predicting the missing QoS (Quality of Service) values of web service candidates those are interested by end users based on content based approach, collaborative filtering method or hybrid method. The working of this web recommendation method is considering that web services are depends on each other. This consideration is not always true, hence resulted into number of redundant or same web services may exist in a recommendation list. This problem later solved recently by presenting the novel method of web recommendation in which results of web service recommendations are diversifying through exploring service usage history. This method is showing the improved performance in quality of web service recommendation results. However end user reviews and feedbacks are not consideration with this method, hence there is still scope of performance improvement.

PROPOSED SYSTEM ARCHITECTURE

They are contributing the existing Diversifying Web Service Recommendation method with proposed method called user relevance review in order to overcome the limitation of web service recommendation. The proposed approach will be used to improve the performance of system. This system shown by EWSRD block in fig 1 with the comparison of existing system with name WSRD. All the functionality use by WSDR are used by proposed method but also use one extra functionality that is user feedback. Below define all functionality of method.

1**) FUNCTIONAL EVALUATION:** -The functional evaluation can be further divided into two parts: Functional Evaluation 1 and Functional Evaluation 2. Functional Evaluation 1 evaluates the relevance of the user's historical interest with Web services use based on a contentbased similarity measure. Content-based similarity is acquired by text similarity. This work only considers Web services that are described by the WSDL. Nevertheless, it is easy to extend our work to handle other kinds of Web services. The user's historical interest can be mined from his/her own service usage or query history. Functional Evaluation 2 predicts the user's potential interest and evaluates its relevance with Web services by employing collaborative filtering based user similarity. This similarity is measured based on the service invocation history of all service users.

2) NON-FUNCTIONAL EVALUATION:- Suppose that m QoS criteria are used for assessing the nonfunctional quality of WSi, its QoS vector is denoted by $\boldsymbol{QSi}$, i.e., $\boldsymbol{QSi}$ = (qi,1 ,qi,2 ,…,qi,m), where qi,j represents the value of the jt□ quality criterion. Generally, there are main two types of QoS criteria. A QoS criterion is considered to be negative if the higher the value, the lower the quality, (e.g., Cost and Response Time). On the other hand, if the higher value, the higher the quality, the QoS criterion is considered to be positive (e.g., Availability and Reliability). Values of different QoS criteria need to be normalized to the same range for different measurement purpose. While before normalization, apply statistical method (i.e., Pauta Criterion method) to preprocess the QoS values in advance to remove the outliers. Here, transform each QoS criterion value to a real number between 0 and 1 by comparing it with the minimum and maximum values of the QoS criterion among all available Web service candidates. After such normalization processing, greater value for any quality criterion means better quality.

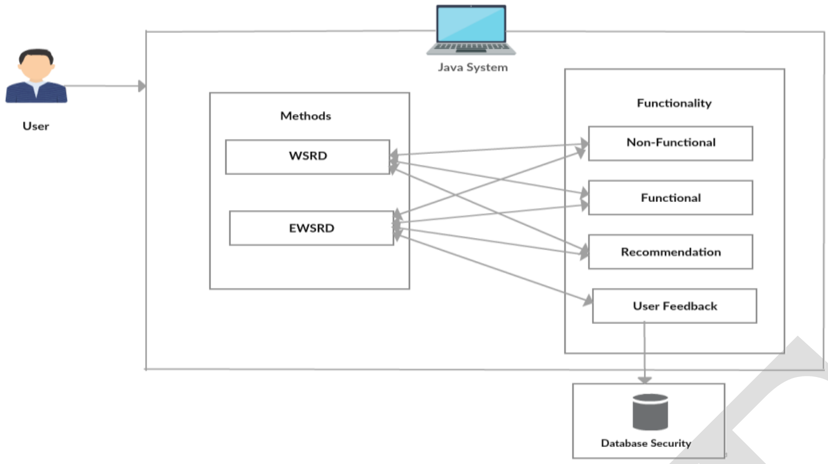

Figure.1. System Architecture

3) RECOMMENDATION:- To recommend web service we use web service graph construction and service ranking method. A web service graph $G = (V,)$ is an undirected weighted graph consisting of a set of nodes V and a set of edges E, wherein a node denotes a Web service candidate, i.e., $vi = WSi$, and an edge denotes that the connected nodes are similar. $V = K$ is the number of nodes (i.e., Web services) in the graph. But here not all the Web services in the Web service pool are used for designing the Web service graph. Only the Web services with a certain relevance to user interest are used. In web service ranking, calculate the score for each node in graph. Then as per score we provide rank to each node and showing top k node. Here node represent the web service

4) USER FEEDBACK:- In this phase try take the user feedback for the recommend web services and generate the log then web service with bad feedback are remove and performing all above steps with to new web service

IV. MATHEMATICAL MODULE

1) Input Dataset
1) User set
2) Web service Set
3) QoS Matrix

Equation 1- $userSimui,uj = 2\times|CSij| / |Sui| + |Suj|$ where Sui and Suj are the sets of Web services used by user ui and uj respectively, $CSij$ is the set of Web services used by both ui and uj , i.e., $CSij = Sui \cap Suj$. If $CSij = 0$, then $u(ui,uj) = 0$.

Equation 2- $\text{wsSim}(WSi,WSj) = \varphi texSim + \phi opSim$
Where $texSim = \cos \boldsymbol{wi}, = \boldsymbol{wi} \cdot \boldsymbol{wj} / |\boldsymbol{wi}| \times |\boldsymbol{wj}|$
where $|\boldsymbol{wi}|$ and $|\boldsymbol{wj}|$ are the Euclidean length of the vector $\boldsymbol{wi}$ and $\boldsymbol{wj}$ respectively, and the numerator is the dot product of $\boldsymbol{wi}$ and $\boldsymbol{wj}$.
2) Algorithms

Algorithm 1 Non-Functional Evaluation

Input: $WSu,1,WSu,2,\cdots,WSu,M$; $\boldsymbol{P}u,1,\boldsymbol{P}u,2,\cdots,\boldsymbol{P}u,M$; ε; $WS1,WS2,\cdots,WSN$; $\boldsymbol{QS}1,\boldsymbol{QS}2,\ldots..,\boldsymbol{QS}N$
Output: $Uu,1,Uu,2,\cdots,Uu,N$
1: for i=1 to N do
2: $\boldsymbol{QS}i' = no(\boldsymbol{QS}i)$;
3: $Ssim = \emptyset$;
4: for j=1 to M do
5: $Si, ws = wsSimWSi,,$;
6: if $Si, ws > \varepsilon and \boldsymbol{P}u, \neq \emptyset$ then

add WSu, into $Ssim$;
end if
end for
if $<Num$ then // Num is a threshold number
Find the top-10 similar users $Usim$that have used WSc,;

$$P_{u,i=}\omega \frac{\sum WS_{u,j\in S_{sim}} S_{i,j}^{ws} X\, P_{uj}}{\sum WS_{u,j\in S_{sim}} S_{i,j}^{ws}} + \omega \frac{\sum_{uk\,\epsilon\, U_{sim}} S_{u,uk}^{user} X\, P_{u,ki}}{\sum_{uk\epsilon\, U\, Sim} S_{u,uk}^{user}}$$

else

$$P_{u,i=}\omega \frac{\sum WS_{u,j\in S_{sim}} S_{i,j}^{ws} X\, P_{uj}}{\sum WS_{u,j\in S_{sim}} S_{i,j}^{ws}}$$

end if
Uu, = $\boldsymbol{QS}i\,'$ × $\boldsymbol{P}u$,;
end for
returnUu, 1, Uu, 2, ⋯, Uu, N;

Algorithm 2 Web Service Graph Construction

Input: $S1\ H$,$S2\ H$,⋯,SNH; $S1\ P$,$S2\ P$,⋯,SNP; Uu,1,Uu,2,⋯,Uu,N; θH, θP, α, β, γ
Output: Web Service Graph $G = (V,)$
$V = \emptyset$, $E = \emptyset$;
for i=1 to N do
if $SiH \geq \theta H$ or $SiP \geq \theta P$ then
add to V;
end if
end for
for each node in V do
$Scoreu$, = αSiH +βSiP +γUu,;
end for
for each pair of nodes vi and v in V do
if $(WSi,j) \geq \tau$ then
add edge $(vi,)$ to E;
end if
end for
return $G = (V,)$;

A Web service graph $G = V$, is an undirected weighted graph consisting of a set of nodes V and a set of edges E, wherein a node denotes a Web service candidate, i.e., $vi = WSi$, and an edge denotes that the connected nodes are similar. $V = K$ is the number of nodes (i.e., Web services) shows in the graph. But here not all the Web services in the Web service pool are used for constructing the Web service graph. Only the Web services with a certain relevance to user interest are used.

Algorithm 3: Diversified Web Service Ranking

Input: Web Service Graph $G = (V,)$, parameter λ, adjacency matrix A
Output: A set S of k ranked Web services
$S = \emptyset$;
while $|S| \leq k$ do
find $vmax = arg$ max $v\in(V-S)$ $(1-\lambda)Scorev + \lambda K\ |Nv - N(S)|$;
S = S∪{$vmax$ };
end while
return S;

Algorithm 4: User Relevance Review

Input: Top K rank web services S.

Output**:** A set WR of k ranked Web services

Step1: US=Accept_User_Feedback_On(S)

Step2: If user Satisfy goto step 10

Step3:-L=GenerateLog (US)

Step4: NF=NonFunctional_Evaluation (L)

Step5: F=Functional_Evaluation (NF)

Step6: D=Diversity_Evaluation (F)

Step7: G=GraphGernerator (D)

Step8: WR=ServicesRanking (G)

Step 9: return US

Step 10: Stop

3) Output Set:-Recommended Web Services List

V. EXPECTED RESULTS

Dataset, To obtain better experimental results, it is ideal to use a real world Web service dataset. We use WS-DREAM dataset.WS-DREAM is a Web service crawling engine that collects publicly available WSDL file addresses from the Internet. It also collected QoS information of these Web services by using 339 distributed computers to monitor the Web services. This dataset has been widely used for performance evaluation by previous work on Web service recommendation

Finally as are suit we got top k diversifying web service list which is recommended by system. Below graphs showing the excepted practical results for proposed work EWSRD. Fig 2 shows Comparison of Precision of EWSRD, WSRD and CF-based approach and Fig 3 shows Accuracy comparison between existing and proposed system.

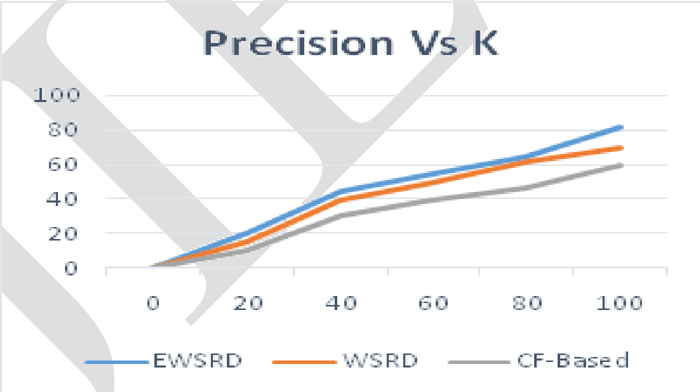

Fig.2 Comparison of Precision of EWSRD, WSRD, CF-Based Methods

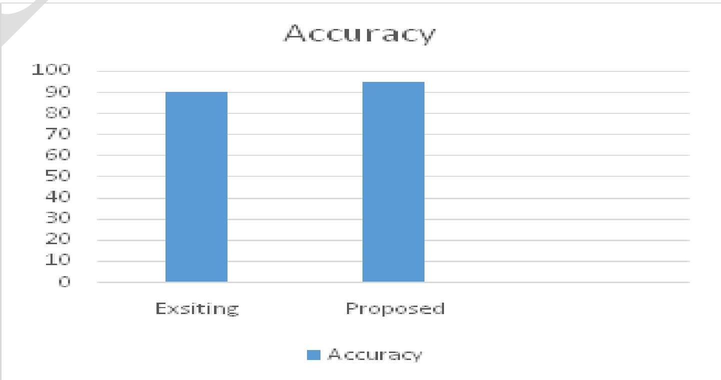

Fig.3Accuracy of Existing and Proposed System

As showing in figures 2 x-axis shows k values and y-axis shows precision percentage. The performance of precision is improved in proposed method, performance of is increase if value of k is increased. Similarly, the accuracy evaluation results showing the proposed approach expected to improve recommendation accuracy as compared to existing method

CONCLUSION AND FUTURE WORK

In this paper, a Web service recommendation approach with diversity using optimizes method user review and usage history is presented to find desired Web services for users. This paper incorporate functional interest, diversity feature and QoS preference for recommending top-k diversified Web services and generate log for web service using user feedback. A diversified Web service ranking algorithm is used to find the top-k diversified Web service ranked list based on their functional relevance including historical user interest relevance and potential user interest relevance, non-functional relevance such as diversity feature and QoS utility. In future work, Web service clustering methods are study to improve the similarity computation and conduct real user survey to determine the usefulness of our method further. In addition, our proposed diversified ranking measure (FS) mainly focuses on the immediate neighborhood information of S in the Web service graph. Other tests will be performed by our diversified ranking measure with k-hop nearest neighbors in the future work

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