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# Web Service Recommendation via Quality of Service Information

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***Abstract:*** **Web services are integrated software components for the support of interoperable machine-to-machine interaction over a network. Web services have been widely employed for building service-oriented applications in both industry and academia in recent years. The number of publicly available Web services is steadily increasing on the Internet. However, this proliferation makes it hard for a user to select a proper Web service among a large amount of service candidates. An inappropriate service selection may cause many problems (e.g., ill-suited performance) to the resulting applications. In this paper, we propose a novel collaborative filtering-based Web service recommender system to help users select services with optimal Quality-of-Service (QoS) performance. This system provides a 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. Thus we can improve the recommendation accuracy and time complexity compared with existing service recommendation algorithms. Proposed method uses enriched NLP protocols to get the recommendation from the user comments. System successfully merges web service ranking and user comments to provide best hybrid solution for proper recommendation.**

***Keywords:*** **Web Service, Quality of Service (QoS), Recommendation, Collaborative Filtering, Pearson's Correlation.**

## I. INTRODUCTION

Selection of a high quality Web service among a large number of web services is not an ordinary task. Some developers implement their own services instead of using publicly available ones, which brings additional overhead to both time and resource. Use of an inappropriate service, may add potential risk to the business process. Hence, effective approaches to service selection and recommendation are necessary, which can help service users reduce risk and deliver high-quality business processes. Quality-of-Service (QoS) is the non-functional characteristics of Web services and considered as the key factor in service selection [1]. QoS is a set of properties including availability, response time, throughput 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 [2].We propose a system which gives recommendation by the similarity measures of the captured response time of all web services to save time of the new user. This system ensures the application in web servers has a proper cooperation with one another by suggesting point of slowness. It also recommend web service via user Comments on the site, which can be read by web crawler.

## II. RELATED WORK

There are three types of recommendations and they are:

***Content-based Recommendations*:** The user will be recommended items similar to the ones the user preferred in the past.

***Collaborative Recommendations*:** The user will be recommended items that people with similar tastes and preferences liked in the past. Collaborative Filtering (CF) is used to predict and recommend possible favourite items for a particular user rating data collected from other users.CF is based on processing the user-item matrix. Most of the memory-based collaborative filtering include user-based approaches [3], [4], [5].User-based approaches predict the ratings of users based on the ratings of their similar users.

***Hybrid approaches*****:** These methods combine collaborative and content-based methods.

In this system we use preference function to calculate the response time of the web service. This response time is get correlated with service using Pearson’s correlation. It measures how well they are related and shows the linear relationship between them. Recommendations on the basis of user comments are given by using Natural Language Processing (NLP) protocol. NLP is a field of computer science concerned with the interactions between computers and human (natural) languages.

## III. OVERVIEW AND DETAILS IN ALGORITHMS

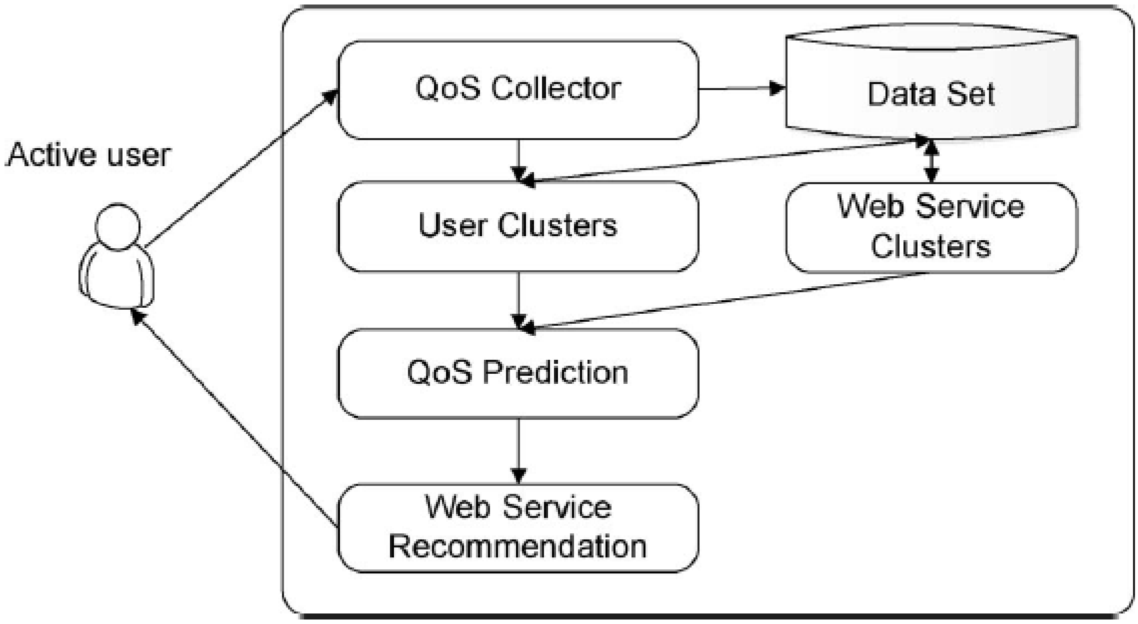


**Fig.1** Architectural Design of the Proposed System

***Algorithms used in natural language processing:***

*Algorithm to find top words*

Step 0: Start

Step 1: Read string

Step 2: divide string into words on space and store in a vector V

Step 3: Identify the duplicate words in the vector and remove them

Step 4: for i=0 to N (Where N is length of V)

Step 5: for ith word of N check for its frequency

Step 6: Add frequency in List Called L

Step 7: end of for

Step 8: return L

Step 9: stop

*Algorithm to find noun*

Step 0: Start

Step 1: Read string

Step 2: divide string into words on space and store in a vector V

Step 3: Identify the duplicate words in the vector and remove them

Step 4: for i=0 to N (Where N is length of V)

Step 5: for ith word of N check for its occurrence in Dictionary

Step 6: if present then return true

Step 7: else return false

Step 8: stop

***User based (Memory based) Collaborative Filtering***

This mechanism uses user rating data to compute similarity between users or items. This is used for making recommendations. This was the earlier mechanism and is used in many commercial systems. It is easy to implement and is effective. Typical examples of this mechanism are neighbourhood based CF and item-based/user-based top-N recommendations.[6] For example, in user based approaches, the value of ratings user 'u' gives to item 'i' is calculated as an aggregation of some similar users rating to the item:

$$r_{u,i} = \operatorname{aggr}_{u' \in U} r_{u',i}$$

Where, 'U' denotes the set of top 'N' users that are most similar to user 'u' who rated item 'i'. Some examples of the aggregation function includes:

$$r_{u,i} = \frac{1}{N} \sum_{u' \in U} r_{u',i}$$

$$r_{u,i} = k \sum_{u' \in U} \operatorname{simil}(u, u') r_{u',i}$$

$$r_{u,i} = \bar{r_u} + k \sum_{u' \in U} \operatorname{simil}(u, u')(r_{u',i} - \bar{r_{u'}})$$

Where, k is a normalizing factor defined as $k = 1 / \sum_{u' \in U} |\operatorname{simil}(u, u')|$ and $\bar{r_u}$ is the average rating of user u for all the items rated by that user.

The neighbourhood-based algorithm calculates the similarity between two users or items, produces a prediction for the user taking the weighted average of all the ratings. Similarity computation between items or users is an important part of this approach. Multiple mechanisms such as Pearson correlation and vector cosine based similarity are used for this.

The Pearson correlation similarity of two users x, y is defined as

$$\operatorname{simil}(x, y) = \frac{\sum_{i \in I_{xy}} (r_{x,i} - \bar{r_x})(r_{y,i} - \bar{r_y})}{\sqrt{\sum_{i \in I_{xy}} (r_{x,i} - \bar{r_x})^2 \sum_{i \in I_{xy}} (r_{y,i} - \bar{r_y})^2}}$$

Where, $I_{xy}$ is the set of items rated by both user x and user y.

***The Pearson Correlation*:**

Correlation between sets of data is a measure of how well they are related. The most common measure of correlation in stats is the Pearson Correlation. The full name is the Pearson Product Moment Correlation or PPMC. It shows the linear relationship between two sets of data. Two letters are used to represent the Pearson correlation: Greek letter rho (ρ) for a population and the letter "r" for a sample.

$$r = \frac{n(\Sigma xy) - (\Sigma x)(\Sigma y)}{\sqrt{[n\Sigma x^2 - (\Sigma x)^2][n\Sigma y^2 - (\Sigma y)^2]}}$$

The results will be between -1 and 1. You will very rarely see 0, -1 or 1. You'll get a number somewhere in between those values. The closer the value of r gets to zero, the greater the variation the data points are around the line of best fit. *High correlation:* .5 to 1.0 or -0.5 to 1.0*Medium correlation:* .3 to .5 or -0.3 to .5 *Low correlation*: .1 to .3 or -0.1 to -0.3

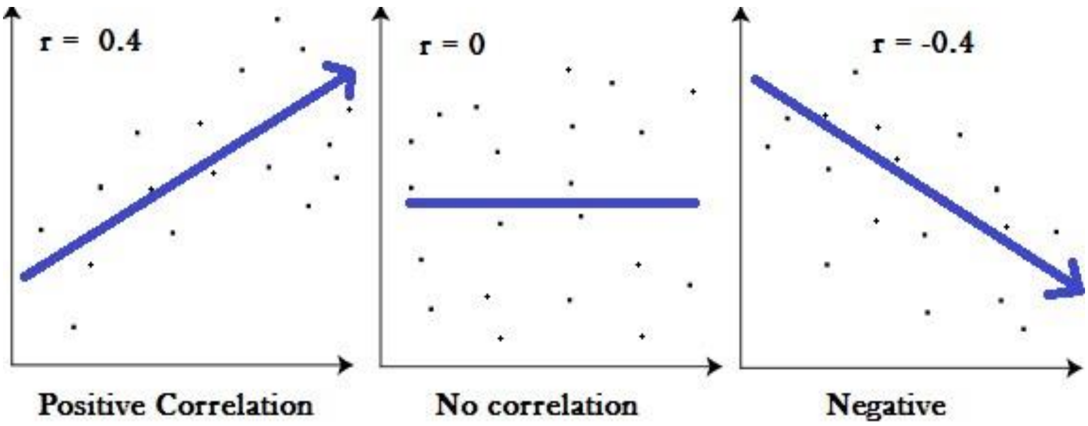


**Fig.3** Graphs of different Pearson's results.

For Example:-

| Subject | x | y | (x)(y) |
|---|---|---|---|
| 1 | 18 | 15,000 | 270,000 |
| 2 | 25 | 29,000 | 725,000 |
| 3 | 57 | 68,000 | 3,876,000 |
| 4 | 45 | 52,000 | 2,340,000 |
| 5 | 26 | 32,000 | 832,000 |
| 6 | 64 | 80,000 | 5,120,000 |
| 7 | 37 | 41,000 | 1,517,000 |
| 8 | 40 | 45,000 | 1,800,000 |
| 9 | 24 | 26,000 | 624,000 |
| 10 | 33 | 33,000 | 1,089,000 |
| Sum | 369 | 421,000 | 18,193,000 |

$$r = \frac{18193000 - \frac{(369)(421000)}{10}}{\sqrt{(15629 - \frac{136161}{10})}\sqrt{(21289000000 - \frac{177241000000}{10})}}$$

$$r = \frac{18193000 - 15534900}{(44.865)(59706.78)} = 0.99$$

x(Age) and y(Yearly Income) have a strong positive relationship.

## IV. CONCLUSION

The proposed system presents a QoS-aware Web service recommendation approach. The idea is to predict Web service QoS values and recommend the best one for active users which achieves better results than existing approaches. It also recommends via user Comments on the site, which can be read by web crawler. We also find that the combination result is much better than the result from any single method. This system will help user to select services with optimal quality of service (QoS).

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