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# Web Service Recommendation Using Location-Aware and Personalized Collaborative Filtering

Smita R.Patil[1], Vikas P. Mapari[2]
Department of Computer Engineering, DYPCOE, Ambi, Maharashtra, India

**Abstract:**
A Web service could be a technique of communication between two electronic devices over a network. web services is widely used for building service-oriented applications. Collaborative filtering is one in all widely used web service recommendation techniques, projected methodology leverages each locations of users and web services once choosing similar neighbors for the target service or user, collaborative Filtering (CF) is wide used for creating web service recommendation. CF-based web service recommendation is employed to predict missing QoS values of web services. Previous QoS prediction Technique rarely contemplate customized influence of users and services once activity the similarity between users and services. QoS factors, like latent period and outturn, typically depends on the locations of web users and services. Existing web service QoS prediction Techniques rarely took this observation into thought, during this we tend to propose a location-aware customized CF methodology for web service recommendation.

**Keywords:** Web Services Recommendation, Quality of service (QoS), QoS Prediction, Collaborative Filtering, Location Aware.

## I. INTRODUCTION

Web service may be a package designed to support practical interaction between machines over a network. With the prevalence of Service-bound design (SOA), a lot of and a lot of web applications area unit created by composing web services. As a consequence, several web services have hyperbolic chop-chop over the last decade. Web service discovery has become a difficult and crucial task for users. The useful needs, users conjointly wish to seek out web services that satisfy their personal non-functional needs. Below this circumstance, service discovery that includes non-functional performance of web services has aroused an excellent deal of interests within the services computing field. QoS of internet services is principally concerned of performance factors that embody convenience, interval, responsibility, throughput, and etc. Values of those QoS factors are sometimes largely addicted to the network distance between the locations of services and users, that don't seem to be totally incorporated within the previous CF recommendation algorithms. CF has been wide employed in business recommendation systems. CF algorithms may be divided into 2 sorts: memory-based and model-based. Counting on characterizing relationships between product things. 2 sorts of approaches of memory-based CF: item-based approaches and user-based approaches. The user-based approach recommends to a user product things collected by different users sharing similar tastes; whereas the item-based approach recommends to a user those things like those the user most popular within the past.

## II. RELATED WORK

This section Introduces the related work on Collaborative Filtering, Web Service Recommendation
Z. Zheng, H. Ma, I. King and M.R. Lyu, [1] have worked on a user-contribution mechanism for web service QoS military operation. They need verified that WSRec get the well expectation accuracy as compare to alternative ways. However there are some following difficulties:

1. It desires service calls; it dead the costs of the service users, It consumes properties of the service suppliers.

2. it's going to estimate service candidates. it's going to not expose appropriate web services to the service users.

3. The estimation of web service isn't specialist for service user. It used methodology that is hybrid cooperative filtering methodology with the assistance of this methodology they'll scale back the higher than difficulties.

J.S. Breese, D. Heckerman, and C. Kadie [2] worked on cooperative filtering or recommender systems usage a information regarding user preferences to calculate subjects a replacement user would possibly similar. They need delineate another task that is depends on correlation coefficients, arithmetic theorem ways and vector-based same calculations, It cannot cope well with sizable amount of things and users, since their on-line performance is slow. it's lesser memory needs. It permits for quicker predictions than a memory-based technique like correlation availableness of votes with that to form calculations..

J.L.Herlocker and M.R. McLaughlin [3] have tested that 2 of the best recommended CF recommendation algorithms have faults that outcome in AN intensely undesirable user expertise. Nearest-Neighbor algorithms work to form picture recommendations with the all image establish that several of the top movies suggested were incorrect, extremely uncertain, or unobjective. This rule poorly enforced as a result of it troublesome to search out the simplest picture from recommendations. Nearest-neighbor rule was dividing into 2 types: User Nearest Neighbor or User-User rule is scheming the similarities between every few users. However this rule contains 2 difficulties one. The active user taking deficient neighbors United Nations agency had stratified AN item.2.The neighbors with little or no association to the active user stratified the image and this fault incontestable quantitatively by the insufficient changed exactitude scores..

Song Jie Gong [4] custom-made recommendation systems is support users to get exciting things. They need used the modification of electronic exchange. Many recommendation strategies square measure work with the cooperative filtering technology; it's been showing to be one in every of the best vital strategies in suggested systems. With the increase of shoppers and merchandise in electronic exchange systems, the time taking nearest neighbor cooperative filtering examine the target of client within the whole client area. Once many accounts is within the user info, it grows the sparsely of knowledge set. There square measure disadvantages of this are1.Scalability within the cooperative filtering.2.Sparsely within the cooperative filtering.
Shao et al.[5]. They projected a user-based CF formula to predict QoS values.

Zheng, et al. [6] projected a hybrid user-based and item-based CF formula to suggest web services, and distributed a series of large-scale experiments supported real web services dataset. They conjointly developed AN increased Pearson parametric statistic (PCC) measuring for user similarity computation, that self-addressed the matter that PCC typically over estimates similarities of users of services UN agency are literally not similar however happen to possess similar

Jiang, et al. [7] implements that the influence of personalization of web service things ought to be take into account into consideration once computing degree of similarity between users.

Zhang et al. [8] advised that to predict web services QoS values. it was sensible to mix users' QoS experiences, atmosphere issue and user input. But the way to get atmosphere issue and user input issue weren't mentioned. Chen et al. [9] were the primary to acknowledge the influence of user location in web services QoS prediction and planned a unique technique. the tactic cluster users into a hierarchy of regions in step with users' locations and their QoS records, so the users in a very region area unit similar. once distinguishing similar users for a target user, rather than looking out the whole set of users, the tactic solely searches the regions that the target user belongs to. Compared with previous connected works, this paper makes the following major contributions. we have a tendency to take into account locations of users and services, and gift a hybrid location-aware QoS prediction methodology. we have a tendency to show that each user location and repair location are often utilized in up performance and accuracy of QoS prediction considerably. We have a tendency to area unit use large-scale real web services QoS dataset to indicate that there exists a relationship between QoS similarity and user (service) location.

## III. OVERVIEW OF WEB SERVICE RECOMMENDATION SYSTEM

It introduces the related work on Collaborative Filtering, Web Service Recommendation, and Self Organizing Map.

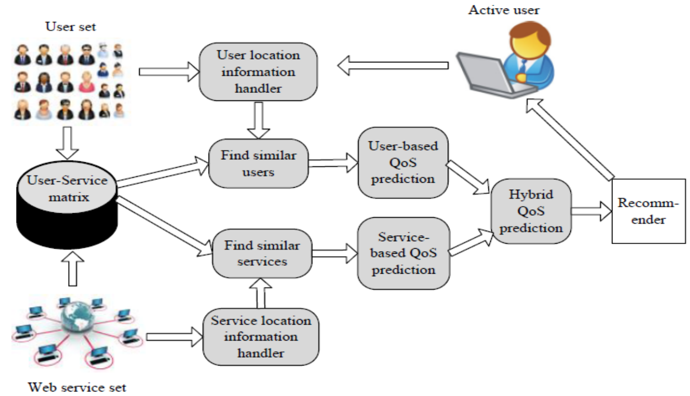


**Figure.1. Overview of Web service Recommendation system**

**User location information handler:** It provides support for efficient user-querying based on location. These modules obtain location information of a user including the network and the country according to the user's IP address.

**Service location information handler:** This handler acquires additional location information of Web services according to either their URLs or IP addresses. It provides functionalities for supporting efficient location based Web service query. The location information includes the network and the country in which the Web service are located.

**Find similar users:** This module finds users who are similar to the active user by considering both the users' QoS experiences and locations. For accurate user similarity measurement and scalable similar user selection, we propose a weighted user-based PCC via exploring QoS variation of Web services and incorporate user locations into similar user selection.

**Find similar services:** This module finds similar Web services for a target service, considering both QoS of Web services as well as service locations. A weighted service-based PCC for measuring similarity between services is proposed

**User-based QoS prediction:** After a certain number of similar users are identified for the active user, this function aggregates the QoS values they perceived on target Web services, and predicts the missing QoS values for the active user.

**Service-based QoS prediction:** After a certain number of similar services are identified for a target Web service, this function aggregates their QoS values to predict the missing QoS values for the active user

**Hybrid QoS prediction:** This function combines the user based QoS prediction and the service-based QoS prediction results, making final QoS predictions.

**Recommender:** After predicting missing QoS values for all candidate Web services, this function recommends Web services with optimal QoS to the active user.

## IV. PROPOSED SYSTEM

We planned an increased measuring for computing QoS similarity between totally different users and between different services. The measuring takes into consideration the tailored deviation of web services' QoS and users' QoS experiences;

therefore on enhance the accuracy of similarity computation. Although many CF-based webs service QoS prediction strategies are planned in recent years, the performance still desires vital improvement. We propose a location-aware customized CF technique for web service recommendation. The planned technique leverages each location of users and web services once choosing similar neighbors for the target user or service to judge the performance of our planned technique, we tend to conduct a group of comprehensive experiments employing a real-world web service dataset. Supported the on top of increased similarity measuring, we tend to planned a location-aware CF-based web service QoS prediction technique for service recommendation. We tend to conducted a group of comprehensive experiments using a real-world web service dataset, that incontestable that the planned web service QoS prediction technique considerably outperforms previous well-known strategies.

### A. Proposed System Algorithms

- We 1st formally outline notations for the convenience of describing our methodology and algorithms.
- The Top-K similar neighbor choice algorithmic program is commonly utilized
- The Top-K similar neighbor choice algorithmic program will be utilized to pick out K internet services that area unit most kind of like the target internet service
- We will see that the algorithmic program 1st searches native users for similar users.
- This algorithmic program encompasses a high likelihood of finding users kind of like the active user in his/her native region.
- Prediction coverage is additionally a crucial metric for evaluating a QoS prediction algorithmic program

### B. Advantages

In addition to the prediction accuracy, another advantage of our methodology is its high potency of QoS prediction. this means that our methodology is a lot of climbable than ancient CF strategies once applied to large-scale service recommender systems. this means that our methodology is a lot of climbable than ancient CF strategies once applied to large-scale service recommender systems. the explanation is that, in most cases we will limit similar neighbor looking to a little set of users (or internet services), particularly once K is little.

## V. MODULE DESCRIPTION

### A. Web services

CF-based web service recommendation aims to predict missing QoS (Quality-of-Service) values of web services. With the prevalence of Service-Oriented design (SOA), a lot of and a lot of web applications are created by composing web services. As a consequence, range of web services has raised quickly over the last decade. Collaborative Filtering (CF) is wide used to recommend prime quality web services to service users. supported the actual fact that a service user might solely have invoked a little range of web services, CF-based web service recommendation technique focuses on predicting missing QoS values of web services for the user.

### B. Collaborative Filtering (CF)

Collaborative filtering could be a methodology of constructing automatic predictions (filtering) regarding the interests of a user by aggregation preferences or style info from several users (collaborating).CF techniques will be typically rotten into 2 categories: model-based and memory-based [10],[11]. Memory-based CF is additionally named neighborhood-based CF. looking on whether or not user neighborhood or item neighborhood is taken into account, neighborhood-based CF will additional be classified into user-based and item based mostly.

### C. Web Service Recommendation

Various recommendation techniques have recently been applied to web service recommendation, like the content- primarily based link prediction-based. Their argued that, for each try of active user and target web service, each the QoS expertise of the users the same as the active user and also the QoS values of the services the same as the target service are often employed for QoS prediction. However, these previous approaches did not exploit the characteristics of QoS within the similarity computation. Supported the normal CF approaches, many enhanced strategies are planned to enhance the pre-diction accuracy. This is often probable if the web services square measure deployed in a very high performance Cloud setting. If the QoS is nice enough (as during this instance), a tiny low variation of QoS values over all users is probably going to be ob-served. Some web services might have a really poor QoS for all users.

### D. Incorporating Qos Variation Into User And Service Similarity Measurement

Previous QoS prediction ways assume that the co-invoked web services have equal contribution weights once computing similarity between 2 users. we have a tendency to argue that the personalized characteristics (e.g., QoS variation) of each web services and users ought to be incorporated into activity the similarity among users and services. web service QoS factors, like interval, avail-ability and responsibility, area unit typically user-dependent. From totally different web services, we are able to derive totally different personalized characteristics, supported their QoS values, as perceived by a spread of users. Some web services could have a awfully smart QoS for all users.

### E. Incorporating Locations of Users and Services into Similar Neighbor Selection

Web services square measure deployed on the web. Thus, QoS of internet services (such as reaction time, responsibility and throughput) is extremely captivated with the performance of the underlying network [12]. If the network between a target user and a target internet service is of high performance, the likelihood that the user can observe high QoS on the tar-get service can increase. There square measure many factors poignant the network performance between the target user and therefore the target service. the foremost vital factors embody network distance and network information measure, that square measure extremely relevant to locations of the target user and therefore the target service. once the user and therefore the service square measure settled at completely different networks that square measure far-flung from one another on the web, network performance is probably going to be poor as a result of each the transfer delay and therefore the restricted information measure of links between completely different networks. In distinction, once the user and therefore the internet service square measure settled within the same network, the user is a lot of possible to watch high network performance.

## VI. LOCATION INFORMATION REPRESENTATION, ACQUISITION, AND PROCESSING

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

### A. LOCATION REPRESENTATION

We represent a user's location as a triple (IPu, ASNu, CountryIDu), wherever informatics denotes the IP address of the user, ASNu denotes the ID of the Autonomous System (AS)1 that IPu belongs to, and CountryIDu denotes the ID of the country that IPu belongs to. Typically, a rustic has several ASs Associate in Nursingd an AS is inside one country solely. The web consists of thousands of ASs that inter-connected with one another. Generally speaking, intra-AS traffic is way higher than inter-AS traffic relating to transmission performance, like response time [13]. Also, traffic between neighboring ASs is healthier than that between distant ASs. Therefore, the Inter-net AS-level topology has been wide wont to live the space between web users [13]. Note that users situated within the same AS aren't continuously geographically shut, and the other way around. as an example, 2 users situated within the same town is also inside completely different ASs. Therefore, notwithstanding 2 users ar situated within the same town, they'll look distant on the web if they're inside completely different ASs. This explains why we decide AS rather than alternative geographic positions, like latitude and great circle, to represent a user's location.

### B. LOCATION INFORMATION

Acquisition exploit the situation data of each internet services and repair users are often simply done. as a result of the users' information processing addresses square measure already identified, to get full location in-formation of a user, we tend to solely have to be compelled to establish each the AS and therefore the country during which he's situated in line with his information processing address. variety of services and databases square measure offered for this purpose (e.g. the Whois search service2). during this work, we tend to accomplished the information processing to AS mapping and information processing to country mapping victimization the GeoLite Autonomous System variety Database3. The info is updated monthly, guaranteeing that neither the information processing to AS mapping nor the information processing to country mapping are outdated.

## VII. SIIMILARITY COMPUTATION AND SIMILAR NEIGHBOR SELECTION

In this section, we first formally define notations for the convenience of describing our method and algorithms. We then present a weighted PCC for computing similarity between both users and Web services, which takes their personal QoS characteristics into consideration. Finally, we discuss in collaborating locations of both users and Web services into the similar neighbor selection.

### A. Similar Neighbor Selection

Similar neighbor choice may be a vital step of CF. choosing the neighbors right almost like the active user is important for correct missing price prediction. In standard user-based CF, the Top-K similar neighbor choice rule is usually utilized [6]. It selects K users that area unit most almost like the active user as his/her neighbors. Similarly, the Top-K similar neighbor choice rules are often utilized to pick K web services that area unit most almost like the target web service. There are unit many issues concerned, however, once applying the Top-K similar neighbor choice rule to web service recommendation. Firstly, in observe, some service users have either few similar users or no similar users attributable to the information meagerness. ancient Top-K algorithms ignore this downside and still opt for the highest K most ones. as a result of the ensuing neighbors don't seem to be really almost like the target user (service), doing this can impair the prediction accuracy. Therefore, removing those neighbors from the highest K similar neighbor set is healthier if the similarity is not any over zero. Secondly, as antecedently mentioned, web service users could happen to understand similar QoS values on a number of web services. But they're not extremely similar. Considering the location-relatedness of web service QoS, we have a tendency to incorporate the locations of each users and web services into similar neighbor choice.

### B. User-based QoS Value Prediction

In this section, we have a tendency to gift a user-based location-aware CF methodology, named as ULACF. ancient user-based CF ways sometimes adopt for missing price predictions. This equation, however, could also be inaccurate for internet service QoS price prediction for the subsequent reasons. Internet service QoS factors like latent period and output, that area unit objective parameters and their values vary for the most part. In distinction, user ratings employed by ancient recommender systems area unit subjective and their values area unit comparatively fastened [9]. Therefore, predicting QoS values supported the common QoS values perceived by the active user intuitively, given 2 users that have identical calculable similarity degree to the target user, the user nearer to the target user ought to be placed a lot of confidence in QoS prediction than the opposite.

### C. Item-based QoS Value Prediction

In this segment, we have a tendency to gift Associate in Nursing item-based location aware CF methodology, named as ILACF. supported the similar thought as ULACF's, we use Eq. to reckon the expected QoS worth for a service supported the QoS values of its similar services .

### D. Integrating QoS Predictions

Due to the poorness of the user-item matrix, to create the missing price prediction as correct as doable, it's higher to totally explore the data of comparable users additionally as similar services. Therefore, we have a tendency to develop a hybrid location-aware CF, named as HLACF that integrated the user-based QoS prediction with the item-based QoS prediction.

## VIII. CONCLUSION

This paper presents a location-aware personalized collaborative filtering methodology for QoS worth prediction and QoS-based web service recommendation. Aiming at raising the QoS prediction performance, we tend to take under consideration the non-public QoS characteristics of each web services and users to cipher similarity between them. We are victimization large-scale real-world web services dataset; we tend to show that the performance of our methodology outperforms existing cooperative filtering primarily based recommendation ways by a big improvement of each prediction effectiveness and potency.

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