# Developing a Robust and Flexible Web Service Framework for Medical Care

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## Abstract

The rapid growth of Internet technologies and availability of web tools created an opportunity to develop a robust and user-friendly web service model for medical care, and it demands urgent solutions as the uncertainty of disease spread threaten humanity. With changing Quality of Service principles, many existing web services need to offer specific medical services that suit practical needs. The provision of an effective service selection and recommendation features that best meet the user's requirements will be able to improve the quality of web service model. The Quality of Service metrics should be calculated and analyzed before optimizing a recommendation technique. Evaluation therefore forms an important part of the process for designing and implementing recommendation systems. Further, predicting Quality of Service indicators accurately from historical background dataset under complex scenarios and combination of conditions is useful. In this perspective, lots of web service methods are studied, and this paper presents our comprehensive analysis mainly focusing on the development of better web service based framework for medical applications.

## Keywords

Web Service, Quality of Service, Medical Application, Genetic Programming, Collaborative Filtering, Recurrent Neural Network.

## Introduction

A case study on healthcare information system addressed interoperability issue using web services (Zhang & Xu, 2006). Nowadays many health care organizations are trying to integrate different systems' functions for better information sharing. The web service system faces challenges in managing huge amounts of patient records, and handling redundant data. Also improving the data security and data sharing is another major concern in healthcare systems. Web service provides a way of dealing with interoperability issue. In web-based medical systems, well defined workflows are being implemented, so, integration is not so easier. Investigation of existing web service protocols to develop web service based technique has been conducted (Rainer & Schahram, 2005).

Some ways of improving health maintenance service using XML a web service has been recently studied (Rajan & Priyanka, 2012). Web-Service systems allow users to browse and compose services quickly. A service-oriented system permits every service provides to provide services, multiple services may provide identical or similar features (Chen et al., 2011).

Authors (Rangarajan et al., 2020) presented the suggested Web-Service selection strategy using metrics for the source code. Code complexity, functionality metrics have been trained for the validation to make the efficient Web-Service selection. QoS attribute of reliability sets the quality criteria for Web-Service selection, Web-Service discovery, and Web-Service invocation.

Service quality is the key to the selection and evaluation of services (Zeng et al. 2004; Yu et al.2007; Zhang et al. 2007), which aims to differentiate between various functionally similar services. In particular, QoS defines a collection of properties that describe user characteristics for a particular Web-service, which includes throughput, reputation, response time, etc. The QoS forecasting is important for useful recommendations on customized service (Zheng et al., 2009). Since the end-users are from geographical areas, the values of the QoS are highly dependent on network settings and geographical areas. Also for the same device, the different users will have very different QoS requirements; the quality of service determined by one user cannot be used similarly by another. Therefore, QoS prediction has become a tedious task (Chen et al., 2013).

Collaborative Filtering (CF) is commonly used to estimate the QoS values of all user providers for a recommendation for customized Web-Service (Shao et al. 2007; Zheng et al. 2009; Rong et al. 2009; Chen et al. 2013). In a complex Internet-environment, the values of QoS typically change over time (Zheng et al., 2012), and the service status, such as customer numbers, and network conditions, also changes over time (Zhang et al., 2011). Therefore, web resources having maximal QoS values do adjust over time.

A recent work of Authors (Chen et al., 2017) dealt with QoS as a nonfunctional property with significant factors. Authors (Xu, et al., 2017) discussed QoS attribute values maintained in different structural formats. Authors (Zheng et al., 2013) proposed—two Web-Services' personalized reliability prediction methods, which include model-based approach, and a neighborhood-based approach. The neighborhood approach uses the previous fault information from the same neighbors, such as users or utilities of the service, to forecast Web-Service reliability. For another way, the model driven methodology applies a factor model which is based on existing web-service failure data which makes reliability forecasts using this factor model to continue.

Based on the QoS values, service is used by the user. Service discovery involves finding an efficient Web-Service based on feedback given by the user. Functional and nonfunctional properties can measure quality. Possible characteristic deals with the conceptual framework of the service. The suitable nonfunctional properties of Web-services can be measured based on the service level agreement. The following major problems shown in Table 1 are caused by the existing systems:

**Table 1 Major problem in the exiting healthcare applications**

| S. No. | Major problems in the existing systems |
|---|---|
| 1. | The patient records from different database systems cannot be easily exchanged by applications. |
| 2. | The reusability is very hard because of the incompatible operating systems or programming languages. |
| 3. | The components may have different meanings depending on the context. |

Proposed web service framework aims to modernize the healthcare services by involving the following key aspects shown in Table 2:

**Table 2 Key focuses for a robust and flexible web services**

| S. No. | Key focus |
|---|---|
| 1. | The predicted QoS value via decomposition of the global and local tensor is combined as missing QoS values. |
| 2. | The Collaborative filtering recommends the top-k objects by collating neighborhood's preferences, aiming to create a list of interesting things, for users. |
| 3. | The nearest neighboring flow graph will help to establish the QoS values missed, in a specific order, to tweak the accuracy of the final prediction. |
| 4. | Deep learning is used for greater precision. |

## Related Work

Web-Services play a very important role in enhancing the quality of medical services. Web-Service selection (Yu et al., 2007), service composition (Ardagna & Pernici, 2007), service recommendation (Fan. et al., 2015), service reliability prediction (Zheng & Lyu, 2010) are the essential areas in the perspective of research. Building a useful service-oriented application needs a vital technique as a service recommendation to identify the recommended services, which satisfy the functional requirement and the QoS constraints. In the real-world, during service invocation, there are many missing values of QoS parameters. Hence QoS forecast has become a needed step to make the decision based on recommendation.

Authors (Peng,et al., 2018) discussed that cloud computing performance primarily depends on the standard of Web-Services offered in cellular networks with restricted storage and computing capacity, like mobile phones. User preferences play an important role in recommending a service. The download is an additional ranking factor which recommends a service for end-users. Authors (Cai et al., 2019) proposed a custom QoS prediction method, for Web-Services here called as chain based factorization of matrix (BMF) blocks. For homomorphic hash, the user verification method has been established and also applying the Byzantine agreement has been considered in order to deal with the unreliable users. After matrix factorization, authors tested the BMF method on real-world Web-Services datasets. Authors (She et al., 2019), on the basis of the computational intelligence model, used the QoS conscious service composition technique for the active service prediction. This is a description of a transitional ambiguity between the qualitative term and its quantitative representation. In the work by authors (Wang et al., 2011), QoS model addressed primarily concerns related to QoS attributes, for composite services, and component services, these refers to the non-functional characteristics and typically specifies a collection of parameters, such as availability, cost, response-time, reliability, response status, etc. This QoS model will be useful in planning the composition of the service while supplementing services and the information needed generally specified in service level agreements.

Authors (Fanjiang et al., 2016) applied search based approach to forecast the QoS attributes using genetic programming. The real world QoS dataset trained in the initial phase to feed as an input for forecasting the QoS values. The trained dataset used for the evolution and prediction process to generate the measurable value. Metrics of mean square error mean average square error applied to find the accuracy of the model. It can be compared with the other models to get the best out of the current models. A time-aware recommendation (Wang et al., 2011) has been proposed for Web-Service using both spatial and temporal approaches. They gave a new, secular QoS predictive approach, to time-conscious Web-Service recommendation. Authors formulated the temporal QoS prediction as a generic regression problem, in which the residuals of the QoS prediction are based on a zero-mean Laplace prior-distribution assumption. End-user and device geo-locations are employed to efficiently recover the most related QoS sequence. While promising performance has been achieved, some limitations have been addressed. At present position, that method allows you to retrieve certain QoS values that cannot be applied, to predict future temporal-QoS-values. They also suggested studying the hierarchical indexing to improve the performance of prediction of spatial-temporal QoS.

For Web-Service recommendations, (Wang et al., 2014) these authors suggested a new credibility assessment method. Using a cumulative sum control map, they detect malicious feedback ratings, and then the influence of subjective user preferences analyzed, using the Pearson Correlation-Coefficient. In addition, to measure malicious feedback scores, they suggest a malicious feedback rating protection method using Bloom filtering, which can enhance the accuracy of recommendations. To use a specific collection of input rating, data of 15 million records used for invocation of Web-Services, the experiment results showed that their calculation methodology will minimize the variance in the calculation of credibility and improve the Web-Service recommendation's performance ratio.

Investigation of the technique for the selection of an efficient Web-Service has been conducted by (Upadhyaya et al., 2015) based on the quality of experience of the users. In the absence of QoS attributes, the features of Quality of Experience (QoE) used for the service selection. QoS is one of the measurement techniques that assist the process of service selection for users. Client feedbacks or reviews of used services collected from the different service providers like Amazon, eBay. The collected reviews kept in a separate database. The HTML structured document converted to a DOM structure. The translated text does the processing of semantic techniques for filtering the attributes as like feature as opinion. It calculates the characteristics of cost, synchronization, upload speed, file sharing, and mobile access. Usually, QoS considers the elements of response time, availability, price, security, and reliability. Despite the fact that the response time has been found, there is no capturing of specific Web-Service status to be considered. In general, there has been no analysis carried out on using Web-Services states for learning user diagnostics.

## Methods of QoS Prediction

### Recommendation for Customized Web-Service Focused on Decomposition of Hierarchical Tensor and QoS Prediction

QoS defines resources such as the response time, performance, and reliability as a non-functional attribute (Cheng et al., 2019). This is a crucial metric for calculating Web-Service efficiency. The prediction accuracy of the QoS rating, however, greatly impacts the results of the recommendations. Improving accuracy of prediction with respect to quality of service is a major concern. This study proposed Web-Service recommendation approach, mainly focused on the decomposition of hierarchical tensor and QoS prediction. The clustering of location and the decomposition of the hierarchical tensor values imported using QoS Hierarchical Topic Detection (HTD). First, QoS HTD clusters users and user – service – time services into multiple local groups based on their global triadic tensors, local models and their location. The decomposition of the hierarchical tensor operates on triadic tensors, locally and globally. Finally, the predicted QoS value via decomposition of the global and local tensor is combined as missing QoS values. A detailed experiment shows that this approach achieves high predictive accuracy and recommends Web-Service efficiency, and can resolve data sparsity in part.

## Collaborative Filtering

(Ma et al., 2018)

Collaborative filtering is a popular way in various ways of research in Web-Service recommendation. Guidelines are based on three simple methods: hybrid approach, content-driven filtering and collaborative filtering (CF). The CF recommendation targets neighborhood's preferences, aims to creating a list of interesting things, for active users. Content-based filtering enhances recommendation using a collection of discrete features, such as styles, producers, and movie actors. These two methods are also merged to build (Wang et al., 2011, Wang et al., 2014) hybrid recommender systems. In general, a CF recommender device operates in three stages. First, it measures the similarities between the active users and others. Second, it chooses the nearest active users based on the strength of correlations gathered from the initial phase. Thirdly, it suggests a list of top-k objects, through collating of the preferences of the nearest-neighbor. In general, collaborative filtering can be divided into a network-based and model-based approach. Matrix Factorization is an essential technique of model based approach in collaborative filtering. It takes the user-level data and the service level data to form the user service matrix. The user service matrix helps to predict the interest of the similar user. Collaborative filtering algorithm also requires active involvement by users, and also a simple way of representing the interests of users and algorithms that suit people with similar interest.

**Table 3 User - Service Matrix**

| Services\User | S1 Newspaper reading | S2 Reading books | S3 Playing Games | S4 Watching movies |
|---|---|---|---|---|
| User 1 | Yes | Yes | No | No |
| User 2 | No | Yes | No | Yes |
| User 3 | No | No | Yes | Yes |
| User 4 | Yes | Yes | No | No |

Inferences of Table 3: finding User 1 and User 2 are the similar users. It predicts the type of the user by accessing the services from services of S1, S2, S3 and S4.

## Network and Location-Aware Medical Service Model based on Nearest Neighbor Selection (NNS) and RNN

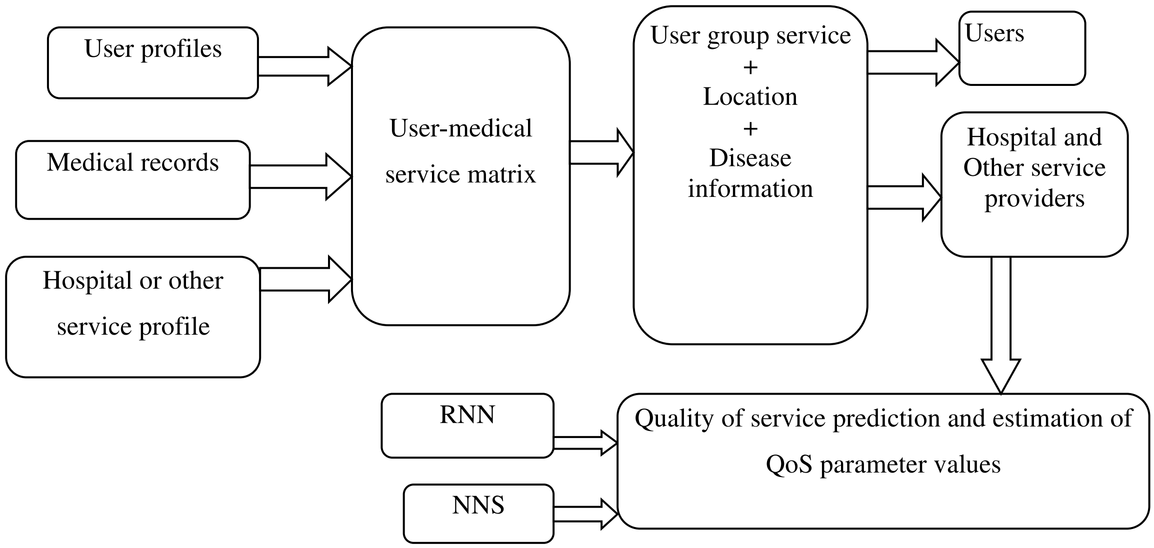


**Fig. 1 Network and location-aware Web Service model**

## Nearest Graph QoS Prediction

(Fu et al., 2018)

This methodology outlines secure service status, and observable QoS values. The Nearest Graph algorithm has been designed to identify balanced or unbalanced candidates. The popularity is determined using the nearest neighboring flow graph, and it helps to establish the QoS values missed, in a specific order, to tweak the accuracy of the final prediction. This algorithm primarily assists users of mobile devices in the cloud world in fog. Stability and popularity are the primary criteria used with the Nearest Graph Algorithm for QoS prediction. The user set diagram describes user name, user weight, and user edge. The Service Set Graph represents a service name, service weight, and service edge.

## Recurrent Neural Network based Approach of QoS Prediction for Service Recommendation

(Olah, 2015; Chen et al., 2019; Britz, 2019)

The variance between the times, the request is received by the server and the time the user receives the response is the answer time. The following factors may be affected: network congestion, request queue, network bandwidth, and change in request arrival rate, disk geometry data, and irregular use and flow patterns, cache. Most Web-Services response time may be too long to accept, developers need to be able to identify those conditions. Faster service is more appealing, attractive and can increase customer satisfaction. Most methods used the same WSDREAM dataset to validate the models using throughput and response time values. Some of the writers sought to compare their methods with the current approaches. Deep learning methodologies allow the algorithm to code for greater precision with correct inputs.

## Results and Discussion

Our research question is how to suggest to end-users an effective health care services using web service? Measurement Metrics are used for Web-Service estimation. Some example metrics are root mean square error (RMSE), recall, mean absolute error (MAE). These are some common evaluation indices that test the validity of the attribute's QoS Prediction. The RMSE function squares any absolute error to find out the goodness of fit. The indices RMSE and MAE are used to determine the reliability of the predicted QoS value. A metric accuracy tests how well ratings for individual products are predicted by a recommender method. The Table 4 illustrates the main approaches for filtering relevant healthcare needs (Brusilovsky, 2007). Numerous parameters were used to evaluate the model while designing and implementing recommender schemes. Recommendation accuracy measurements fall into three categories: predictive accuracy measurements, accuracy level measurements, and classification accuracy measurements.

**Table 4 Approaches for filtering**

| Filtering method/ Knowledge sources | Knowledge-based filtering | Content filtering | Collaborative filtering | Location based filtering |
|---|---|---|---|---|
| Domain knowledge | X | | | |
| User's need | X | | | |
| User's ratings | | X | X | |
| User's location | | | | X |

In several cases (Herlocker et al., 2004; Del et al., 2008; Gunawardana & Shani., 2009), to check recommender schemes, Root Mean Square Error (RMSE), Mean Squared Error (MSE) and Normalized Mean Absolute Error (NMAE) were used. Classification accuracy category includes ROC (Receiver Operating Characteristic), F1 metric, precision, nDCG (Normalized Discounted Cumulative Gain), recall and other associated metrics. These measures are derived from work on information retrieval, which calculate the fraction of prediction. In this evaluation, suggestion extraction can check which search results are successful or not (Del Olmo & Gaudioso, 2008; Wang. et al., 2013). The Table 5 presents some interesting results observed from the density range 0 to 30%.

**Table 5 Result analysis**

| **Metrics\Algorithm** | | **MAE** | **RMSE** |
|---|---|---|---|
| **QoSHTD** | Response time/s | 0.467 | 0.987 |
| | Throughput | 18.345 | 52.32 |
| **NN Graph method** | Response time/s | 0.472 | 1.124 |
| | Throughput | 24.326 | 63.543 |
| **Collaborative filtering** | Response time | - | 1.3 |

Rank accuracy metrics are different from predictive, and classification accuracy metrics, which can be used to calculate the consistency of the product requirements. Rather they concentrate on the price of the suggested products being ordered. The Pearson product-moment correlation coefficient, NDPM (Normalized Distance-based Quality Measure), half-life utility metrics are some commonly used rank accuracy metrics. If the users benefit from the services and reuse the services, the important factors can be analyzed rather than checking whether a recommender program is effective or not.

## Conclusion

This paper presented various web service methods, and recommendation techniques that uses collaborative filtering, Network location aware selection, Nearest graph QoS prediction, personalized Web-Service selection, Recurrent neural network, and analyzed how to make QoS prediction for an efficient health care service system. Among all the existing web service based methods, it was observed that the RNN based model gives better accuracy than the machine learning models. The QoS metrics have been considered as a key metrics for measurement and evaluation. Any medical dataset can be applied to automatically learn from patient records. Deep learning based Web service model built for medical care can bring the best quality of service than the available models. Our detailed analysis presented with many recommendation aspects.

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