QoS Prediction for Web Service in Mobile Internet Environment

Qibo Sun[1], Lubao Wang[1], Shangguang Wang[1], You Ma[1], Ching-Hsien Hsu[2]
[1]State Key Laboratory of Networking and Switching Technology, Beijing University of Posts and Telecommunications, Beijing 100876, China
[2]Department of Computer Scienceand Information Engineering, Chung Hua University, Hsinchu 707, Taiwan
imbarainbao@gmail.com; {qbsun;sgwang;youma}@bupt.edu.cn; chh@chu.edu.tw

Abstract—**QoS prediction plays an important role in Web service recommendation. Many existing Web service QoS prediction approaches are highly accurate and useful in Internet environments. However, the QoS data of Web service in mobile Internet is notably more volatile, which makes these approaches fail in making accurate QoS predictions of Web services. In this paper, by weakening the volatility of QoS data, we propose an accurate Web service QoS prediction approach based on the collaborative filtering algorithm. This approach contains three processes, i.e., QoS preprocessing, user similarity computing, and QoS predicting. We have implemented our proposed approach with an experiment based on real-world and synthetic datasets. The results demonstrate that our approach outperforms other approaches in Mobile Internet.**

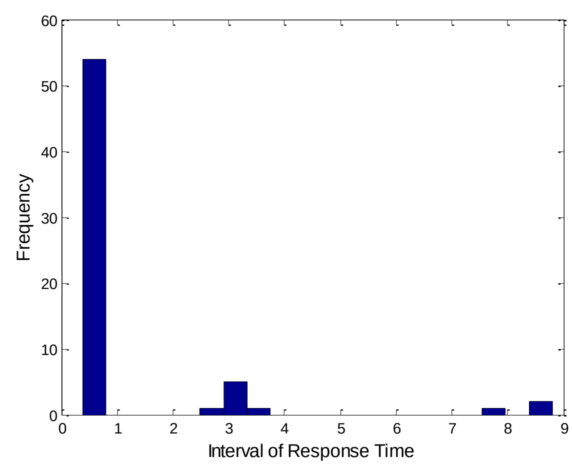
Keywords*-W*eb services; QoS; collaborative filtering; similarity computing

I. INTRODUCTION

With the rapid development of broadband wireless invoked technology and all aspects of mobile devices technology (Deng et al., 2015a; Deng et al., 2014; Deng et al., 2015b), the Internet is no longer confined to the PC. More and more smart mobile devices invoke the Internet, forming the mobile Internet. The mobile Internet is a new industry that uses mobile devices (such as smart phones, e-books, iPad) to obtain business and services (Dharmasiri et al., 2013). Relying on the growing popularity of mobile devices, Web services are in a rapid state of development in mobile devices and provide considerable convenience for consumers in their daily lives and work (Garcia-Barrios, Qerkini & Safran, 2009; Meschtscherjakov et al., 2011).

Faced with more and more Web services, users are in urgent need of a recommendation system to help them obtain high quality Web services. Hence, how to know which Web service performs well on Quality of Services (QoS, which includes response time, availability, and delay variation) becomes a crucial issue. The QoS data of Web services is greatly influenced by the different geographical locations of users and the Internet connections between users and Web services. Different users may observe different QoS data when invoking the same Web service. Thus, many Web service QoS prediction approaches are proposed, such as WSRec (Zibin et al., 2009; Zibin et al., 2011; Zibin & Lyu, 2009), agFlow (Liangzhao et al., 2004), MCKP (Yu & Lin, 2005), UPCC (Breese, Heckerman & Kadie, 1998), IPCC (Resnick et al., 1994), and other approaches (Li et al., 2010; Lingshuang, 2007), to find better Web services in advance. These approaches are very accurate and useful in Internet environments. Compared with the traditional Internet, which can transmit information stability, when transmitting information on the Mobile Internet, delay often occurs, as well as packet loss, etc., which makes the QoS data of Web service volatile (Taking the response time (one attribute of QoS) as an example, Figure 1 shows the QoS volatility based on real world data[1]). Existing approaches often predict QoS by means of: (1) randomly selecting one time QoS data from invoked Web services; (2) employing the mean QoS data of invoked Web services. Therefore, when traditional approaches are adopted in the Mobile Internet environment, the volatile QoS data will cause serious errors in QoS prediction.

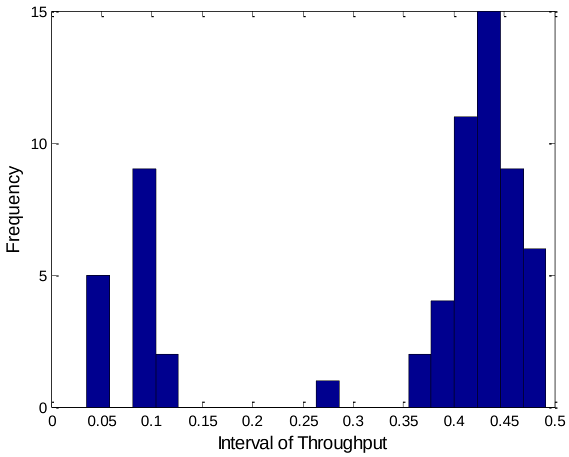
To obtain a thorough understanding of QoS volatility, we give some concepts. As shown in Fig.1, most of the QoS data were within a small range; we called these QoS data "*normal data*". Meanwhile, parts of the QoS data were not in the small range; we called this QoS data "*abnormal data*".



(a)The abscissa represents the interval of different response times. The ordinate represents the frequency of each interval among

[1] http://www.wsdream.net

the 64 times they were invoked. The distribution of the 64 times repeated response time data in each value interval shows obvious volatility and is split into normal data and abnormal data. This is because the QoS data are volatile in the Mobile Internet.



(b) The abscissa represents the interval of different throughput. The ordinate represents the frequency of each interval among the 64 times they were invoked. The distribution of the 64 times repeated throughput in each value interval shows obvious volatility and is split into normal data and abnormal data. This is because the QoS data are volatile in the Mobile Internet.

Figure 1. The distribution of QoS data.

As we know, when users invoke Web services in Mobile Internet environments, packet loss, delay and retransmission phenomenon will commonly occur. As a result, QoS data of the Mobile Internet have greater volatility. Although the number of abnormal values is very small, they often degrade the accuracy of QoS prediction for Web services. Taking the response time as an example, the abnormal data are usually much larger than the normal data. Thus, whether using the mean of all historical QoS data or the random one time QoS data of historical QoS data to predict, larger errors will occur. Hence, it is very essential to reduce the abnormal QoS data for accurate QoS prediction.

In this paper, we propose an accurate QoS prediction approach for Web services in Mobile Internet environments. We first need to preprocess the historical QoS data to reduce the impact of volatile data by using log processing. Secondly, we calculate the similarity among users based on collaborative filtering by using PCC, which we have improved. Finally, we predict the QoS data we need, based on some similar users and the normal data, by filtering the data with normal data intervals and weighted processing.

To verify the performance of our approach, we implement our approach and conduct experiments using a dataset named WSDream[2]. This dataset offers real-world data and includes 4532 Web services from public sources on the Web. One hundred and forty-two distributed users from Planet-Lab are invoked for evaluating the QoS performance of Web services over64 time intervals. The dataset contains nearly 1 million service response time records. Based on this dataset, we conduct experiments to compare our approach with two other approaches and study the parameters. The results demonstrate that our approach outperforms other approaches in Mobile Internet environments.

II. RELATED WORKS

We have learned of some research investigations that discussed QoS models of Web Service (Ouzzani & Bouguettaya, 2004). As we know, Web services are expected to be the key technology in enabling the next installment of the Web in the form of Service Web. With the rapid development of web service, there are many Web Services that are similar in function. Thus, we need to choose the Web service that is more suitable. Therefore, we should know the QoS of each Web service in advance. If users have not invoked some Web services, it`s necessary to predict them. Based on some papers, we find that there are many useful approaches for predicting the QoS of Web services and then choosing a suitable one to invoke, such as collaborative filtering (Li et al., 2010; Zibin et al., 2009) (Lingshuang, 2007; Zhang et al., 2010), clustering (Yuliang et al., 2011),etc.

Most of the QoS prediction approaches rely on collaborative filtering, and there are many proposed approaches. For example, Z. Zbin et al. (2009) aimed at improving current Web Service recommendation methods. Their contribution has three aspects: firstly, they proposed a systematic mechanism so that users can collect the QoS data of Web services from the real-world. Then, they designed a new, effective and hybrid collaborative filtering algorithm to realize the recommendation. Compared with other well-known traditional filtering approaches, the hybrid collaborative filtering algorithm can obviously improve the recommendation quality. Finally, to verify their Web service recommendation algorithm, this paper conducts a large-scale analysis based on several experiments. Based on the research, they also proposed many approaches (Zibin et al., 2011; Zibin & Lyu, 2008a; Zibin & Lyu, 2009; Zibin & Lyu, 2008b). These approaches are very accurate and useful, and their research efforts also brought much inspiration to my research. However, in their approaches, they only collected one time invoked QoS data. Thus, if using them in Mobile Internet environments, the prediction results will become inaccurate. Lingshuang et al. (2007) proposed an approach for predicting the QoS of Web service, based on the similarity among different users' experiences. The core concept of their approach is to determine the users who have similar historical experiences for some Web service. The authors also trust that they may have similar experiences for other services. This approach includes two steps. First, they calculated the similarity between two users based on their historical QoS data. Second, they predicted the QoS data of uninvoked Web services for users based on the QoS data of similar users. Wei Lo et al. (2012) presented a collaborative QoS prediction framework based on location-based regularization.

Not only collaborative filtering but also clustering can be used to get more accurate QoS prediction results. For example, Z. Jieming et al. (2012) proposed an original

[2] http://www.wsdream.net

clustering-based QoS prediction framework based on a set of fixed landmarks (some devices that can access the Internet, for example, computers) distributed across the Internet. These landmarks can periodically monitor available Web services so that the QoS prediction can be more accurate. Yuliang Shi et al. (2011) proposed an approach that can obviously improve the accuracy of QoS prediction. Firstly, this approach clusters users into different groups according to their locations and network condition, which could be used as a QoS prediction basis, and then based on the historical QoS data of service users who are in the same cluster. In addition, there are many excellent approaches based on other algorithms (Liangzhao et al., 2004; Yu & Lin, 2005; Zhang, 2010; Zibin et al., 2009,;Zibin et al., 201;, Zibin & Lyu, 2009).

All the above proposed some useful approaches for predicting the QoS data, and then, based on the result of prediction, they can choose the most suitable Web Service to recommend users to invoke. No matter which algorithm is chosen, these approaches can all obtain accurate prediction results when used in stable network environments. However, in the Mobile Internet environment, these prediction approaches will produce larger prediction errors. Thus, we proposed an approach to reduce volatility and finally obtain more accurate QoS predictions.

III. OUR APPROACH

According to analysis and to implement some prediction approaches, we found three factors that caused larger prediction errors:

(1) Because of the impact of volatility, the use of one time QoS data for invoking Web Services cannot necessarily reflect the real situation of the QoS. Thus, it is not reliable to predict the QoS based on only one time QoS data because it will cause larger prediction errors.

(2) Because of the volatile QoS data, if we calculated the similarity between users based on the general QoS dataset, we cannot obtain the correct similar users to predict. The results always appear as errors.

(3) When allowing a user to invoke a Web Service repeatedly and then record the QoS data, we find that these values are volatile. Thus, it is important to know which value can reflect the normal situation.

As a result, volatility is the primary factor that causes many outstanding prediction approaches to obtain larger errors in Mobile Internet environments. In the approach of this paper, we focus on how to avoid the impact of volatility.

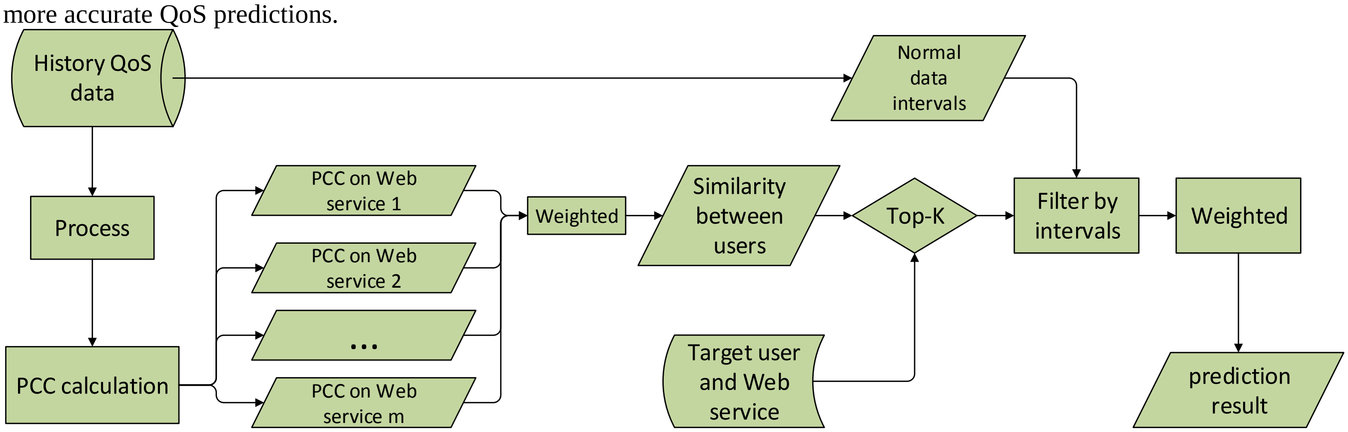


Figure 2. The procedure of our approach.

Hence, to avoid the volatility of QoS data, we proposed a Web service QoS prediction approach (called WSQP). In this approach, we first use a preprocessing strategy to reduce the volatility of QoS data. Then, we adopt the Pearson Correlation Coefficient (PCC) to find similar users. Finally, we predict the QoS data by using normal QoS data, which can be obtained from the historical QoS data of similar users.

WSQP generally comprises the following three steps:

- QoS preprocessing strategy. Preprocessing the historical QoS data to reduce the impact of the volatile data.
- User similarity computation. Calculating the similarity of a target user with other users to obtain the set of similar users.
- QoS prediction. Through the historical QoS data of similar users that invoke target Web Services, we can choose the range of the prediction, then finally obtain the QoS prediction value.

To directly demonstrate the process of our approach, we show the process in Fig.2. As shown in Fig.2, WSQP first uses preprocessing strategy to reduce the volatility of QoS data. Then, we adopt the Pearson Correlation Coefficient (PCC) to find similar users. Finally, we predict the QoS data by using normal QoS data, which can be obtained from all similar users' historical QoS data.

A. *QoS preprocessing strategy*

In this paper, we assume $q_{a,j}^{r}$represents the historical QoS data of user$a(a = 1,2,3, \dots)$, who repeatedly invokes Web service $j (j = 1,2,3, \dots)$ for the r $(r = 1,2,3, \dots)$ times. The historical QoS data set of user a, who repeatedly invokes Web service j a total of t times, is $Q_{a,j}^{history} = \{q_{a,j}^{1}, q_{a,j}^{2}, \dots, q_{a,j}^{r}, \dots, q_{a,j}^{t}. \}$, where r represents the ordinal number of invoking, the maximum of whichis t.

To weaken the volatility of the QoS data from Web services in Mobile Internet environments, a strategy is used as follows:

$$p_{a,j}^{r} = \ln(q_{a,j}^{r}) \quad (1)$$

where $p_{a,j}^{r}$ represents the preprocessed result of the historical QoS data $q_{a,j}^{r}$; r represents the ordinal number of invoking, the maximum of whichis t. The historical QoS dataset of user a, who repeatedly invokes Web service j a total of t times, can be transformed to a data set that has reduced the volatility, i.e., $Q_{a,j} = \{p_{a,j}^{1}, p_{a,j}^{2}, \ldots, p_{a,j}^{r}, \ldots p_{a,j}^{t}\}$.

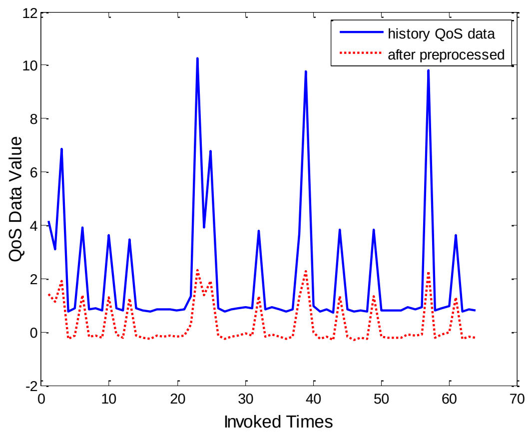


Figure 3. The ordinate represents the value of QoS data, and the abscissa represents the amount of times invoked. After being preprocessed, the volatility of historical QoS data had been obviously reduced.

As shown in Fig.3, when a user invoked a Web service repeatedly, the historical QoS data showed severe volatility. However, after the QoS data were preprocessed, the volatility of the preprocessed result was obviously reduced and the values of abnormal data become closer to normal values. Therefore, after the QoS data are preprocessed, the prediction errors will be greatly reduced in subsequent calculations.

B. User similarity computation

The Pearson Correlation Coefficient (PCC) has been introduced in many recommender systems for calculating similarity because it can be easily implemented and can achieve high accuracy. PCC is used to calculate the similarity between two users (a and u) according to the following equation:

$$sim_{a,u} = \frac{1}{n}\sum_{l=1}^{n} \frac{\frac{1}{t}\sum_{r=1}^{t}(p_{a,l}^{r} - E_{a,l})(p_{u,l}^{r} - E_{u,l})}{\sqrt{D_{a,l}}\sqrt{D_{u,l}}} \quad (2)$$

where $sim_{a,u}$ represents the similarity between two service users a and u; $E_{a,l}(E_{a,l} = \frac{1}{t}\sum_{r=1}^{t} p_{a,l}^{r})$ represents the average value of $Q_{a,l}$; $E_{u,l}(E_{u,l} = \frac{1}{t}\sum_{r=1}^{t} p_{u,l}^{r})$ represents the average value of $Q_{u,l}$; $D_{a,l}(D_{a,l} = \frac{1}{t}\sum_{r=1}^{t}(p_{a,l}^{r} - E_{a,l})^2)$ represents the variance of $Q_{a,l}$; $D_{u,l}(D_{u,l} = \frac{1}{t}\sum_{r=1}^{t}(p_{u,l}^{r} - E_{u,l})^2)$ represents the variance of $Q_{u,l}$.

Although PCC can provide accurate similarity calculation, it will overestimate the similarity among users who are not actually similar but happen to have similar QoS experiences for a few common invoked services (McLaughlin & Herlocker, 2004). To address this problem, we use a significance weight to reduce the influence of a small number of similar common services invoked. An enhanced PCC for the similarity calculation between two users is defined according to the following equation:

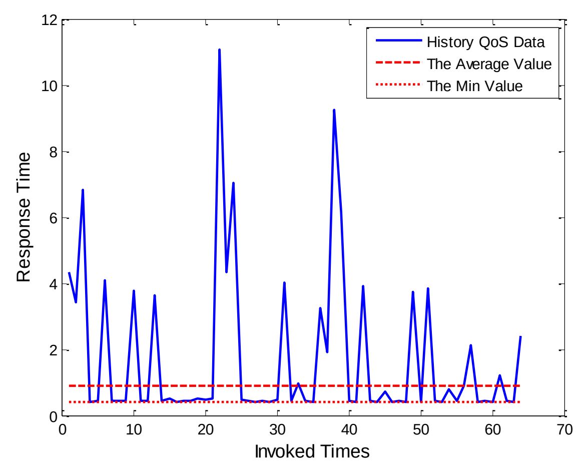
$$sim\grave{}_{a,u} = \frac{|US_a \cap US_u|}{\sqrt{|US_a| \times |US_u|}} sim_{a,u} \quad (3)$$

where $sim\grave{}_{a,u}$represents the similarity value between user a and user u; $|US_a \cap US_u|$ represents the number of Web service items that are invoked by both users; $|US_a|$ and $|US_u|$ are the number of Web services invoked by user a and user u, respectively.

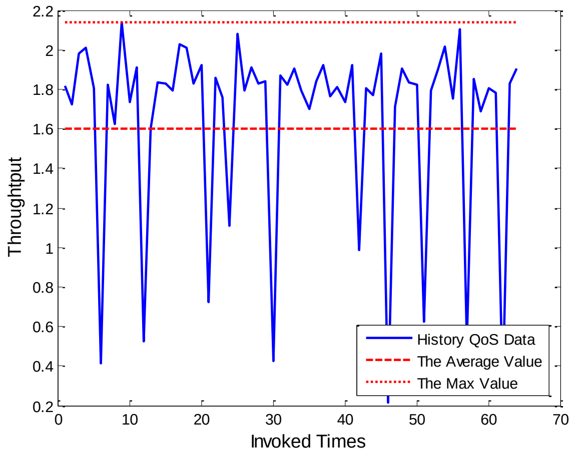
C. QoS prediction

Based on the similarity between every pair of users, if we want to predict the QoS data of user a who invokes Web service j, we first need to find the top-K similar users. Then, the similar users set of user a is $U_{sam(a)} = \{US_1, US_2, \ldots, US_c, \ldots, US_K\}$. , where c represents the ordinal number of the Web service in $U_{sam(a)}$, the maximum of which is K; K represents the users` number of $U_{sam(a)}$. This parameter will be analyzed in Section Ⅳ.C.

In addition, we define a normal data interval based on the characteristics of the QoS data and filter the normal data from the QoS data with it. The normal data interval only includes the normal data. For example, as shown in Fig.4, the values of response times tend to become larger when affected, and the values of throughput tend to become smaller when affected. Thus, for the response time data, the normal data interval should be $(p_{min}, E_{u_c,j})$($E_{u_c,j}$ represents the average value of $Q_{u_c,j}$,i.e.,$E_{u_c,j} = \frac{1}{t}\sum_{r=1}^{t} p_{u_c,j}^{r}$). For the throughput, the normal data interval should be $(E_{u_c,j}, p_{max})$. p_{min} represents the smallest value in $Q_{u_c,j}$. p_{max}represents the largest value in $Q_{u_c,j}$.



(a)The ordinate represents the value of response times and the abscissa represents the number of times invoked. The data of response time tends to become larger when affected. Thus, we set the minimum value and the average value of response time data preprocessed as the interval boundary, i.e., we defined the values in $(p_{min}, E_{u_c,j})$ as normal data.



(b)The ordinate represents the value of throughput and the abscissa represents the number of times invoked. The data of throughput tends to become smaller when affected. Thus, we set the maximum valueand the average value of throughput data preprocessed as the interval boundary, i.e., we defined the values in$(E_{u_c,j}, p_{max})$ as normal data

Figure 4. The normal data interval.

With the normal data interval, we can filter the QoS data and pick out the normal data. Next, we obtain the mean of normal data as follows:

$$F(u_c, j) = \frac{1}{v}\sum_{e=1}^{v} p_{u_c,j}^{e} \quad (4)$$

In the above equation, $p_{u_c,j}^{e}$ represents a QoS data item in $Q_{u_c,j}$, which is in a normal data interval; v represents the number of QoS data that are in the normal data interval.

After this, we can remove the greatest amount of abnormal data. We can also predict the QoS data accurately based on the QoS data of these K similar users in $U_{sam(a)}$asaccording to the following equations:

$$F_{wight} = \frac{\sum_{c=1}^{K} sim`_{a,u_c}(F(u_c,j) - \frac{1}{K}\sum_{b=1}^{K} F(u_b,j))}{\sum_{c=1}^{n} sim`_{a,u_c}} \quad (5)$$

$$Forecast = \frac{1}{K}\sum_{c=1}^{K} F(u_c, j) + F_{wight} \quad (6)$$

Where $Forecast$ represents the prediction QoS data of user a who invokes Web service j; u_c represents a user of $U_{sam(a)}$; $c = 1,2,3, \dots, K$; K represents the number of similar users of user a; $u_c(1 \le c \le K)$ represents a user who is similar to user a.

IV. Experiments

To verify the performance of our approach, we implement our approach[3] and conduct experiments based our previous work (Ma et al., 2015; Sun et al., 2014; Wang et al., 2014a; Wang et al., 2011; Wang et al., 2014b; Wang, Zhu & Yang, 2014; Wang, Sun & Yang, 2010) using a dataset[4] named WSDream. It contains nearly 1million service response time records. We conduct experiments to compare WSQP (our approach) against WSRec (Zibin et al., 2009) and AVG (which is based on the average of historical QoS data) in terms of response time. In addition, due to WSRec only using one response time value as the data of one user who invoked one Web service to calculate, in our experiments, we randomly select one response time value from 64 iterations of values for calculation.

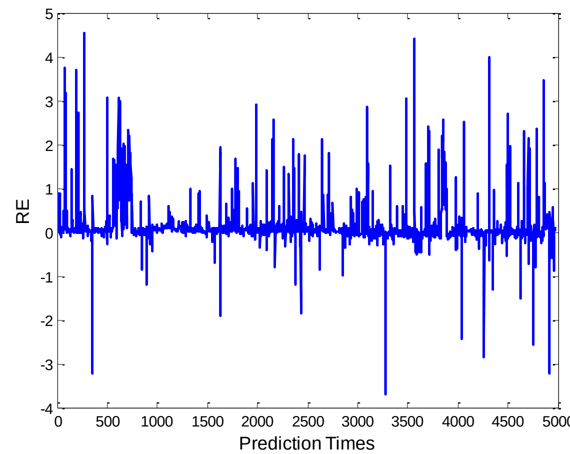
A. *Comparison results on relative error*

In this section, we conducted experiments to compare WSQP with other approaches in terms of relative error (RE).

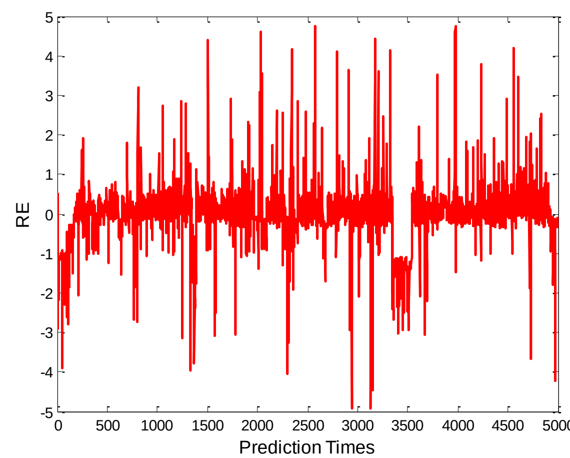
Define: RE represents the relative prediction error and can be calculated as:

$$RE = F - F_{real} \quad (7)$$

where F is the predicted QoS data; $F_{real}$is the real value, which we deleted before predicting the QoS data; the smaller the absolute value of RE is, the more accurate the prediction.



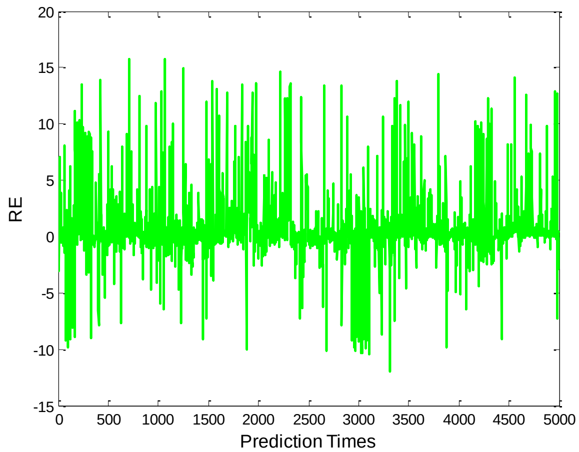
(a)The relative error (RE) of 5000 predictions using WSQP



(b) The relative error (RE) of 5000 predictions using WSRec

[3] http://www.sguangwang.com/Source code/wang-demo.avi

[4] http://www.wsdream.net



(c) The relative error (RE) of 5000 predictions using AVG

Figure 5. The ordinate represents the relative error we defined and the abscissa represents the times of prediction. By comparing WSQP with WSRec and AVG based on the same datasets, the RE of WSQP is the smallest over the majority of prediction experiments. As we defined, the smaller the absolute value of RE is, the more accurate the prediction. Thus, we can conclude that our approach (WSQP) is more accurate.

As shown in Fig.5 (a), most RE is maintained with in a small range. Thus, WSQP can avoid the influence of the abnormal data and obtain a better prediction result. In Fig.5 (b), there are many larger errors than in Fig.5 (a), and these errors generally have apositive value. In Fig.5 (c), AVG is seriously influenced by the abnormal data. Thus, the RE of prediction is much larger than that of the other two approaches. In these experiments, the RE of WSQP is the smallest over the majority of prediction experiments. As we defined, the smaller the absolute value of RE is, the more accurate the prediction. Thus, we can conclude that our approach (WSQP) is more accurate.

B. Comparison results on mean absolute error

We use Mean Absolute Error (MAE) to evaluate the prediction quality. MAE can be calculated according to follows:

$$MAE = \frac{\sum_{a,j}\left|F^{a,j} - F^{a,j}_{real}\right|}{N} \quad (8)$$

where $F^{a,j}$ represents the prediction QoS data of user *a* who invoked Web service *j*; $F^{a,j}_{real}$ is the real value of user *a* who invoked Web service *j*, which we deleted before predicting the QoS data; *N* is the number of predictions. The smaller the absolute value of MAE is, the more accurate the prediction.

As shown in Fig.6 $(N = 100)$, we find that, after comparing WSQP, WSRec and AVG on MAE, the MAE based on WSQP is the smallest over the majority of prediction experiments. This means that our approach can significantly improve the accuracy of QoS predictions for Web services in Mobile Internet environments. Thus, we can further judge that our approach (WSQP) outperforms WSRec and AVG in Mobile Internet environments.

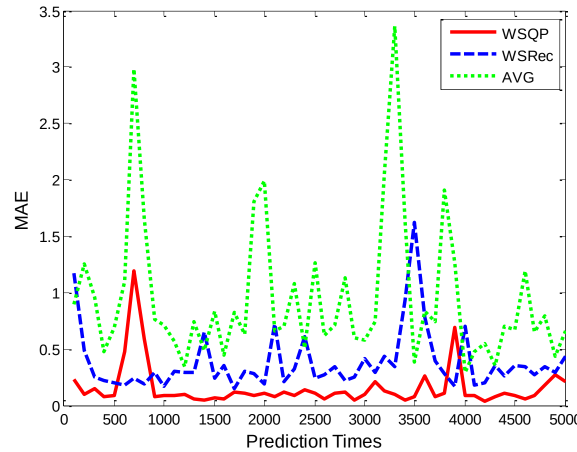


Figure 6. The ordinate represents the mean absolute error and the abscissa represents the times of prediction. By comparing WSQP, WSRec and AVG on MAE, the MAE based on WSQP is the smallest over the majority of prediction experiments. Thus, we can further judge that our approach (WSQP) outperforms WSRec and AVG in Mobile Internet environments.

C. Comparision results on root-mean-square error

Not only compared the results on MAE, we also use root mean square error (RMSE) to evaluate the prediction quality. RMSE can be calculated according to follows:

$$RMSE = \sqrt{\frac{\sum_{a,j}\left(F^{a,j} - F^{a,j}_{real}\right)^2}{N}} \quad (9)$$

where $F^{a,j}$ represents the prediction QoS data of user *a* who invoked Web service *j*; $F^{a,j}_{real}$is the real value of user *a* who invoked Web service *j*, which we deleted before predicting the QoS data; *N* is the number of predictions. The smaller the absolute value of RMSE is, the more accurate the prediction.

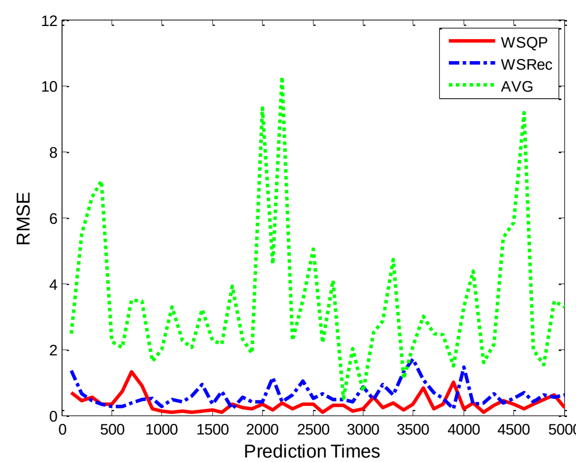


Figure 7. The ordinate represents the mean absolute error and the abscissa represents the times of prediction. By comparing WSQP, WSRec and AVG on RMSE, the RMSE based on WSQP is the smallest over the majority of prediction experiments. Thus, we can

further judge that our approach (WSQP) outperforms WSRec and AVG in Mobile Internet environments.

As shown in Fig.7 $(\mathrm{N} = 100)$, we find that, after comparing WSQP, WSRec and AVG on RMSE, the RMSE based on WSQP is the smallest over the majority of prediction experiments. This means that our approach can significantly improve the accuracy of QoS predictions for Web services in Mobile Internet environments. Thus, we can further judge that our approach (WSQP) outperforms WSRec and AVG in Mobile Internet environments.

D. Comparison on different density of user-item matrix

For testing WSQP, we conducted many experiments on different density of user-item matrix, and compared the results on MAE (N=100) in Fig.8:

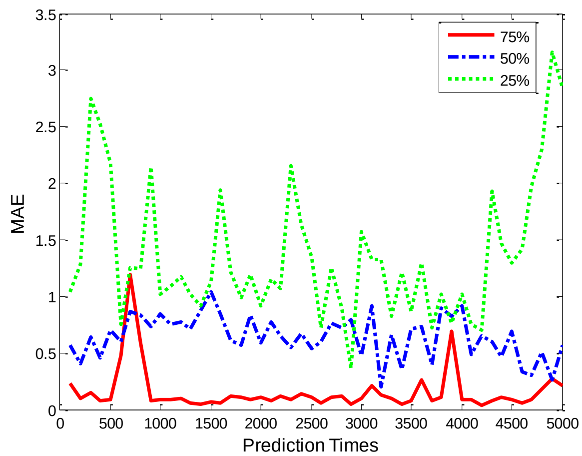


Figure 8. The ordinate represents the MAE (N=100) and the abscissa represents prediction times. Different lines represent the results on different density of user-item matrix. The higher the density is, the more accurate and stable the prediction. When the density lower than 50%, for example 20%, the results is unstable and inaccurate.

As shown in Fig.8, we conducted three experiments on different density of user-item matrix (75%, 50%, and 25%). The experiments indicate that the higher the density is, the more accurate and stable the prediction. When the density lower than 50%, for example 20%, the results is unstable and inaccurate. That means when the density higher than 50%, our approach can predict more accurate and more stable.

E. The Parameter K

To determine the value of *K*, we perform many experiments on different Top-*K*, and the MAE $(\mathrm{N} = 200)$of these experiments are shown in Fig.9.

As shown in Fig.9, when *K* is 1 and 2, MAE is the least and acceptable. To obtain more accurate and reliable results, we should take into account more similar users. Thus, we trust that, in these datasets, *K*=2 is appropriate. In the above experiments, we performed all of them based on *K*=2

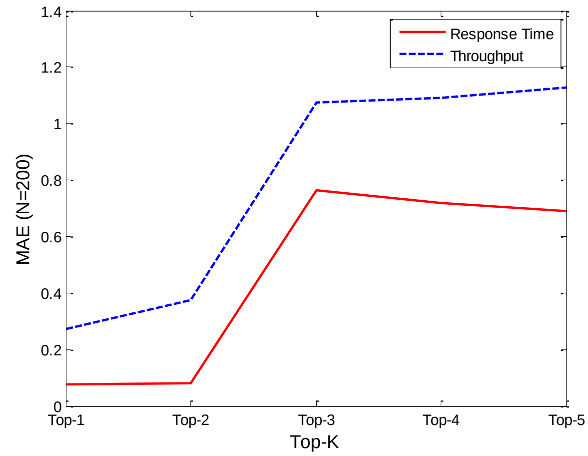


Figure 9. The ordinate represents the MAE (N=200) and the abscissa represents different Top-*K*. When *K* is 1 and 2, MAE is the least and acceptable.

V. CONCLUSIONS

Through the analysis and presentation of this paper, we learned that the QoS data of Mobile Internet, especially the response time data, is so unstable. Thus, it is obviously not exact to use only one time QoS data. How to avoid abnormal data by an easy approach is an important breakthrough of this paper.

In this paper, we presented an easy and accurate QoS prediction approach for Web services in Mobile Internet environments. The QoS data acquired from the real-world Internet only needs an easy approach for processing, and then it can be directly applied to prediction. This approach is highly reliable, has a wide application environment and also shows its prediction strengths. The experimental results show that our approach obtains a more accurate QoS prediction than other approaches.

Due to the limitation of the data sets, there are still errors observed among similar users and the prediction of QoS data.

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