Skyline Service Selection based on QoS Prediction

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***Abstract*—In this paper, we propose a Skyline service selection approach based on QoS prediction. We first consider the QoS history records as time series and predict the QoS values by using Autoregressive Integrated Moving Average (ARIMA) model to provide more accurate QoS attributes values. And then we calculate the uncertainty of the prediction result by adopting an improved Coefficient of Variation. In order to downsize the search space, we employ Skyline computing to prune redundant services and then perform Skyline service selection by using Mixed Integer Programming. Extensive experimental results show that our approach has a better performance than other approaches.**

Keywords-service selection; QoS prediction; skyline service

I. INTRODUCTION

With the rapid development of cloud computing platform, the number of services deployed in the cloud is increasing rapidly, which makes it more difficult for users to obtain the composite service with high reliability in a relatively short time. Although the existing service selection methods have achieved good results, but there are still three problems:

1) Limited QoS history records. In previous studies, the QoS attributes values are generally expressed as the arithmetic mean of the historical records. In fact, if the QoS history records of Web service have an upward or downward tendency, it will not be accurate that denote the further QoS attributes values only based on the means of QoS history records, and it will influence the success rate of the final Web service composition.

2) Ignore the QoS uncertainty. Due to the dynamic Web service environments, the true QoS attributes values of some candidate services will deviate from the aggregation QoS attribute value [1], which makes the reliability of service selection low, and even lead to the failure of service selection.

3) Poor real-time performance. When the service users have to face a mass of candidate services with the same functionality but different QoS attributes values, many excellent service selection optimization algorithms still consume a huge amount of computing time.

In view of the above three problems, we propose a Skyline service selection approach based on QoS prediction. Our approach contains four steps. The first step is QoS prediction, in which we create a model by analyzing the time series of the QoS history records based on ARIMA model in time series analysis, and then use the model to predict the QoS attributes values of candidate services. The second step is QoS uncertainty computing, in which we adopt an improved Coefficient of Variation to compute the uncertainty of prediction results and filter the candidate services with high uncertainty. In the third step, we adopt the Skyline computing to downsize the solution space further, and improve the real-time performance. The last step is Skyline service selection, in which we use Mixed Integer Programming to find the best Skyline services with the higher reliability and lower time cost.

II. OUR APPROACH

A. ARIMA model for QoS prediction

To improve the reliability of service selection, we adopt ARIMA model to predict QoS attributes values. The QoS attributes of services are considered as random variables, and the QoS history records are considered as time series. Based on a large number of the QoS history records, we use ARIMA model which can predict the QoS values in the future. To build ARIMA model [2], we need to different the time series data until it is smooth. And then build ARMA model of the smooth time series as follows:

$$x_t = \varphi_1 x_{t-1} + \varphi_2 x_{t-2} + \cdots + \varphi_p x_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (2)$$

where $\{x_t\}$(t=1,2,…) is a QoS history records in t time periods, $\{\varepsilon_t\}$ is a white noise sequence which cannot be observed and contain the tendency of the QoS history records time series, p and q are estimated according to the autocorrelation and partial autocorrelation functions of the QoS history records time series, $\{\varphi_p\}$ and $\{\theta_q\}$ are determined by matching the QoS history records.

Having been built ARIMA model for QoS prediction, we can predict the QoS attributes values in the $(t+1)^{th}$ time period, and then we can also obtain the predicted value of each history record value. Hence in this paper, we can estimate the reliability of the prediction result by the deviation between the predicted QoS history values and the real QoS history records.

B. QoS uncertainty computing

To reduce the uncertainty of service selection, we will compute the uncertainty of prediction results using an improved Coefficient of Variation. The improved Coefficient of Variation (ICV) can be expressed by the following:

$$ICV = \tilde{S} / \bar{X} \times 100 \quad (2)$$

with

$$\overline{X} = \frac{1}{t}\sum_{i=1}^{t} x_i \tag{3}$$

$$\tilde{S} = \sqrt{\frac{1}{t-1}\sum_{i=1}^{t}(x_i - \hat{x}_i)^2} \tag{4}$$

where x_i represents the QoS attribute history record value in the i^{th} time period, $\hat{x}_i$ represents the QoS predicted value, t represents the number of time period, $\overline{X}$ is the mean of the historical records, $\tilde{S}$ is the improved standard deviation. Compared with natural Coefficient of Variation [3], $x_i - \bar{x}$ is replaced by $x_i - \hat{x}_i$. The sum of squared residuals is used to reflect the uncertainty of the predicted QoS attributes values in ICV. By using ICV, we can find and filter the candidate services with high uncertainty.

C. *Skyline computing*

After QoS uncertainty computing, the rest of the search space is still large, most of the rest candidate services are redundant. Therefore, we adopt Skyline computing [4] to downsize the search space further. Skyline computing can filter the redundant services, and the remaining services are called *Skyline services*. And then we only need to select the best services from the Skyline services [5].

D. *Skyline servcie selection*

QoS uncertainty computing and Skyline computing reduce a large number of redundant services, and speed up the service selection process. Then we need to select the best Skyline services. As it is well known that service selection problem is a multi-objective optimization model [1]. In this paper, we adopt the linear weighted model to transform this problem into a single objective optimization [6], and then we can get a utility function which can represent the objective function. Finally, the Mixed Integer Programming is adopted to solve this single objective optimization problem for finding the best Skyline service selection solution.

III. Performance Evaluation

In this section, we compare our approach called ASMIP with MIP approach [7] and SkylineMIP approach [6] based on a real-world service QoS dataset [8] in terms of computing time and reliability.

Figure 1 shows that the comparison results of reliability, where we use the previous 245 QoS attribute history records (the total number is 250) to select service, and use the 246th history record to compute the QoS utility values of the selected service. As shown in Figure 1, similar to other approaches, our approach also has high reliability. The reliability value of our approach is near to 1, which means that our approach can find the best Skyline service. Note that in Figure 1, the reliability of MIP and SkylineMIP approach is similar. The main reason is that Skyline computing don't influence the reliability of service selection. Figure 2 shows the comparison results of computation time where the number of candidate services is from 100 to 1000. As shown in Figure 2, our approach is much better than other approaches, and it is 10%, 24% shorter than MIP and SkylineMIP on average. The main reason is our approach filters a large number of redundant services, and downsizes the search space.

In a word, as shown in Figures 1and 2, our approach can find the best Skyline service selection solution with lower computation time than other approaches.

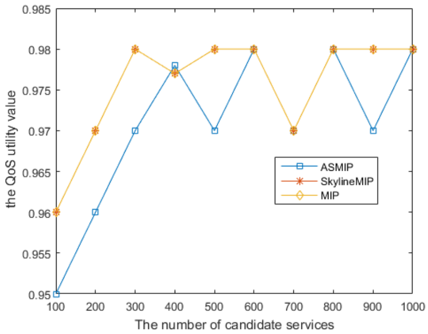

Figure 1. Comparison results on reliability

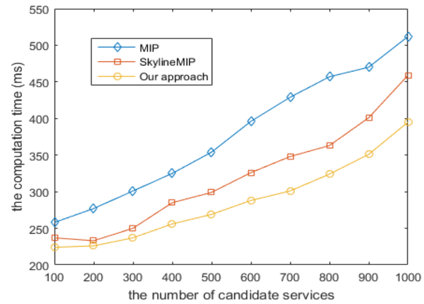

Figure 2. Comparsion results on computing time

IV. Conclusion

In this paper, we proposed a reliable and fast Skyline service selection approach based on Skyline computing and ARIMA model. Its key idea is to perform Skyline service section based on QoS prediction. Experimental results show that compared to previous approaches, our approach can significantly improve the real time performance of Skyline service selection with reliability guarantee.

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