Efficient Algorithm for Predicting QOS in Cloud Services

Sangeeta R. Alagi, Srinu Dharavath

Abstract— ***Now a days, Cloud computing is becoming more popular research topic. Building high-quality cloud applications is a critical research problem and it has lot of demand. QoS rankings provide valuable information for making optimal cloud service selection from a set of functionally equivalent service candidates. To obtain QoS values, real-world invocations on the service candidates are usually required. Inorder to avoid the time-consuming and expensive real-world service invocation,. Here, in this paper we have proposed Cloud Rank Framework for QoS ranking prediction framework for cloud services. In this approach ,we have also described Amazon.com recommendation amd SMICloud approach with their Pros and Cons. We have also briefly compare our proposed approach with previous work with respect to response time, throughput and cost estimation.***

Our proposed approach gives better result than previous work. This proposed a personalized ranking prediction framework Cloud Rank, used to predict the QoS ranking of a set of cloud services without requiring additional real-world service invocations from the intended users. For making personalized ranking prediction it uses past experience of other use. It generally uses utilizing content information Technique.

Index Terms— **Cloud Computing, Cloud Service Provider, Ranking Prediction, Personalization, Quality-of-Service.**

I. Introduction

Cloud computing is nothing but an Internet-based computing service, where user can share the available configurable resources for e.g. Infrastructure, Platform, Database, Hardware resources ,software etc. Now a days, cloud computing becomes very popular. Cloud computing platform is strongly promoted by the various leading industrial companies such as e.g., Amazon, Google, Microsoft, IBM, etc. Applications which has been deployed in the cloud environment are large scale and complex. Due to the rising popularity of cloud computing, now it has become research topic that how to build high-quality cloud applications and deploy on the cloud.

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Sangeeta R. Alagi *ME Computer Engineering, G. S. MOZE College of Engineering Balewadi, Pune, Maharashtra – India .*

Srinu Dharavath, *, Assistant Professor, Computer Engineering, G. S. MOZE College of Engineering Balewadi, Pune, Maharashtra – India.*

In order to measure the nonfunctional performance of cloud services we usually use parameter called quality-of-service (QoS). QoS is an important research topic in cloud computing. When we try to select optimal cloud service from a set of functionally equivalent services, we can use QoS values of cloud services for assisting decision making. In traditional component-based systems approach, software components are invoked locally, but on the other hand in cloud applications, cloud services are invoked remotely through the Internet connections. In cloud service Client-side performance influenced by the unpredictable Internet connections. Because of this unpredictable Internet connection different cloud applications may get different levels of quality for the same cloud service.

Our proposed approach consist of following module:
First, we have tried to identifies the various critical problem associated with the personalized QoS ranking for cloud services. Also we have proposed a QoS ranking prediction framework in order to address the problem. The CloudRank is the first personalized QoS ranking prediction framework for cloud services.

Second, we have conducted various experiments in order to identify the ranking prediction accuracy of our ranking prediction algorithms compared with other competing ranking algorithms. We have also compared our Framework to previous approach with respect to Response Time, Throughput and Cost estimation. For all this parameter our approach give better result.

II. Literature Survey

A.Amazon.com Recommenadation

Here, in this work [3] author have proposed Recommendation Algorithm which determines a set of customers whose purchased and rated items. The working of this algorithm is quite simpler that it aggregates items from all the similar customers, and it eliminates items the user has already purchased it has been already rated. It allows user to recommends the remaining items This proposed approach also used to distinguish the online store for each customer, but it needs to apply recommendation algorithms for targeted marketing, both online as well as offline.

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Advantages:
(i) This proposed approach gives high quality recommendations to the user .
(ii) Results showed that this proposed recommendation system perform less offline computation than traditional collaborative filtering techniques.
Limitation:
(i) We need to apply this recommendation algorithms for the targeted marketing, both online and offline.
(ii) We need to support for offline retailers also by using various forms of customer ommunication like, postal mailings, coupons, etc.

B SMICloud :

Here[4], author have proposed a framework to measure the quality of Cloud services. It is possible to makes major impact and creates healthy competition among the various Cloud providers to satisfy their Service Level Agreement (SLA) .Tthus SMICloud improve their Quality –of-Services (QoS).

In this work author have proposed an Analytical Hierarchical Process (AHP) based ranking mechanism which estimate the cloud services based on different applications depending on QoS requirements.

Analytical Hierarchical Process (AHP) based ranking mechanism generally used only for quantifiable QoS attributes such as Accountability, Cost, Performance, Security, Privacy, and Usability. This approach is suitable for non-quantifiable QoS attributes such as Service Response-time, Accuracy, Transparency, Availability, Reliability etc.

SMI Cloud consist of following three module:

I.SMICloud Broker:

SMI Cloud receives request from the customer those who want to deploy an application. It collects all requirements and performs the discovery and ranking of these services by using other components called SMICalculator and Ranking systems. SLA Management is the component that keeps track of Service Level Agreement of each customers with Cloud providers and their history. The Ranking System is used to ranks the services which has been selected by the Cloud Broker that are appropriate for user requirements and of user needs. The SMI Calculator is used to calculates the various KPIs value in order to rank the system for prioritizing the Cloud services.

II. Monitoring:
This particular component of SMICloud discovers the Cloud services which can satisfy user'sl QoS requirements. Then, it monitors the performance of the Cloud services such as speed of memory, storage capacity ,networking parameter, bandwidth etc. It also monitors that how SLA requirements of previous customers are being satisfied by the Cloud provider

III. Service Catalogue:
This component stores the services and their features of Cloud providers.

Advantages and limitation of SMI cloud:
(i) SMICloud provide us uniform way to evaluate the relative ranking of Cloud services for each type of QoS attribute.
(ii) Performance monitoring and analysis tools of SMICloud are used to rank and measure the QoS of various Cloud services according to user's applications.
Limitation:
(i) It is not possible to measure Non quantifiable QoS attributes.
(ii) SMI Cloud is not that much compatible with various QoS attributes

III. PROBLEM STATEMENT WITH MOTIVATION

personalized cloud service QoS ranking is used to evaluate all the candidate services at the user-side. It is also used to rank the cloud services based on the observed QoS values. But, this approach is impractical in reality, because sometime we may have to charge for the particular cloud services. Even if we consider the invocations are free, but while the executing a large number of service invocations, it is very is time consuming and resource consuming process. It is also difficult for the cloud application designer to evaluate the cloud services effectively ,if the number of candidate services are in large number.
So, in order to solve this problem, we have proposed a personalized ranking prediction framework, called CloudRank. By using CloudRank it is possible to predict the QoS ranking of a set of cloud services.
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IV. SYSTEM IMPLEMENTATION

A. System Architecture

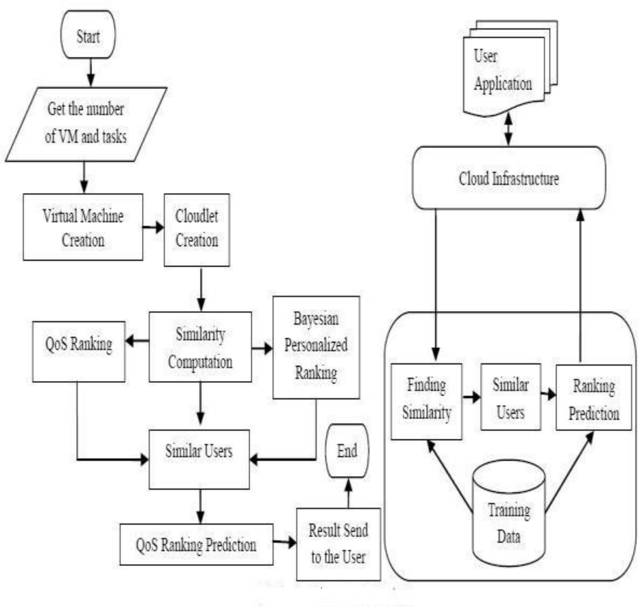

Figure 4.1: System Architecture of Cloud Rank.

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Above figure 2.1 shows the system architecture of our proposed CloudRank framework, which provides us personalized QoS ranking prediction for various cloud services. The Cloud Rank Framework consist of following modules:

I. Similarity Computation:

First, based on the user-provided QoS values, we have to calculate similarities between the active user and training users.

For Ranking similarity computations we need to compare the users QoS rankings on the commonly invoked cloud services. For example ,Suppose if we have a set of four cloud services, on which two users have observed response-times of say <1, 2, 4,3> and <2, 4, 5,6>, respectively. From the above example we can clearly say that The response-time values on these services observed by the two users are completely different from each other and resopnse time always depend upon the Internet connection.

The Kendall Rank Correlation Coefficient (KRCC) can be used to evaluate the degree of similarity by considering the number of inversions of service pairs .

The KRCC value for the two users u and v can be calculated by the following formula :

$$Sim(u,v) = \frac{C-D}{N(N-1)/2}$$

Where:

N = the number of services,

C= the number of concordant pairs between two lists,

D is the number of discordant pairs,

and there are totally N(N -1)/2 pairs are available for N cloud services..

II .Find the Similar Users

By calculating similarity values between the current active user with other training users, the similar users can be identified.

the Top-K similar users for making QoS ranking prediction. In our approach, a set of similar users S(u) is identified for the active user u by the following formula:

$$N(u) = \{v | v \in T_u, Sim(u,v) > 0, v \neq u\},$$

where T_u is a set of the Top-K similar users to the user u and Sim(u, v)> 0 excludes the dissimilar users with negative similarity values.

III. QoS Ranking Prediction

After identifying the similar users , we have used two algorithms CloudRank1 and CloudRank2 for the personalized service ranking by taking advantages of the past service usage experiences of similar users. Finally, the ranking prediction results can be provided to the active user.

We can obtaine the training data for CloudRank framework from the QoS values provided by other users and the QoS values collected by monitoring cloud services.

V. MATHEMATICAL MODEL

A. Analysis of Computational Complexity :

consider there are n cloud services and m users, we can calculate the worst case computational complexity of the proposed Cloud Rank algorithms. Already we have came across the computational complexity of Sim(a, u) by KRCC is $O(n^2)$ since there are N(N-1)/2 cloud services are available.

In order to find similar users we need to calculate the similarities between the active user with all the m training users. So ,therefore there are totally m times of similarity computations. So, the total computational complexity of similarity computation is $O(n^2 m)$ when using the KRCC similarity measure.

After the identification of similar users, we need find out the preference values between different pairs of cloud services. There are totally n(n – 1)/2service pairs. For each pair, in the worst case, we need to get QoS values from the Top-K similar users for making preference value estimation. Since there are at most m similar users, the total computational complexity of preference value computation of an active user is $O(n^2m)$ Based on the preference values. computational complexities of CloudRank1 and CloudRank2 are both equal to $O(n^{2)})$.

VI. EXPERIMENTAL RESULT

For the implementation of this proposed framework Java Technology has been used . The CloudSim toolkit supports both system and behavior modeling of Cloud system components for example data centers, virtual machines (VMs) and various other resources.

A. Response Time

In order to evaluate the performance of our proposed Cloud Rank framework we have used various attributes for the measurement of QoS of cloud services. Response-time refers to the total time duration between the user sending a request to a cloud service and receiving a response from that service to the user. Figure 5.1 shows the Comparision of Resoponse Time between cloud rank and Bayesian Ranking approach[2].

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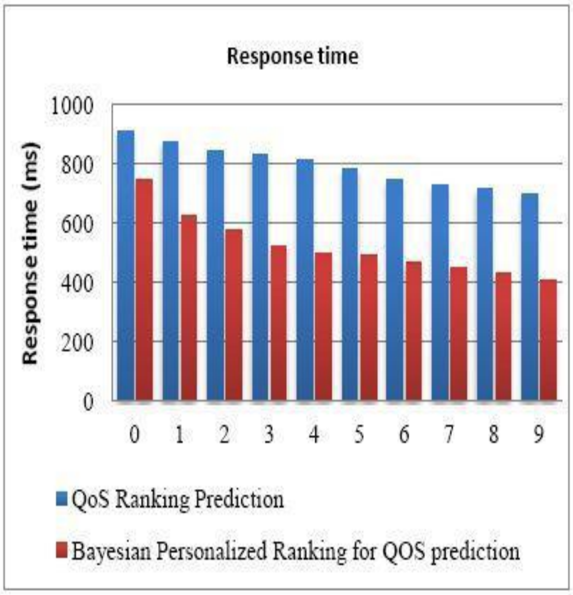

Figure 6.1: Comparision of Resoponse Time between QoS Rank and Bayesian Ranking.

From the above comparision chart we can show that proposed Bayesian personalized ranking method [2] for Qos predication method resonse quick than the Qos ranking predication method for the server.

B.Throughput

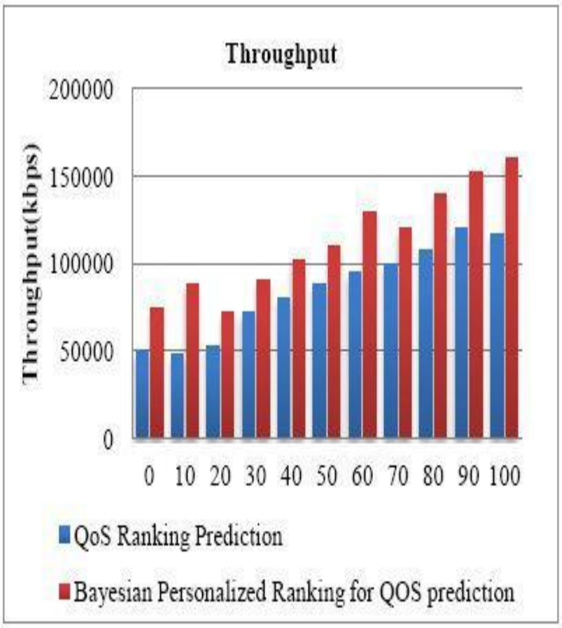

Figure 6.2: Comparision of Throughput between QoS rank and Bayesian Ranking.

Above figure 5.2 shows the result of QoS Throughput for QoS ranking prediction and Bayesian Personalized Ranking method for QoS Prediction. From above chart we can easily shows that proposed Bayesian Personalized Ranking method for QoS Prediction methods achieves higher throughput result than QoS ranking prediction methods for services.

Cost Estimation:

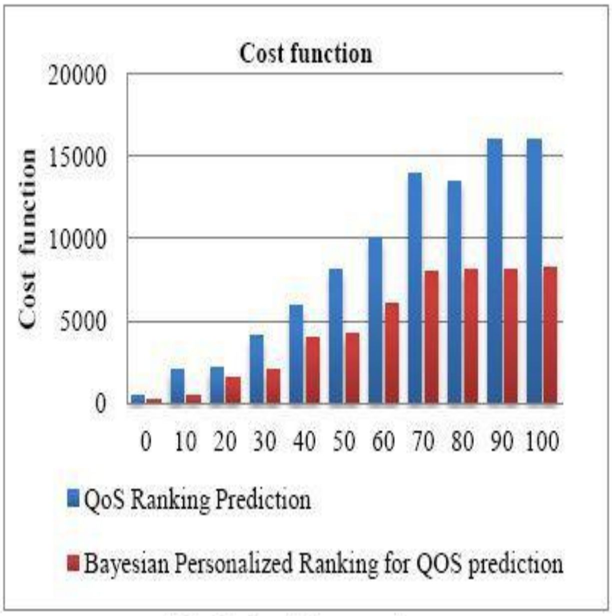

Figure 6.3: Comparision of Cost between QoS Rank and Bayesian Ranking.

.Figure 6.3 shows the result of QoS cost function result for QoS ranking prediction and Bayesian Personalized Ranking method [2] for QoS Prediction, it shows that our proposed Bayesian Personalized Ranking method for QoS Prediction methods achieves lower costt than QoS ranking prediction methods for services

VII. CONCLUSION AND FUTURE WORK

Our proposed framework is used to predict QoS ranking for cloud services. There is no need to require an additional service invocation while making QoS ranking. The training dataset is taking an advantage of past user experience of other users. The QoS value implies the prediction of the ranking accuracy. We have proposed Bayesian ranking for Qos prediction for computing the service ranking based on the cloud application designer's preferences. Experimental results[2] show that our approaches outperform existing rating-based approaches and the traditional greedy method.

As our current approaches only rank different QoS properties independently, we [2] will conduct more investigations on the correlations and combinations of different QoS properties. We will also investigate the combination of rating-based approaches and ranking-based approaches, so that the users can obtain QoS ranking prediction as well as detailed QoS value prediction. Moreover, we will study how to detect and exclude malicious QoS values provided by users.

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