International Journal of Scientific & Engineering Research, Volume 6, Issue 4, April-2015 24
ISSN 2229-5518

QoS Ranking Prediction Framework for Cloud Services

J.Subathra, P.Latchoumy

Abstract— The rising popularity of cloud computing makes building high quality cloud applications a critical and urgently required research problem. 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. The existing system focuses on QoS ranking prediction for cloud services by taking advantage of the past service usage experiences of other consumers. This framework requires no additional invocations of cloud services when making QoS ranking prediction. Two personalized QoS ranking prediction approaches are proposed to predict the QoS rankings directly. The Proposed system is designed to improve the ranking accuracy of the approaches by exploiting additional techniques. When a user has multiple invocations of a cloud service at different time, the proposed system will explore Levenshtein distance calculation approach to find similarity for cloud services by employing information of service users and cloud services. Cloud Rank approach provides reliable service to the user.

Index Terms— Quality of Services, Ranking Prediction, Cloud Services, Optimal Cloud Service Selection.

1 INTRODUCTION

Cloud computing is Internet-based computing, and it is shared by a configurable resources that is provided to computers and other devices as services. Different cloud applications may receive different levels of quality for same cloud services so that the optimal service selection becomes important The QoS ranking of cloud services for a user (e.g., cloud application 1) cannot be transferred directly to another user (e.g., cloud application 2), since the location of the cloud applications are quite different. Some service invocations can produce irreversible effects in the real world. Moreover, when the number of candidate services is large, it is difficult for the cloud application designers to evaluate all the cloud services efficiently.

The cloud removes the need for you to be in the same physical location as the hardware that stores your data. There are number of functionally equivalent services in the cloud Due to unreliable internet connections different cloud applications may receive different levels of quality for same cloud services so that optimal service selection becomes important. Cloud computing provides three main services, namely Software as a Service (SaaS), Platform as a Service (PaaS), and Infrastructure as a Service (IaaS). In Software as a Service (SaaS), Clients can use the software that is provided by the provider, which usually need not to be installed on their own machine and they can use the software directly from the cloud and it is usually a one of many services (i.e.)Gmail, search engine. In Platform as a Service (PaaS), Clients can run their own applications on the platform provided; General platforms are Linux and Windows. In Infrastructure as a Service (IaaS), Client can put their own operating system on cloud.

- *J.subathra is currently pursuing master degree program in B S Abdur Rahman University, Chennai. E-mail: subathrait.jeeva24@gmail.com*
- *Ms. P. Latchoumy working as an Assistant Professor (Selection Grade) in B S Abdur Rahman University, Chennai.E-mail: lak75dhana @gmail.com.*

The personalized ranking prediction framework, named as Cloud Rank, is used to predict the QoS ranking for the set of cloud services without any additional real-world services invocation from the intended users. This approach takes advantage of the past usage experiences of other users for making personalized ranking prediction for the current user.

A. Optimal Service Selection

QoS is an important research topic in cloud computing and grid computing [2] [3]. There are a number of functionally equivalent services in the cloud, so the optimal service selection becomes important. Making an optimal cloud service selection from a set of functional equivalent services, QoS values of cloud services provide valuable information to assist decision making. Client-side performance of cloud services is greatly influenced by the unreliable internet connections. Therefore, different cloud applications may receive different levels of quality for the same cloud service. The training data in the CloudRank framework can be obtained from the QoS values collected by monitoring cloud services.

2 RELATED WORK

QoS Ranking Prediction on Cloud Services

The QoS ranking prediction works under the issue of building high quality cloud applications. The employee is used to describing the non-functional characteristic of employed and Web services is consider as an important differentiating point of different Web services. To evaluate the target Web service and share their observed Web service QoS information from users in different geographic locations collaborate with each other.

Z.Zheng, X.Wu, and J.Wang et al. [1] have proposed a Cloudrank Prediction Framework that predicts the QoS Ranking directly instead of predicting the experimental QoS values. These approach aim to predict the QoS values for different users. The target Cloud services used to rank the employee by predicted QoS values. The major challenge of making QoS-driven Cloud service quality ranking is that the user locations are different, so the Cloud service quality ranking of a user cannot be transferred directly to another user. In the existing system, it is personalized QoS Ranking for cloud services. It evaluates all the user-side Cloud services and rank the Cloud services based on the observation from QoS performance. Moreover, it is really a difficult task for the service users to calculate all the Cloud services themselves, since it exists a huge number of Cloud services in the Internet.

Z.Zheng and I.King et al. [5] Investigate about QoS-Aware Web Service by Collaborative Filtering proposed Hybrid collaborative filtering method that to increase the performance of Recommender System. It includes the novel hybrid collaborative filtering algorithm for Web service QoS value prediction, an efficient and a user-contribution mechanism for Web service QoS information collection. It is used to collect and store the systematic QoS information and it provides better feasibility of Web service recommender system but it needs to monitor and investigate the real world QoS properties of Web services.

Saurabh Kumar Garg, Steve Versteeg and RajKumar Buyya et al. [6] have described a framework to measure the prioritize Cloud services and the quality. This framework tends to make a major impact and creates healthy competition between Cloud providers to satisfy their Service Level Agreement (SLA) and increase their Quality–of-Services (QoS). The existing system proposed a ranking mechanism based on Analytical Hierarchical Process (AHP), which can estimate the cloud services based on different applications depending on QoS requirements. This technique is used to quantify the QoS attributes such as Accountability, Agility, Assurance of Service, Cost, Performance, Security, Privacy, and Usability. There is not suitable for non-quantifiable QoS attributes such as Service Response-time, Sustainability, Suitability, Accuracy, Transparency, Interoperability, Availability, Reliability and Stability.

Z.Zheng, Y.Zhang and M.R Lyu et al. [9] describes the Cloudrank approach and proposed a greedy algorithm. It tends to rank the sequence of the components instead of service. The rank of each set of items to be treated by the explicitly rated items and the unrated items equally. It does not assure that the explicitly rated items will be ranked correctly.

N.N.Liu and Q.Yang et al. [11] A collaborative filtering approach that addresses the item ranking problem directly by modeling user preferences derived from the ratings. Then, it measures the similarity between users based on the correlation between their rankings of the items rather than the rating values and propose new collaborative filtering algorithms for ranking items based on the preferences of similar users. Experimental results on real world movie rating data sets show that the new collaborative filtering approach outperforms traditional collaborative filtering algorithms significantly on the NDCG measure for evaluating ranked results. So here a QoS ranking prediction system is proposed to overcome the limitations of the existing system.

3 SYSTEM DESIGN

The architecture explains that the service selection process based upon ranking mechanism. It predicts the services before it provided to the user.

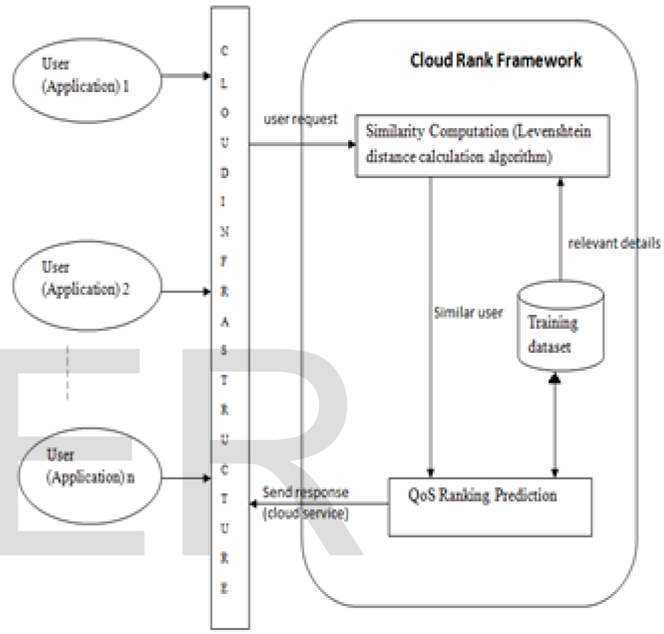

Fig.1. QoS Ranking Prediction Framework

The Fig. 1 depicts the ranking perdition system, user request the Service to the cloud provider, the cloud provider will refer the training dataset for relevant user details then the similarity computation to analyze and find out the similar user then prediction the ranking accuracy using QoS values that observed by the service user. The training dataset is taking an advantage of past user experience of other users. QoS values are response time and throughput value. Finally system predict the better service to the user.

4 METHODOLOGY

A. Levenshtein distance calculation for similarity computation

Step 1: Initialization

a) Set n to be the length of s, set m to be the length of t.
b) Construct a matrix containing 0..m rows and 0..n columns.

c) Initialize the first row to 0..n,
d) Initialize the first column to 0..m.

Step2: Processing
a) Examine s (i from 1 to n).
b) Examine t (j from 1 to m).
c) If s[i] equals t[j], the cost is 0.
d) If s[i] doesn't equal t[j], the cost is 1.

Step 3: Result
Step 2 is repeated till the sim(u,v) value is found

The user request is consider as a string, then the string will be evaluated by row and column-wise in matrix formation. The row is referred by user request and the column is referred by resides services in the training datasets. S[i] is equal to t[j] means cost is zero, else cost is one. The process is going until d[n] is found.

B. Cloud Rank algorithm:

a. Cloud Rank 1

Steps:

$$\psi(i,j) = \sum_{v \in N(u)^{ij}} w_v (q_{v,i} - q_{v,j}) \qquad \text{------ (1)}$$

where v is a similar user of the current u, $N(u)^{ij}$ is a subset of similar users, who obtain QoS values of both services i and j, and ω_v is a weighting factor of the similar user v, which can be calculated by

$$w_v = sim(u,v) \Big/ \sum_{v \in N(u)^{ij}} sim(u,v) \qquad \text{------ (2)}$$

ω_v makes sure that a similar user with higher similarity value has greater impact on the preference value prediction in (1). With (1) and (2), the preference value between a pair of services can be obtained by taking advantage of the past usage experiences of similar users.

Given a preference function Ψ which assigns a score to every pair of services i; j $\in$ I, From I quality ranking can be choosed, that agrees with the pairwise preferences as much as possible. Let ρ be a ranking of services in I such that ρ (i)> ρ (j) if and only if i is ranked higher than j in the ranking ρ. We can define a value function $V^{\Psi}(\rho)$ as follows, which measures the consistency of the ranking ρ with the preference function

$$v^{\psi}(\rho) = \sum_{ij:\rho(i)>\rho(j)} \psi(i,j) \qquad \text{------ (3)}$$

b. Cloud Rank 2

Steps:
Calculate Confidence Values:

The preference values ψ(i, j) in the CloudRank1 algorithm can be obtained explicitly or implicitly. When the active user has QoS values on together the services i and j, the preference value is attained explicitly. Assuming there are three cloud services a, b, and c. The active users have invoked service a and service b previously. The list further down shows how the preference values of can ψ (a, b), ψ(a, c), and ψ(b, c) be attained explicitly or implicitly.

- Ψ (a, b) Obtained explicitly.
- Ψ (a, c) Obtained implicitly by similar users with similarities of 0.1, 0.2, and 0.3.
- Ψ (b, c) Obtained implicitly by similar users with similarities of 0.7, 0.8, and 0.9.

In the above example, we can see that different preference values have different confidence levels. It is clear that C (a, b) > C (b, c) > C (a, c) where C represents the confidence values of different preference values. The confidence value of ψ(a, b) is higher than ψ(a, c), since the similar users of ψ(b, c)have higher similarities.
CloudRank2, which uses the following, rules to compute the confidence values:

1. If the user has QoS value of these two services i and j. The confidence of the preference value is 1.
2. When employing similar users for the preference value prediction, the confidence is determined by similarities of Similar users as follows:

$$c(i,j) = \sum_{v \in N(u)^{ij}} w_v \, sim(u,v) \qquad \text{------- (4)}$$

where v is a similar user of the current u, $N(u)^{ij}$ is a subset of similar users, who obtain QoS values of both services i and j, and ω_v is a weighting factor of the similar user v,which can be calculated by

$$w_v = sim(u,v) \Big/ \sum_{v \in N(u)^{ij}} sim(u,v) \qquad \text{------ (5)}$$

ω_v makes sure that a similar user with higher similarity value has greater impact on the confidence calculation. Equation (4) guarantees that similar users with higher similarities will generate higher confidence values. This algorithm achieved more accurate ranking prediction of cloud services.

5 IMPLEMENTATION AND RESULTS

To evaluate our proposed QoS prediction approach, this system implemented in web service. It collects a large scale of web service QoS dataset for conducting various experiments.

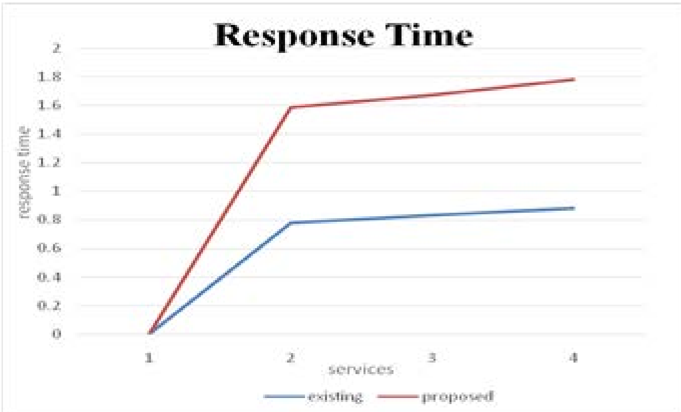

Fig.2.Value distribution using response time

Fig.2 shows the variance between the existing service and proposed service response time. According to that, the services are alloted by ranking method.

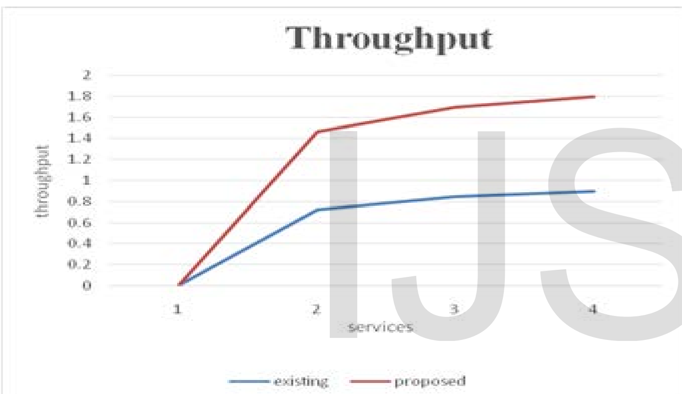

Fig.3. Value distribution using throughput

The above Fig.3 This experimental result provides the best service to the users thus it improves the throughput of the proposed system.

6 CONCLUSION

In this paper, our proposed system 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.

REFERENCES

[1] Zibin Zheng, Xinmiao Wu, Yilei Zhang,Michael R. Lyu, Fellow and Jianmin Wang, "QoS Ranking Prediction for Cloud Services", IEEE transactions on parallel and distributed systems, vol. 24, pp.1213-1221, 2013.

[2] Ms. M.Subha, Mr. K. Saravanan,"Achieve better ranking accuracy using cloudrank framework for cloud services", International journal of engineering trends and technology – vol.6, pp.307-312, 2013.

[3] P.Latchoumy, P.Sheik Abdul Khader,"Job Scheduling with Failure Prevention Strategies in Grid Computing Environment", International Journal of Advance Technology in Engineering, Volume 1, October 2013.

[4] P.Latchoumy, P.Sheik Abdul Khader ,"A Combined Approach Proactive and Reactive Failure Handling for Effective Job Execution in Computational Grid", paper presented at International Conference on Advance Computing, Networking and informatices(ICACNI),Raipur,India,June 12-14 ,2013.

[5] Hamzeh Khazaei, Jelena Mi_si_c, and Vojislav B. Mi_si_c, "Performance Analysis of Cloud Computing Centers Using M/G/m/m+r Queuing Systems" IEEE TRANSACTIONS ON PARALLEL AND DISTRIBUTED SYSTEMS, vol. 23, 2012.

[6] Chenxing Yang, Baogang Wei, Jiangqin Wu, Yin Zhang, Liang Zhang "CARES: A Ranking-Oriented CADAL Recommender System" IEEE TRANSACTIONS ON PARALLEL AND DISTRIBUTED SYSTEMS, 2012.

[7] Z.Zheng,H.Ma,M.R Lyu,and I.King,"QoS-Aware Web Service Recommendation by Collaborative Filtering",IEEE Trans.Service Computing ,vol.4, pp.140-152, 2011.

[8] Saurabh Kumar Garg,Steve Versteeg and RajKumar Buyya,"SMICloud: A Framework for comparing and Ranking Cloud Services",Published in Fourth IEEE International Conference on Utility and Cloud Computing in 2011.

[9] Zibin Zheng, Hao Ma, Michael R. Lyu, and Irwin King "WSRec: A Collaborative Filtering Based Web Service Recommender System" IEEE Transactions on Services Computing, 2011.

[10] Alexandru Iosup, Simon Ostermann, M. Nezih Yigitbasi, Radu Prodan,Thomas Fahringer, and Dick H.J. Epema[, "Performance Analysis of Cloud Computing Services for Many-Tasks Scientific Computing" , IEEE Transactions on Parallel and Distributed Systems, Volume. 22, 2011.

[11] Z.Zheng,Y.Zhang,and M.R Lyu,"CloudRank: A QoS-Driven Component Ranking Framework for Cloud Computing", Proc.Int'l Symp.Reliable Distributed Systems(SRDS'10), pp.184-193,2010.

[12] Emine Yilmaz, Javed A. Aslam, Stephen Robertson," A New Rank Correlation Coefficient for Information Retrieval", IEEE transactions on parallel and distributed systems,2010.

[13] N.N.Liu and Q.Yang,"Eigenrank: A Ranking-Oriented Approach to Collaborative Filtering",Proc.31st Int'l ACM SIGIR Conf. Research and Development in Information Retrieval, pp. 83-90,2008.