ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization) Vol.2, Special Issue 1, March 2014

Proceedings of International Conference On Global Innovations In Computing Technology (ICGICT'14)

Organized by

Department Of CSE, JayShriram Group Of Institutions, Tirupur, Tamilnadu, India on 6th & 7th March 2014

Achieve Ranking Accuracy Using Cloudrank Framework for Cloud Services

R.Yuvarani[1], M.Sivalakshmi[2]

M.E, Department of CSE, Syed Ammal Engineering College, Ramanathapuram, India

ABSTRACT: Building high Quality cloud applications becomes an immediately required research problem in cloud computing technology. Non-functional performance of cloud services is generally described by Quality-of-Service (QoS). To acquire QoS values, real-world usage of services candidates are generally required. At this time, there is no framework that can allow users to estimate cloud services and rank them based on their QoS values. This paper intends to framework and a mechanism that measures the quality and ranks cloud services for the users. CloudRank framework by taking the advantage of past service usage experiences of other users. So it can avoid the time consuming and expensive real life service invocation. This methodology determines the QoS ranking directly using the two personalized QoS ranking prediction approach namely, CloudRank1 and CloudRank2. These algorithms make sure that the active services are correctly ranked. The core determination is ranking prediction of client side QoS properties, which likely have different values for dissimilar users of the same cloud service. It estimates all the applicant services at the user-side and rank the services based on the observed QoS values.

Keywords: cloud services, CloudRank, Quality-of-service, ranking prediction.

I. Introduction

Recent days the cloud computing technology is popular because it is an attracting technology in the field of computer science. Cloud computing is internet based computing that generally referred the shared configurable resources (e.g., infrastructure, platform, and software) is provided with computers and other devices as services. Cloud computing entrusts services with a customer's data, software and computation over a network. The customer of the cloud can get the services through the network. In other words, users are using or buying computing services from others. Cloud can provide Anything as a Service (AaaS). In Cloud technology the QoS based service selection is an essential research topic. When many services offer similar functionality QoS values show a critical role for separating the optimal service for that particular task [8]. Because many number of cloud services are available. Since the user points of view, it is difficult to choose the best service and what mechanism used to select their services [6]. Qos models are associated with End-Users and providers.

In existing system Component-based system [15], cloud applications usually involve several cloud components communicating with each other over application programming interfaces, such as through web services. The process of this cloud application is collected by a number of software components, where each component fulfils a specified functionality. While there are a number of functionally equivalent services in the cloud, optimal service selection becomes essential. Once construct the best cloud service selection from a set of functionally the same services, QoS values of cloud services give key information to help decision making. Software components are invoked locally, whereas in cloud applications.

Cloud services are invoked remotely by Internet connection. Client-side performance of cloud services is thus seriously influenced by the unpredictable Internet connections. Therefore, different cloud applications may receive dissimilar levels of quality for the matching cloud service.so it need the additional invocations of cloud services**.** But it has following cons:

(1) When the number of applicant services is huge, it is complicated for the cloud application designer to estimate all the cloud services resourcefully

(2) QoS is very low so Improve the overall quality, by replacing the low quality components with better ones.

(3) It does not guarantee that the employed services will be ranked correctly.

Our proposed paper overcome above problems using Personalized ranking prediction framework, named Cloud Rank, it is the first personalized ranking prediction framework to calculate the QoS ranking of a set of cloud services not including requiring in addition real-world service invocations from the intended users. This approach takes gain of the past usage experiences of other users for building personalized ranking prediction for the Active user. It use the two algorithm namely cloudrank1 and cloudrank2.

This paper overcomes the existing system and it has the following pros:

(1) It avoids time-consuming and expensive real-world service invocations.
(2) It does not require additional invocations of cloud services.
(3) It takes the advantage of past usage experiences from other users.
(4) Identify the dangerous trouble of personalized QoS ranking for cloud services and proposes a QoS ranking prediction framework to tackle the problem.
(5) Achieve better ranking accuracy for cloud services compared with other ranking algorithm.
(6) Publicly release this service QoS data set for future research, so make this experiment reproducible.

II. RELATED WORK

There have been many studies of Quality-of-Service for cloud services. Since this work explores the issue of building high quality cloud applicattions.Quality-of-Service (QoS) is usually describing the non-functional characteristics of services and employed as an important differentiating point of different Web services. Users in different geographic locations collaborative with each other to evaluate the target Web services and share their observed Web service QoS information. Areas related to this work include the following: QoS Evaluation of Web Services, Neighborhood-based QoS Prediction of Web Services, and Model-based QoS Prediction of Web Services.

2.1 QoS Evaluation of Web Services

To accomplish efficient Web service evaluation, we recommend a distributed QoS evaluation framework for Web services. This framework employs the idea of user- collaboration, which is the means the concept of Web 2.0. In our framework, users in different geographic locations distribute their observed Web service QoS information. That information is stored in a centralized server and will be reuse for any other users.

2.2 Neighborhood-based QoS Prediction of Web Services

To exactly predict the Web service QoS values, we suggest a neighborhood-based collaborative filtering approach for predict the QoS values for the active user by employ past Web service QoS data from other similar users. Our approach systematically combine the user based approach and the item-based approach and it requires no Web service invocations and can help service users find out appropriate Web services by analyze QoS information from their similar users.

2.3 Model-based QoS Prediction of Web Services

The neighborhood-based QoS prediction approach has several drawbacks, including (1) the computation complexity is too high, and (2) it is not easy to find similar users/items when the user-item matrix is very sparse. To address these drawbacks, we plan a neighborhood-integrated matrix factorization (NIMF) approach for Web service QoS value prediction. Our approach explores the social wisdom of service users by systematically fusing the neighborhood based and the model-based collaborative filtering approaches to achieve higher prediction accuracy.

Item-Based Top-N Recommendation Algorithms that determine the similarity among the different items from the set of items to be suggested. The steps in this class of algorithms are (i) the method used to calculate the similarity between the items, and (ii) the method used to combine these similarities in order to calculate the similarity between a bin of items and a candidate recommender item. The goal of top-N recommendation algorithm was to categorize the items purchase by an individual consumer into two classes: like and dislike. This algorithm is faster than the conventional user-neighborhood based recommender systems and it provide recommendation with comparable or better quality. The proposed algorithms are independent of the size of the user–item matrix [1].

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization) Vol.2, Special Issue 1, March 2014

Proceedings of International Conference On Global Innovations In Computing Technology (ICGICT'14)

Organized by

Department Of CSE, JayShriram Group Of Institutions, Tirupur, Tamilnadu, India on 6th & 7th March 2014

Automatic Weighting Scheme for Collaborative Filtering that automatically computes the weights for different items based on their ratings from training users. The new weighting scheme will create a clustered distribution for user vectors in the item space by bringing users of similar interest's closer and separating users of different interests more distant but it provides low performance than Pearson Correlation Coefficient method [2].

The Collaborative Filtering technique that predict the missing data. It is making automatic predictions (filtering) about the interests of a user by collecting taste information from many other users (collaborating). User-based collaborative filtering predicts the ratings of active users based on the ratings of similar users found in the user-item matrix, Item-based collaborative filtering predicts the ratings of active users based on the information of similar items computed but it increases the density of User-Item Matrix and it predict some of the missing data only [18].

Collaborative filtering approach that addresses the item ranking problem directly by modeling user preferences derived from the ratings. It performs ranking items based on the preferences of similar users and it is used to identifying and aggregating the preferences in order to produce a ranking of items but it need to including data smoothing for improving traditional rating oriented collaborative filtering and then it has to utilize content information to our ranking-oriented approach [19].

III. ARCHITECTURE

The CloudRank framework provides optimal service selection from the more number of equivalent functionalities. Quality-of-service can be measured at the server side or at the client side. Client-side QoS properties provide more realistic measurements of the user usage experience. The generally used client-side QoS properties include response time, throughput, failure probability, etc. the system architecture of, which provides personalized QoS ranking prediction for cloud services. Within the framework it has many modules there are:

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization) Vol.2, Special Issue 1, March 2014

Proceedings of International Conference On Global Innovations In Computing Technology (ICGICT'14)

Organized by

Department Of CSE, JayShriram Group Of Institutions, Tirupur, Tamilnadu, India on 6th & 7th March 2014

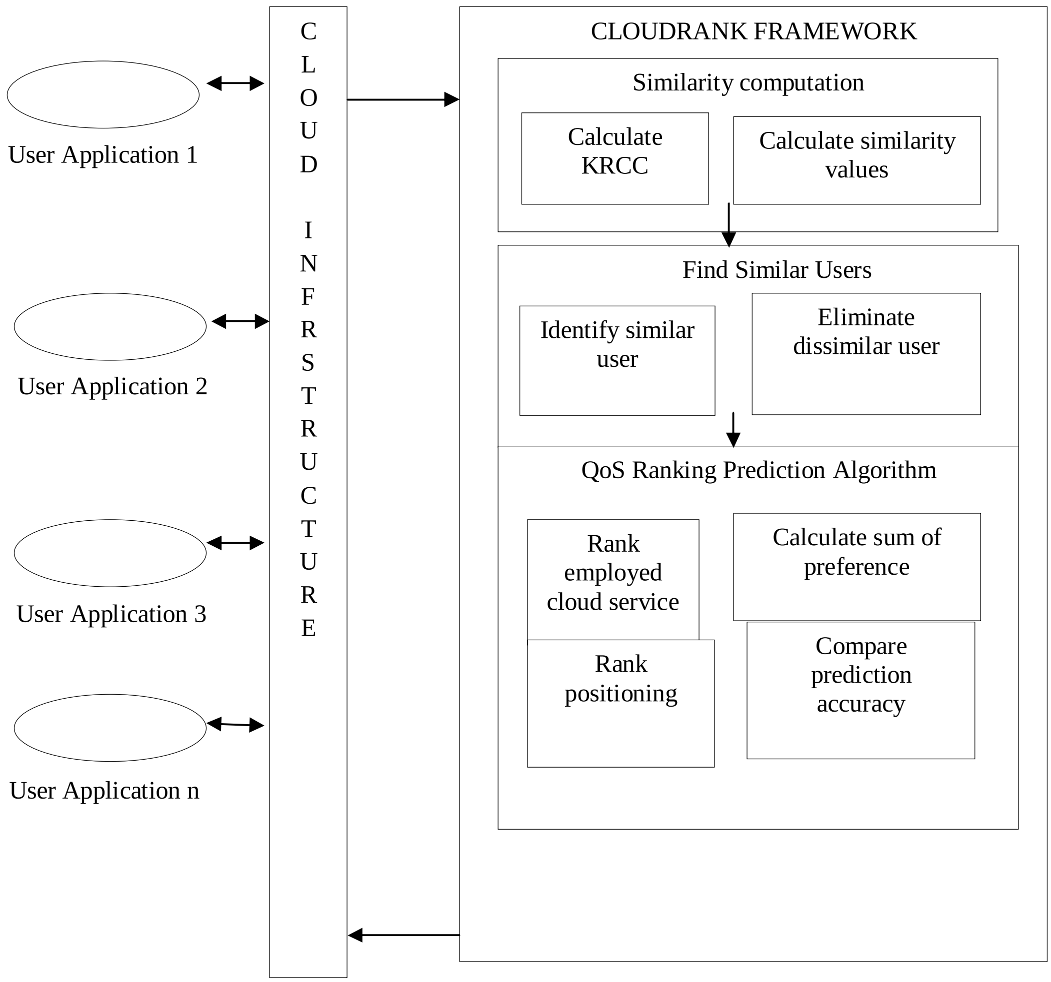

Fig.1. Architecture

A. Similarity Computation

The similarity computation of active users and training users are calculated based on the user provided qos values using Kendall Rank Correlation Coefficient (KRCC).It evaluates the degree of similarity by considering the number of inversions of service pairs which would be needed to transform one rank order into the other. The KRCC value of user's u and v can be calculated by,

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

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization) Vol.2, Special Issue 1, March 2014

Proceedings of International Conference On Global Innovations In Computing Technology (ICGICT'14)

Organized by

Department Of CSE, JayShriram Group Of Institutions, Tirupur, Tamilnadu, India on 6th & 7th March 2014

Where N is the number of services, C is the number of concordant between two lists, D is the number of discordant pairs, and there is totally N (N-1) /2 pairs for N cloud services. Ranking similarity is determined between the users. The response-time values on set of cloud services observed by the users are different.

B. Find Similar Users

Set of similar users can be identified to the Active user. Information of all the users for making ranking prediction, which may include dissimilar users. QoS values of dissimilar users will greatly influence the prediction accuracy. In our approach, a set of similar users is identified for the active user u by,

$$N(u) = \{v|v \in T_u, Sim(u, v) > 0, v \neq u\} \qquad (2)$$

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. The value of Sim (u, v) in 2 is calculated by (1)

C. Personalized Service Ranking

First predict the missing QoS values before making QoS ranking. Accurate QoS value is predicted using rating-oriented collaborative filtering approach. It does not lead to accurate QoS ranking prediction use two ranking algorithm.

D. Provide the Service to Active User

Personalized service ranking takes the advantage of past usage experiences of similar users. Then ranking prediction results are provided to the active user. Further exact ranking prediction results can be achieved through providing QoS values on more cloud services.

IV. ALGORITHM

In previous paper use the greedy based algorithm, it treats the explicitly rated item and unrated item equally so it does not use effectively and also does not guaranteed to delivered the services. So in our paper use the two ranking algorithm, the first one is CloudRank1 and next is CloudRank2.

Calculate sum of preference

Our ranking-oriented approaches predict the QoS ranking directly without predicting the corresponding QoS values. Rank the employed cloud services in E based on the observed QoS values stores the ranking, where t is a cloud service and the function $\rho_e(t)$ returns the corresponding order of this service. The values of $\rho_e(t)$ are in the range of, [1, |E|] where a smaller value indicates higher quality.

CloudRank1Algorithm:

Step 1:

Compute the sum of preference values with all other services by $\pi(i) = \sum_{j \in I} \psi(i, j)$.Larger $\pi(i)$ value indicates more service s is less than i. The value of the preference function $\psi(i,j)$ is anti symmetric, i.e., $\psi(i. j)= - \psi(j, i)$The preference function $\psi(i, j)$ where service i and service j are not explicitly observed by the Active user u.

$$\varphi(i, j) = \sum_{v \in N(u)^{ij}} w_v (q_{v,i} - q_{v,j}) \qquad (3)$$

Step 2:

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

$$w_v = \frac{Sim(u,v)}{\sum_{v \in N(u)^{ij}} Sim(u,v)} \qquad (4)$$

w_v makes sure that a similar user with higher similarity value has greater impact on the preference value prediction in (3).With (3) and (4), the preference value between a pair of services can be obtained by taking advantage of the past usage experiences of similar users.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization) Vol.2, Special Issue 1, March 2014

Proceedings of International Conference On Global Innovations In Computing Technology (ICGICT'14)

Organized by

Department Of CSE, JayShriram Group Of Institutions, Tirupur, Tamilnadu, India on 6th & 7th March 2014

The Consistency of the ranking ρ with the preference value calculated by

$$v^{\varphi}(p) = \sum_{i,j:\rho(i)>\rho(j)} \varphi(i,j) \qquad (5)$$

Step 3:

In this step, services are ranked from the highest position to the lowest position by picking the service t that has the maximum π(t) value. The selected service t is then removed from I and the preference sum values ψ (i) of the remaining services are updated to remove the effects of the selected service t

It treats the employed services in E and the non-employed service in I - E identically which may incorrectly rank the employed services. This step, the initial service ranking is updated by correcting the rankings of the employed services in E. Thus this algorithm guarantees that the employed services are currently ranked.

CloudRank2 Algorithm:

Step 1:

Calculate Confidence Values:

The preference values $\psi(i,j)$ in the CloudRank1 algorithm can be obtained explicitly or implicitly. When the active user has QoS values on together the services i and service 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 $\psi(a,b)$, $\psi(a,c)$, and $\psi(b,c)$ be attained explicitly or implicitly.

- $\psi(a,b)$Obtained explicitly.
- $\psi(a,c)$ Obtained implicitly by similar users with similarities of 0.1, 0.2, and 0.3.
- $\psi(b,c)$ 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 $\psi(a,b)$is higher than $\psi(a,c)$, since the similar users of $\psi(b,c)$ have higher similarities.

Step 2:

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:

$$C(i,j) = \sum_{v \in N(u)^{ij}} w_v \, \mathrm{Sim}(u,v) \qquad (6)$$

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

$$w_v = \frac{\mathrm{Sim}(u,v)}{\sum_{v \in N(u)^{ij}} \mathrm{Sim}(u,v)} \qquad (7)$$

w_v makes sure that a similar user with higher similarity value has greater impact on the confidence calculation. Equation (6) guarantees that similar users with higher similarities will generate higher confidence values. This algorithm achieved more accurate ranking prediction of cloud services.

ISSN(Online): 2320-9801
ISSN (Print): 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization) Vol.2, Special Issue 1, March 2014

Proceedings of International Conference On Global Innovations In Computing Technology (ICGICT'14)

Organized by

Department Of CSE, JayShriram Group Of Institutions, Tirupur, Tamilnadu, India on 6th & 7th March 2014

V. CONCLUSION

In this work, we have developed an efficient and effective utilization of cloud services access from the cloud providers. It is greatly useful for the cloud users that decide the best cloud services. We recommend a personalized QoS ranking prediction framework for cloud services, which need no additional service invocations when making QoS ranking. By taking advantage of the past usages experiences of other users, in our ranking approach find out and aggregates the preferences between pairs of services to produce a ranking of services. At last performance is enriched by efficiently utilizing the cloud services. The future work includes a low level specification for the user preferences and enhancing the proposed trade-off algorithm by adaptively controlling the number of concurrent proposals in a burst mode proposal to reduce the computational complexity. Improve the more ranking accuracy of this approach by using additional techniques and perform more investigations on the correlations and combinations of different QoS properties. Publicly release the QoS data set for future research.

REFERENCES

[1] M. Deshpande and G. Karypis, "Item-Based Top-n Recommendation,"ACM Trans. Information System, vol. 22, no. 1, pp. 143-177,2004.
[2] R. Jin, J.Y. Chai, and L. Si, "An Automatic Weighting Scheme for Collaborative Filtering," Proc. 27th Int'l ACM SIGIR Conf. Research and Development in Information Retrieval (SIGIR '04), pp. 337-344, 2004.
[3] 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.
[4] Z.Zheng and M.r.Lyu,"WS-DREAM: A Distributed Reliability Assessment Mechanism for Web Seervices,"Proc.38th Int'l Conf.Dependable Systems and Networks (DSN '08), pp.392-397, 2008.
[5] Mandeep Devgan, Kanwalvir Singh Dhindsa," A Study of Different QoS Management Techniques in Cloud Computing ", International Journal of Soft Computing and Engineering (IJSCE) ISSN: 2231-2307, Volume-3, Issue-3, July 2013.
[6] Mr.K.Saravanan, Lakshmi Kantham ,Assistant Professor, PG Scholar, Department of Computer Science and Engineering, Anna University Tirunelveli Region,Tirunelveli – 627007,Tamilnadu,"An enhanced QoS Architecture based Framework for Ranking of Cloud Services", International Journal of Engineering Trends and Technology (IJETT) - Volume4Issue4- April 2013.
[7] Mandeep Devgan, Kanwalvir Singh Dhindsa," QoS and Cost Aware Service Brokering Using Pattern Based Service Selection in Cloud Computing", International Journal of Soft Computing and Engineering (IJSCE) ISSN: 2231-2307, Volume-3, Issue-2, May 2013.
[8] P.A. Bonatti and P. Festa, "On Optimal Service Selection," Proc.14th Int'l Conf. World Wide Web (WWW '05), pp. 530-538, 2005.
[9] W.W. Cohen, R.E. Schapire, and Y. Singer, "Learning to order things," J. Artificial Intelligent Research, vol. 10, no. 1, pp. 243-270, 1999.
[10] P. Resnick, N. Iacovou, M. Suchak, P. Bergstrom, and J. Riedl, "Grouplens: An Open Architecture for Collaborative Filtering of Netnews," Proc. ACM Conf. Computer Supported Cooperative Work, pp. 175-186, 1994.
[11] B. Sarwar, G. Karypis, J. Konstan, and J. Riedl, "Item-Based Collaborative Filtering Recommendation Algorithms," Proc. 10th Int'l Conf. World Wide Web (WWW '01), pp. 285-295, 2001.
[12] J. Wu, L. Chen, Y. Feng, Z. Zheng, M. Zhou, and Z. Wu,"Predicting QoS for Service Selection by Neighbourhood-Based Collaborative Filtering," IEEE Trans. System, Man, and Cybernetics, Part A, to appears
[13] L. Zeng, B. Benatallah, A.H. Ngu, M. Dumas, J. Kalagnanam, and H. Chang, "QoS-Aware Middleware for Web Services Composition,"IEEE Trans. Software Eng., vol. 30, no. 5, pp. 311-327, May2004.
[14] Z. Zheng, H. Ma, M.R. Lyu, and I. King, "WSRec: A Collaborative Filtering Based Web Service Recommender System," Proc. Seventh Int'l Conf. Web Services (ICWS '09), pp. 437-444, 2009.
[15] 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.
[16]K.Vivekanandan1 , S.Neelavathi, S.Subhashree, G.Kavitha, and S.Kavitha,Pondicherry Engineering College, India.,"User-Rating Based QoS Aware Approach for SelectionOf Updated Web Services to Web ServiceComposition"Email: **kvivek27@yahoo.com,neelabaski@gmail.com.**
[17] Emprical analysis for predictive algorithm for collaborative filtereing,J.S. Breese, D. Heckerman, and C. Kadie, Proc. 14th Ann.Conf. Uncertainty in Artificial Intelligence (UAI '98), pp. 43-52, 1998
[18] H. Ma, I. King, and M.R. Lyu (2007), Collaborative Filtering technique.
[19] N.N. Liu and Q Yang (2008), collaborative filtering approach