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WEB MINING BASED CLOUD SERVICE RANKING AND RECOMMENDATION MECHANISM FOR PERSONALIZED USER IN CLOUD COMPUTING

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ABSTRACT

Lately, there is a rapid increase in the demand of CC-Cloud Computing. Companies offering cloud services have are now endowed with new enhancement in their list of services which includes: WB-Web Mining and DM-Data Mining taking into consideration variety of available computing resources. Recently, the RS-Recommender systems are offering improvised services to the users by minimizing the user's cost time so as to quickly achieve the required outcome. The approach of Cloud computing is the need of the hour and has turned out to be the computing infrastructure for the present generation computing. There exist numerous cloud vendors offering varied sort of cloud services as mentioned in the SLC - Service Level Catalogue. Selecting the best suitable cloud service for particular applications tends to be a difficult task. Among various challenges and issues faced by the CSP (cloud service provider), disappointment among the users related to the CSP stands the prime most. The reason being that there exists numerous cloud services having same functionalities but different non-functional attributes. In order to identify the most appropriate CSP the most suitable cloud service attributes and selected quality along with the feedback of the users is taken into consideration. In this research work proposed to achieve to Rating based service selection techniques for best cloud services selection processing and Multi-step matching algorithm for predict the best cloud service to be recommended personalized users. The main objective of this work is to recommend a methodology for choosing the most appropriate cloud service for the users from the environment of cloud computing. The mechanism updates the cloud service provider dynamically in order to deliver services. The constructed structure and related workflow involves following stages: first-cloud service filtering, second - selection, third - prediction, lastly, Ranking and recommendations. The CSS (cloud services selection) then handles the system by employing Rating Based Selecting Techniques, further, selecting quality and most appropriate cloud services is predicted by adopting MSM- Multi-Step Matching Algorithm and eventually, RBSR - Requirement Based Similarity Ranking Techniques (RBSR) is incorporated for suggesting the top most cloud service to be ranked to the personalized user. The scope of this research is to recommend best cloud service for personalized user. It's observed and analyzed that the personalized Cloud services recommendation system is yielding better performance compared to the present proposed techniques.

Keywords: *Cloud services, Multi-Step Matching Algorithm, Requirement Based Similarity Ranking Technique, Service Level Catalogue, Cloud Service Selection, web mining, and recommendation system.*

1. INTRODUCTION

Clouds can be considered as a computing system environment where users associates with a pool of inter-connected and distributed computing nodes thereby employing various cloud shared resources/services. In a Cloud computing scenario services are being offered to the clients on demand basis. Various services delivered by the CC to its clients include: Iass – (Infrastructure-as-Service), Pass (Platform-as-Service) and Sass (Software-as-Service). The technique of Web mining illustrates how the traditional techniques of data mining are applied over the web resources facilitating subsequent growth of these techniques taking into account the web-data framework specifically. RS (Recommender system) is a significant technique that assures to deliver valuable recommendations to the users and yielding satisfactory results. Multiple cloud services are being launched in the CC environment since the cloud users are growing in large numbers. With this, there is an increase in similar/relevant cloud services which makes the process of selecting the best cloud service amidst the available relevant/similar services (in the SLC) extremely complex. Selecting the best suitable cloud service for particular applications tends to be a difficult task. Among various challenges and issues faced by the CSP (cloud service provider), disappointment among the users related to the CSP stands the prime most. The reason being that there exists numerous cloud services having same functionalities but different non-functional attributes. It is difficult for the user to find the best cloud service. The current research recommends a methodology for choosing the most appropriate cloud service for the users from the environment of cloud computing. The mechanism updates the cloud service provider dynamically in order to deliver services. Following are the stages involved in the proposed mechanisms: Cloud Service - collection, Cloud Service-Filtering, Cloud Service-Selection, Rating Based Selection Technique, Prediction by employing Multi-Step Matching Algorithm, Cloud Service - Ranking, RBSR-Requirement Based Similarity Ranking Approach, and Cloud Service – Recommendation. Large volume of cloud services with supported details are assembled via online web portals. Various cloud service parameters are: RAM, memory, Cost and Qos. The next stage is of Filtering where unrelated data is eliminated. That is, attributes that are useless and not required are eliminated in the data filtering stage. Once the filtering is completed, cloud service selection takes place. While performing Cloud service selection numerous functionally similar services exists within the cloud. The appropriate cloud service is chosen on the basis of the listed cloud service required by the user. Using Rating based Selection Technique the selected cloud service is analyzed. The Qos parameter may alter in the SLC (Service Level Catalogue), the rating is performed based on that. The rating-based method aims to predict the QoS values with highest precision. Thereafter, the Multi-step matching algorithm is utilized for prediction. Next comes the ranking of cloud service. In order to rank the cloud service users requirement is taken into consideration and relying upon that cloud service with highest quality is ranked. All the cloud services ranks are evaluated by the Cloud service ranking on the basis of Qos values. Eventually, RBSR (Requirement based similarity ranking)is implemented to analyze the Qos (quality of service) attributes thereby ranking the best cloud service amidst the various cloud services that are functionally equivalent and then suggesting it to the personalized user. The aim of the proposed model is to propose the topmost cloud service to the user. The proposed model is examined on the basis of Accuracy. The target of the proposed system is to generate output relying upon the users priorities. The proposed cloud service recommendation model is evaluated and compared with rest of the traditional recommendation models. The outcome reveals that the proposed recommendation system consumes low time and yields accurate output compared to rest of the traditional recommendation system.

This research work is classified as follows: Section 2 -presents related work. Section 3 - presents the proposed methodology. Section 4 - presents the results achieved and discussions. Lastly, Section 5 concludes the work.

2. RELATED WORK

Md Whaiduzzaman et. al., proposes that Cloud Computing provides its distinctive services to various cloud customers anywhere and anytime in a pay-as-you-go manner. Cloud services offer services that are dynamically accessible over the Internet on a demand basis. Based on the requirements of the cloud customer best suitable services are being chosen. Various techniques are recommended concerning the cloud service selection issue, one of the technique being: MCDA (multi-criteria decision analysis) which permits the cloud user to make a selection amidst a variety of options available. The current work analyzes the application of MCDA in cloud service selection within the cloud computing environment. Numerous MCDA (multi-criteria decision analysis) techniques are identified and synthesized to offer a comprehensive analysis of the proposed technology for readers in general [1].

Parwat Singh Anjana et. al., proposes that availability of multiple cloud services in a CC environment results in the difficulty of selecting the best appropriate cloud service for the user. For resolving this issue employing a CSB (Cloud Service Broker) having knowledge of users Qos needs and service offerings will prove advantageous for CSPs (cloud service provider) and the users too. The current research proposes a Fuzzy Rough Set based Cloud Service Brokerage Architecture, which helps in selecting and ranking the services relying upon users QoS needs and supervise the service execution too. For reducing the dimension fuzzy rough set technique is imbibed and for ranking the CSPs (cloud service providers) weighted Euclidean distance is utilized. The experimental outcome of the research study reveals that the recommended technique is resilient, scalable, and yields in better output involving reduced search time [2].

Subha et.al, proposes that in order to evaluate Non-functional performance of cloud services QoS (quality-of-service) factor is utilized. Usually the cloud services in a cloud environment are triggered remotely via Internet. It's not possible to transfer the cloud services QoS ranking of a particular user to some other user because the cloud applications are located differently. The need occurs of a personalized QoS Ranking which can analyze the entire candidate services on the user end but in actual it's not possible. The existing research proposes a Cloud Rank framework which discards time utilizing and costly real-world service invocations and performs the QoS ranking prediction directly without calculating the respective QoS values. The proposed approach delivers an accurate ranking without the QoS values.[3]

Nivethitha Somu et al., (2017) [1] presents that there exists a large number of CSPs(Cloud Service Providers) in the cloud environment, as a result it becomes difficult for the CUs(Cloud Users) to select the best suitable CSP according to their needs. To resolve this, an appropriate service selection framework is designed which aids the users in choosing the best cloud service provider and simultaneously encourage the CSPs to abide by and fulfill the SLA(Service Level Agreement) also improvising the QoS (Quality of Service). The service selection framework allocates random weights to the QoS attributes and replace the missing data randomly as a result of which the CSPs ranking is no accurate. Hence to accurately rank the CSPs (cloud service providers), HGCM - Hyper graph based Computational Model and MDHP - Minimum Distance-Helly Property algorithm are being proposed. The dataset employed by the researches include the QoS attributes based dataset and synthetic dataset. Based on various studies, the output delivered by MDHP (Minimum Distance-Helly Property) algorithm assures that the ranking algorithm to be computationally attractive and scalable.[4]

XiaogangWang et, al, (2015) [2] presents that in the CC environment CSS (Cloud service selection) is gaining intense demand and popularity. As there exist numerous cloud service resources in a dynamic cloud environment, it becomes complicated for the user to choose the most appropriate cloud service concerning their applications, mostly related to online real-time applications. The shortcoming of the service selection framework is that it offers low quality, increased computing cost and high processing time. Resultant, a dynamically adaptive learning technique is designed for the CSS (cloud service selections) that depicts the adaptive features. The technique is built to optimize the CSS (cloud service selection) dynamically, delivering the best output to the user [5].

Nivethitha Somuet, al (2018) [3] presents that for CSS (Cloud service selection) the research offers an remarkable solution be adopting service ranking on the basis of QoS (Quality of Service) attributes to identify the best suitable CSPs (Cloud Service Providers) amidst a large pool of functionally similar CSPs. But since it takes only few parameters the service level ranking is quiet low and is not considered as an appropriate CSP selection approach. A trustworthy approach of HBFFOA (Hypergraph –Binary Fruit Fly Optimization Algorithm) for service ranking is introduced to identify the most trustworthy and appropriate CSP (cloud service providers). To omit local optima, a mutational probability function is utilized in HBFFO. HBFFOA Performance is evaluated by utilizing WSDream#2 dataset, recognizing user's needs, compliant CSPs, service ranking, data credibility etc…[6]

Zhu et al. (2015) [4] in a cloud environment trust assessment can be achieved on the basis of QoS (Qualities of Service) attributes. There exist numerous cloud services pertaining to real-world applications in a cloud scenario. A suitable sensor network provider is chosen which does not depend on any nodes. ATRCM-Authenticated trust and reputation calculation and management system are implemented for wireless sensor network integration and CC. ATRCM provides three type of functions alongside offering authentication service for CSPs (cloud service providers) and sensor network providers [7]

PeiYun Zhang et, al., (2018) the concept of CC (Cloud computing) has turned out to be a significant and essential commercial application and scientific computing model. There are many

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trust related issues dealt with the data and computing resources residing in the clouds. There is lack of confidentiality and cloud services QoS history is retrieved across varying time intervals. A newly built trust model and related algorithm is proposed to reduce the trust management overhead and enhance the competence of malicious node detection by utilizing domain partition. It's a model or a mechanism that prioritize Cloud services and evaluates its quality. By implementing such mechanism there is a remarkable effect which also builds a competition between the CSPs (cloud service providers) to fulfill their SLA (Service Level Agreement) and enhance their QoS (Quality of Service) [8].

Constanta Zoie et.al, the cloud marketplace and cloud users may require scientific decision making techniques for evaluating the cloud service providers and ranking them relying upon their necessities/requirements. Amidst the various techniques proposed for evaluating and ranking the CSPs(cloud service providers), MADM -Multi Attribute Decision Making is one of them. TOPSIS (is Technique for Order Preference by Similarity to the Ideal Solution) is a very popular method of MADM technique. Implementation of the recommended E-TOPSIS approach is discussed in the research work for evaluation and ranking of cloud service providers in terms of SMI (Service Measurement Index) factor [9].

Xu Wu et. al., presents, which targets on reliable trust-centric service selection and recommendation in the environment of mobile cloud computing. A novel SSRM - service selection and recommendation model is being proposed which considers the user related information and priorities/likings to compute the user similarity. Moreover, the Prop Flow algorithm is imbibed to compute the relational degree amidst services thereby enhancing the accuracy of ranking outcome. The SSRM method encourages a personalized and trustworthy selection of cloud services by considering mobile user's trust requirements [10].

Ma et al. proposes the approach of a time-aware service selection by adopting interval neutrosophic set. For choosing trustworthy cloud services amidst a pool of existing services requires considering and framing the time aware service selection with adjustments amidst potential risk and performance costs as a MCDM issue which builds a list of ranked services by employing INS-Interval Neutrosophic Set theory. The experimental output reveals that the recommended technique perform efficiently in both the modes of service selection i.e., risk-sensitive as well as the performance cost-sensitive mode, though avoiding the fluctuations concerning user context information within multi cloud computing environments [11].

Whaiduzzaman et al. [12] presents identification and synthesizing of various MCDA-multi-criteria decision analysis techniques, offering a comprehensive examination of the proposed technique for readers in general. Moreover a taxonomy is presented fetched from surveying the present work. It's clear from the output that the MCDA techniques are efficient enough and can be employed for CSS though other techniques don't opt for the similar service.

This [13][14] proposes a CSS (cloud service selection) technique that make use of QoS (Quality of Service) history of various cloud services across different time intervals and thereafter conduct parallel multi-criteria decision analysis for ranking of cloud services in every time slot according to preferences of the user and predict the complete ranking of existing options for CSS before the results are aggregated. By imbibing this technique the cloud service user is assisted in choosing the most appropriate cloud service as required. The shortcoming of the proposed methodology being that it handles the cloud service selection in pre-interaction phase itself. But there is a requirement of working on post-interaction service migration decisions too along with various essential parameters including migration cost related to service disruption and data transfer for the process of decision-making.

Fan et al. proposes the mechanism of multi-dimensional trust-aware CSS (cloud service selection) depending on the approach of evidential reasoning by aggregating the multi-dimensional trust feedback ratings in order to build the CSPs reputation values. The experimental outcome reveals that the technique works effectively within cloud systems but it's restricted to suggesting an optimal cloud service which fulfills the users QoS (Quality of Services) requirements.[15]

Wang et al. proposes the method of dynamic cloud service selection by adopting an adaptive learning mechanism incorporating, incentive, forgetting, and degenerate functions that understands the self-adaptive regulation for optimizing subsequent service selection based on the existing service selection status. The research presents a CSS model employing the CSB (cloud service brokers) which aids the user in choosing the required cloud services. Though the brokerage

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scheme mentioned in the work generally accepts that brokers are trustworthy and give no assurance or guarantee concerning the rightness of the recommended services [16].

Do et al. proposes the method of dynamic cloud service selection that offers a price game within the heterogeneous cloud environment/marketplace. The research work surveys the price competition in a diversified cloud marketplace, identifying the cost and advantages of cloud service application thereby selecting the most appropriate service by examining market-related factors. Though only a single service is considered by the paper. But there exists multiple cloud services in actual cloud marketplace. Moreover the SLA (service level agreement) factor is also not considered by the paper which is essential for the cloud users [17].

M.Tang et.al, proposes the approach of enhancing service trust evaluation by adopting 'TRUSS', a trustworthy selection framework for CSS. The paper recommends an integrated trust evaluation method in order to build an effective trust evaluation middleware for TRUSS, by combining both the subjective and objective trust assessment. The performance of the proposed framework is evaluated by carrying out Simulation-based experiments, though the method makes an assumption that the major service users are honest and that more number of unfair ratings are given by the dishonest users [18].

Yuli YANG et.al, proposes the algorithm of multi- attribute trusted cloud service selection. The major challenge hindering the wide spread propagation and application of cloud services is the Security issue. It's not easy to promptly choose the best trustworthy cloud service complying with user likings/preferences as well as particular functional requirements. Resultant, Multi-granularity selection standard of trust levels on the basis of Gaussian cloud transformation is being framed. Thereafter, on the basis of cloud analytic hierarchy the calculation model of user preferences is constructed. Eventually, the trusted cloud service selection algorithm is recommended that relies upon two-step fuzzy comprehensive evaluation and is authenticated experimentally [19].

Lianyong Qi, et.al, proposes the service recommendation in a distributed cloud environment. From the benefit point of view, a CSP requires to suggest its services to maximum users and make use of the integrated data for service recommendation thereby enhancing the recommendation accuracy. The proposed approach is – 'service recommendation based on distributed-locality sensitive hashing', abbreviated as (SerRecdistri-LSH) and the approach is privacy-preserving and scalable. WS-DREAM, which is a service quality dataset validates the proposed approach related to the factors such as scalability, recommendation accuracy and the privacy preservation ability [20].

3. PROPOSED WORK

3.1. Overview

Web mining involves combining the information assembled from both the traditional data mining approach and the World Wide Web. Here, the technique being proposed is 'web based filters' which aids in choosing the most appropriate and dynamically varying cloud services. Selecting the best suitable cloud service for particular applications tends to be a difficult task. Among various challenges and issues faced by the CSP (cloud service provider), disappointment among the users related to the CSP stands the prime most. Using the online web portal the cloud services are fetched and undergoes filtering to eliminate attributes that are irrelevant. Next comes the selection process wherein the cloud service is chosen from existing list of services. Thereafter the Rating based Selecting technique is imbibed to analyze the varying Qos value in SLC. On the basis of experienced/honest users ratings, trustworthy cloud service are identified using RBST. Next, to rank the cloud services multi-Step matching algorithm is implemented. Ranking for all the cloud services is done by analyzing all the cloud services on the basis of QoS values. Eventually, by implementing RBSR (Requirement based Similarity ranking) technique most appropriate service is ranked amidst variety of cloud services which are functionally equivalent thereby suggesting the best one to the personalized user.

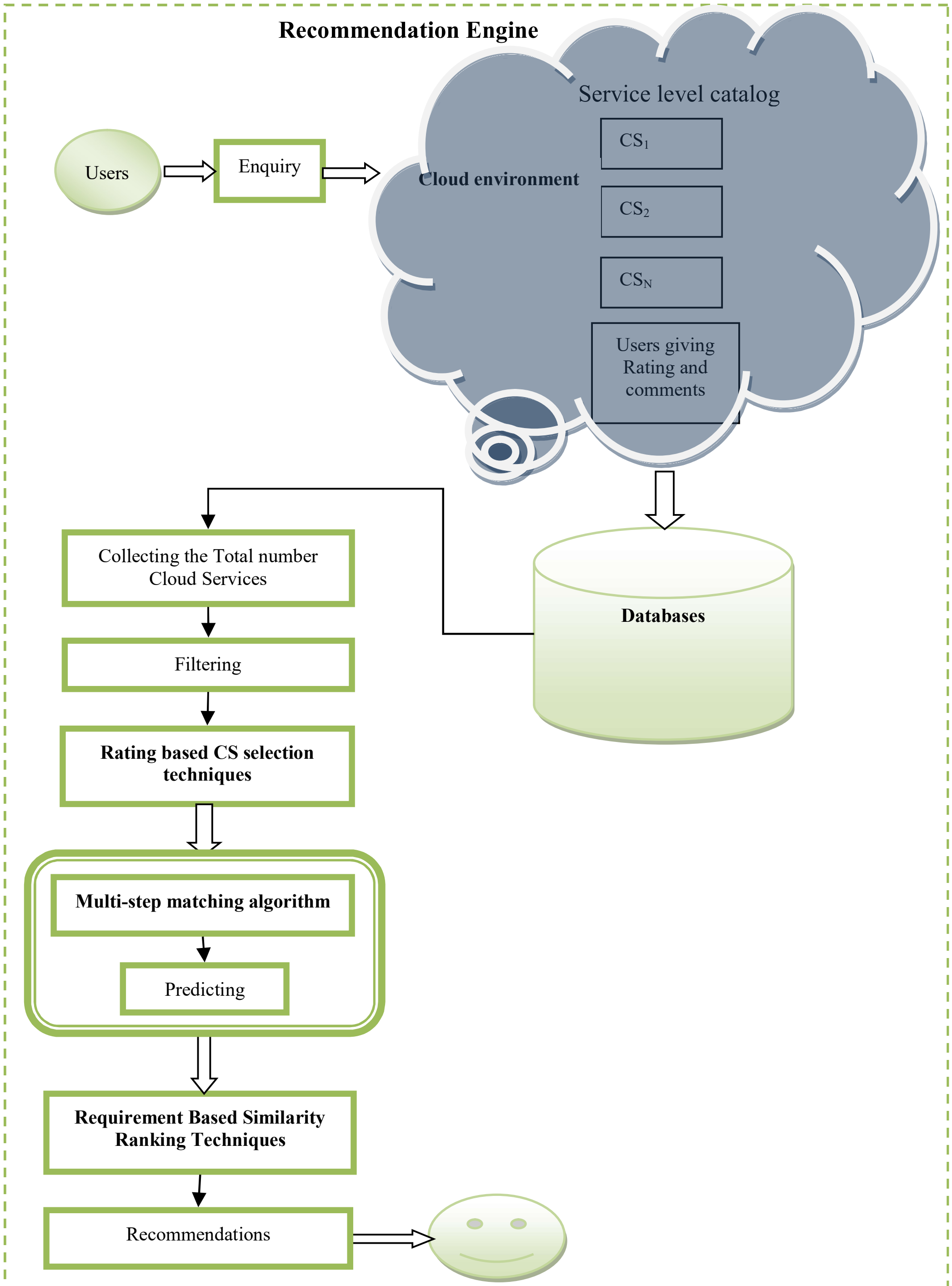

Fig 1: Overall proposed architecture

3.2. *Collection of cloud service*

A cloud service is a service provided by the cloud service providers to the cloud users through Internet on a demand basis. The huge amount of cloud service and our supporting details are collected from the web portals through the online. Various cloud service parameters are: RAM, memory, Cost and Qos. Usually list of resources along with cost offered by the cloud services are maintained and displayed on CSPs website. For distinguishing among various services the QoS values forms the deciding factor. Various QoS attributes are: safety, security, accuracy, scalability, availability, throughput, confidentiality, efficiency, response, cost, time, delay, reliability integrity, privacy, feedback etc....

3.3. *Filtering of Cloud Services*

Filtering of cloud services involves the process of eliminating or discarding irrelevant, duplicate or sensitive data and keeping only the required data according to users requirements. Filter function is quiet complex which mainly removes non-required attributes from the cloud service. Various offers and QoS attributes are given by the CSP which undergoes filtering keeping users' needs in mind. It purely withholds the required data to be encompassed in the analysis. Filtering is also termed as data "drill-down or 'sub-setting' data. Thereafter, for performing selection, Cloud services are enlisted.

3.4. *Cloud service Selection*

While performing Cloud service selection numerous functionally similar services exists within the cloud. The appropriate cloud service is chosen on the basis of the listed cloud service required by the user. Here QoS values pertaining to cloud services aids in decision making process. The qualities measure and best of a specific service is called "the Reputation." Which primarily relies on users' actual experience in using the specific service.

3.5. *Rating based Selection Technique*

Amidst variety of available cloud services the user selects the one based on QoS norms referring the list. List of QoS requirements is given by the client and by utilizing service discovery cloud services list will be formulated. Cloud services list as well as QoS requirements are referred by SLC. Normally, the cloud service holds a value, but concerning business growth at times CSPs offers dynamic Qos values offering in the SLC. The ratings in SLC can go high or down based on the QoS values provided. Eventually, most suitable quality of cloud service can be shortlisted taking in ratings in account. The trust values pertaining to cloud services can be fetched from the SLC. And by considering trust values and work rating, Sorting of cloud services takes place. Focus of rating-based method is to predict QoS values very precisely. The algorithm for rating based selection approach is mentioned below.

Algorithm: Rating based service selection techniques:

Initialize the cloud services Xi=(i=1,2,…,n);

Initialize QoS and supporting details → (Weight a, b and c …..);

Calculate the rating of each cloud services;

While (t < Max number of iterations)

For each cloud services

Update the position of the current cloud services

End for

Experience user giving rating → values;

Dynamic offering → Service level catalogs();

Calculate the rating of all cloud services

Update QoS values(offering);

t=t+1

If improve solution

Compute to frequency of rating given by users per CS;

Dynamic changing the attribute values(offering);

(CS(i)= 1; CS(i) <= CSs_Length(); i++) {// whole attributes detecting sum and avg

If(whole Weight(i) >= (threshold)

If(weight (i)<= (max(i))||(weight(i) != null) { // users average ratting values= max for given CS

Ratting ++ // Ratting automatic increasing;

Else

Ratting -- // Ratting automatic decreasing;

Arrange the weighted average ratings in ascending order

Finally selected in ratting based CSPs

}}

3.6. *Prediction*

Prediction involves identifying relationship between Cloud services and investigating the risk involved pertaining to any cloud services. The Qos values of cloud services are bound to alter in case some offers are given by the cloud service dynamically. Prediction uses the cloud service rating to enlist the proposed cloud service. Prediction means analyzing and forecasting the cloud services that offers highest appropriate service.

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3.7. *Multi-step matching techniques:*

Input: huge amount of services: S=s1,s2,….sn

Output: Overall similarity: sim(s1,s2,….sn)

Procedure()

Calculate synthetic similarity of service descriptions sim_s(s1,s2,….sn)

$$sim(c,q) = \frac{\sum_{i=1}^{N} w_{i,c} \cdot w_{i,q}}{\sqrt{\sum_{i=1}^{N} w_{i,c}^2 \sqrt{\sum_{i=1}^{N} w_{i,q}^2}}}$$

Calculate the features similarity sim_f(s1,s2,….sn)

$$sim_f(s_{1,2,}s_n) = \frac{|obj_{s1} \cap obj_{s2} \cap obj_{sn}|}{\min(|obj_{s1}, obj_{s2}, obj_{sn}|)}$$

Calculate the hierarchical services similarity sim_h(s1,s2,….sn)

$$sim_{onth}(s_{1,2,3}, s_n) = \frac{\sum_{i=1}^{n} \max_{1 \le j \le m} sim_{onth}(c_i, c_j)}{n}$$

Sum = 0

For each concept c_i in s_n where 1<= i <= n

MaxSim = -1

For each concept c_j in s_n where 1<= j <= m

If c_i and c_j have relationship

$sim_{onth}(c_i,c_j)$=1;

Else If c_i and c_j are sibling concepts

Calculate Lowest_Common for each

Calculate content-based similarity using

$sim_{onth}(c_i,c_j)$= $sim_{LIN}(c_i,c_j)$; Else

Calculate distance-based similarity

Calculate IC for each concept

Calculate content-based similarity

Calculate concepts hierarchical similarity $sim_{onth}(c_i,c_j)$ End If

If $sim_{onth}(c_i,c_j)$=> MaxSim

MaxSim = $sim_{onth}(c_i,c_j)$ End If End For

Sum = Sum + MaxSim

End For

$sim_{onth}(s_i,s_{j,...,}\ s_n)$== Sum / n

Calculate the overall services similarity sim ($s_i,s_{j,...,}\ s_n$);

$$sim(s_{1,2}, s_n) = a.sim_f(s_{1,2,3}, s_n) + b.sim_f(s_{1,2,3}, s_n) + c.sim_{onth}(s_{1,2,3}, s_n)$$

Return sim ($s_i,s_{j,...,}\ s_n$);

End

3.8. *Cloud service Ranking*

In CC environment for ranking the best suitable services end-to-end cloud services QoS values need to be evaluated. Service quality includes various computing features namely service performance (availability, response time and reliability), business and economic factors (reputation, price and usability), security and trust. Once the end-to-end QoS values are computed, ranking of candidate cloud services is performed for end users by adopting the service selection system. QoS ranking involves ranking of candidate cloud services at the user end on the basis of observed QoS values.

3.9. *Requirement based similarity ranking approach*

For ranking the most appropriate cloud service the QoS (Quality-of-Service)attributes are taken into consideration. The cloud services Qos attributes provide significant data which aids in decision making. It encompasses non-functional performance of cloud services. The similarity amidst users QoS requirement and the cloud service is compute by comparing the QoS values mentioned in SLC. Using similarity measures the degree of match is found which stands for the similarity amidst a request and a dynamic changing/published service. Eventually, services that are similar service gets removed and using a ranking mechanism best suitable services are ranked accordingly. For this purpose QoS similarity ranking method for cloud services is recommended taking in account previous services based experiences. This significantly reduces the time and cost involved in the process.

Algorithm: Requirement based ranking techniques

For the ranking process best suitable cloud service and ranked quality is selected. In order to perform ranking, user's requirement based similarity ranking approaches are adopted which reviews and choose the best appropriate cloud service for specific personalized users.

Similarity ranking model ();

Step1: SLC based rank model

Review result→ true;

If (CS== matching attributes & performance (high))

Selected→ CS = true;

Ranked one side→ set of cloud service (step1 model)

Step 2: Recommended rank Model

Recommended results→ true;

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If(R_CS== matching attributed& performance (high)) || (R_CS == Matching (users_Req))

Selected → CS= true;

Ranked one side→ set of cloud service (Step2 model)

Step 3: Repeated based rank Model

Repeated CSs→ false;

If(RE_CSs==matching attributed & performance (high))||(RE_CSs==matching (users_Req))

Selected → CS= true;

Ranked one side→ set of cloud service (Step3 model)

Threshold =30; Ranked models= 20;

For(CSs=1;Cs(i)<= CSs_Length();CSs++){

If ((CS(QoS)== ranked models) || (Rn >= threshold(i))||(Retting (D>=Max))){

To ranked CS

Finally→single output of(one CSP)

→Forward to personalized User; End

}}}

3.10. *Recommendation of Cloud Service*

Recommender systems typically suggest a list of cloud services and have helped user make informed and make better decisions while selecting best cloud service. Recommendation systems play an important role in enhancing overall user experience, especially in the online. The Recommendation system is one which comprehends user's interests and proposes the best of all cloud services. Approaches adopted for detecting and ranking the best cloud services (with user QoS attributes) includes: Multi-step algorithm for prediction, Rating based selection and requirement similarity ranking approach. There exist numerous cloud services in the suggested list. Eventually using the recommendation mechanism best cloud service is recommended for the personalized user.

3.11. *Calculation of Preference*

The ranking-oriented approaches predict the QoS ranking directly without predicting the corresponding QoS values. A user's preference on a pair of services can be modeled in the form $\varphi^k = I \rightarrow IR$ where $\varphi^k(i,j) >$ means that quality of service i is better than service j when QoS parameter k is considered and is thus more preferable for the active user and vice versa. The value of the preference function $\varphi^k(i$ indicates the strength of preference for parameter k and a value of zero means that there is no preference between two services. The preference function $\varphi^k(i$ is anti-symmetric, i.e.,

$$\varphi^k(i,j) = -\varphi^k(j,i)$$

$$\varphi^k(i,i) = 0 \; for \; all \; i \in I$$

Given the user-observed QoS values on two cloud services, the preference between these two services can be easily derived by comparing the QoS values, where $\varphi^k(i,j) = q_i -$ To obtain the preference values regarding pairs of services that have not been invoked or observed by the current user, the preference values of similar users S(u) are employed. The basic idea is that the more often the similar users in S(u observe service i as higher quality than service j, the stronger the evidence is of $\varphi^k(i,j) >$for the current user. This leads to the following formula for estimating the value of the preference function $\varphi^k(i$ where service i and service j are not explicitly observed by the current user u

$$\varphi^k(i,j) = \sum_{v \in N(u)^{ij}} W_v\left(q_{v,i} - q_j\right) * W_k$$

where v is a similar user of the current user u, $N(u$ is a subset of similar users, who obtain QoS values of both services i and j, wk is the weight assigned to QoS parameter k and wv is a weighting factor of the similar user v, which can be calculated by

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

wv makes sure that a similar user with higher similarity value has greater impact on the preference value prediction

3.12. Performance Metrics

The research work presents Cloud services recommendation relying upon personalized user preference. Huge volume of data is considered for evaluating the Cloud service recommendation system and the experimental output yields in high efficiency. Also it resolves the issue concerning information overload caused by searching across heavy volume of data that is generated dynamically. For computing systems performance and stability few parameters are analyzed and calculated which are being mentioned below:

The proposed system of cloud service recommendation is analyzed by employing RMSE-Root Mean Square Error, Recall, accuracy and precision.

- TP-True Positive: If case in point being positive (recommended results) it's recommended- positive.
- FN-False Negative: If case in point being positive (recommended results) it's recommended-negative
- TN-True Negative: If case in point being negative (recommended results) it's recommended-negative.
- FP-False Positive: If case in point being negative (recommended results) it's still recommended- positive. A general way of evaluating Recommendation involves computing the deviation of the recommended from actual value which forms the foundation for the RMSE-Root Mean Square Error.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i - R_i)^2} \quad (1)$$

Here N resembles the set of all user-item pairings (i) which includes predicted rating ˆRi and a known rating Ri that has not been utilized for recommendation model. The other common measure includes PME - probability of the misclassification error.

$$PME = \sqrt{\frac{\sum_{i\epsilon N}(R_i - \hat{R}_i)^2}{|N|}} \quad (2)$$

Performance measures adopted for the algorithms evaluation have their root. Accuracy is yet another popular measure being used, which resembles fraction of correct recommendations against total possible recommendations.

Confusion Matrix

Actual/Predicted	Negative	Positive
Negative	True Positive	True Negative
Positive	False Negative	False Positive

Various performance measures can be retrieved from the confusion matrix. To perform data-mining process in a recommender system the algorithms performance relies upon its capability to comprehend essential patterns in the data set. Accuracy is yet another popular measure being used, which resembles fraction of correct recommendations against total possible recommendations.

$$Accuracy = \frac{\text{Correct Recommendations}}{\text{Totla Possible recommendations}} = \frac{TP+TN}{TP+FP+TN+FN} \quad (3)$$

$$Recall = \frac{\text{Correctly recommended Items}}{\text{Total useful recommendation}} = \frac{TP}{TP+FN} \quad (4)$$

$$Precision = \frac{\text{Correctly recommended Items}}{\text{Total recommended items}} = \frac{TP}{TP+FP}$$

Popular single-valued measure is the F-measure. It is defined as the harmonic mean of precision and recall.

$$F - score(efficiency) = 2 * \frac{Recall * Precision}{Recall + Precision}$$
$$= \frac{2}{1/Precision + 1/Recall}$$

Here, in this proposed technique of Multi-step matching algorithm to evaluating and proceeding outcome for 2k datasets. Let's start with an example confusion matrix for a binary Ranking (though it can easily be extended to the case of more than two classes):

Actual/Predicted (2000)	Negative	Positive
Negative	True Positive (1903)	True Negative (20)
Positive	False Negative(50)	False Positive (27)

TP = 1903; TN = 20; FP = 50; FN = 27

$$Accuracy = \frac{1903+20}{1803+50+20+27} * 100$$
$$= \frac{1923}{2000} = 0.9615 * 100$$

Accuracy (%) = 96.15 (%)

$$Y = {}^{1}/_{2}\, g_0 t^2 = (2)\; Y = {}^{1}/_{2}\, g_0 t^2 (2) = \frac{2Y}{g_0} = \frac{g_0 t^2}{g_0}$$

$$\frac{2Y}{g_0} = \sqrt{t^2} = \text{Time}$$

$$\text{Time} = \sqrt{\frac{2y}{g_0}}$$

4. RESULT AND DISCUSSION

Clouds can be considered as a computing system environment where user's associates with a pool of inter-connected and distributed computing nodes thereby employing various cloud shared resources/services. Multiple cloud services are being launched in the CC environment since the cloud users are growing in large numbers. With this, there is an increase in similar/relevant cloud services which makes the process of selecting the best cloud service amidst the available relevant/similar services (in the SLC) extremely

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complex. To resolve these issues the research work proposes to incorporate the Multistep-Matching algorithm and Rating based selection Technique. Main focus of the rating-based techniques lies in predicting QoS values very precisely. The work contains illustration of experiments performed the current research followed with results overview. The target lies in enhancing the accuracy of the approach. The comparison is conducted among Rating based Technique with rest existing techniques namely Greedy and Rough Set Theory. RBST yields in high accuracy output.

This work has been designed as well as implemented in the cloud computing environment; huge number of datasets related to Cloud services are being successfully assessed, and thus greatly energy efficient. The following configurations have been taken into account for conducting the experiments: Windows 8, CPU G2020, Intel Pentium 9R), processor speed 2.90 GHz. Software configuration used is as given below: Operating System-> Windows 8,.The dataset that has being used had collection of QoS aspects in the data of 2000 service providers. JAVA environment and entire dataset have been incorporated. MYSQL databases depict output results which can be retrieved; they may be stored and managed in MYSQL. Initially, collection and the process of uploading QoS aspects in the 2000 cloud services datasets were carried out.

Table 1: *Comparison Of Techniques*

S.NO	Techniques	Accuracy (%)	Efficiency	Time (s)
1	Greedy	78.0	82.0	52.97
2	Rough set Theory	90.0	88.0	50.0
3	Rating based Technique	93.0	90.0	38.0

The Table 1 depicts the comparison of dynamic offering cloud services Selection Techniques. Overall performance with output generated is compared with rest of the existing techniques like Greedy algorithm, Rough set Theory along with RBT-Rating based Technique. The recommended Rating based Selection technique yields in enhanced output compared to the existing system. Thereafter an overall performance is carried out in the paper including factors like Efficiency, accuracy and time.

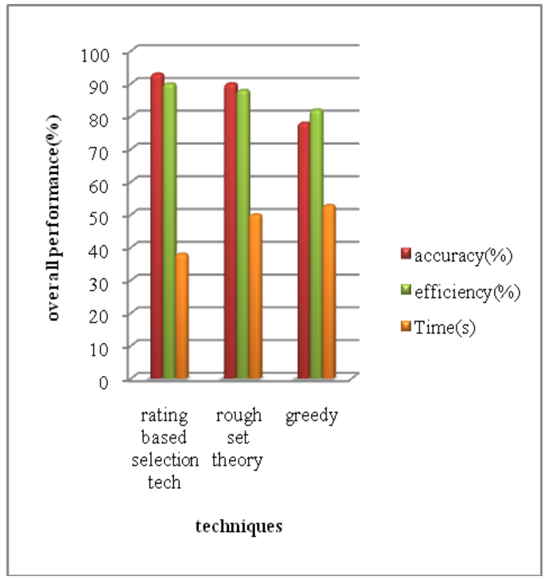

Fig 2: *Comparison Of Selection Techniques*

The fig 2, presents the comparison of result generated in dynamic offering cloud services Selection Techniques. The graph reveals overall performance and compares it with rest of the existing techniques like Greedy and Rough set Theory along with Rating based Technique. The recommended Rating based Selection technique yields in enhanced output compared to the existing system. Thereafter an overall performance is carried out in the paper including factors like Efficiency, accuracy and time.

Table 2: *Comparison of Techniques*

S.NO	Techniques	Accuracy(%)	Efficiency(%)
1	Active LeZi	86	85.5
2	Apriori	81.69	84.89
3	Hybrid	93.02	94.40
4	Multi-Step Matching	96.2	93.5

The Table 2 presents comparison of best and quality cloud service Prediction Techniques. It depicts the overall performance and output that are being compared with rest of the current prediction techniques namely Apriori, Active LeZi, Hybrid with Multi-Step Matching. The proposed technique of Multi-Step Matching prediction yield in higher output compared to rest other existing prediction systems. Thereafter an overall performance is carried out in the paper including factors like Efficiency, accuracy and time.

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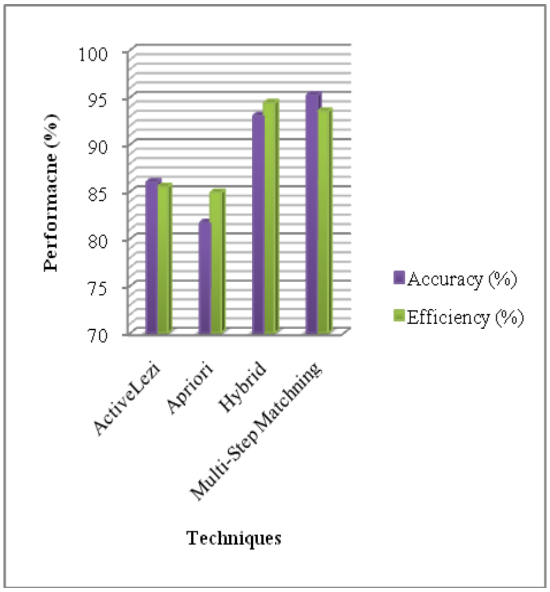

Fig 3: *Comparison of Techniques*

The fig 3 presents comparison of best and quality cloud service Prediction Techniques results. The graph reveals the performance of prediction technique and the output results that are being compared with rest other existing prediction techniques. The proposed technique of Multi-Step Matching prediction yield in higher output compared to rest other existing prediction systems

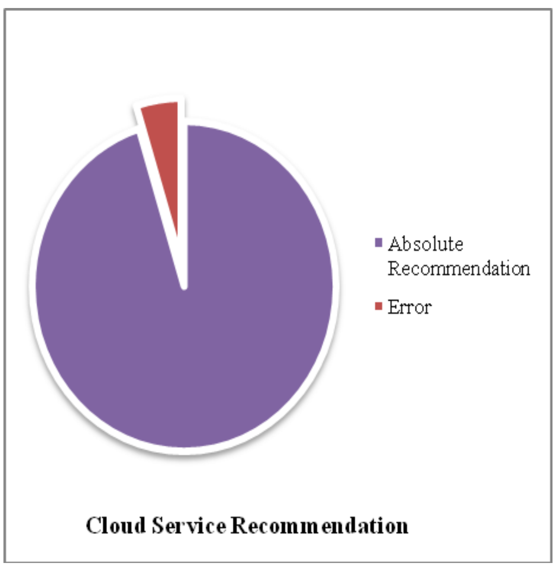

Fig 4: *Error performance*

The fig 4 presents the Error Performance for recommendation system results over the cloud service recommendation, revealing an accuracy of 95.2% and error is 4.8%.

5. PERFORMANCE COMPARISON

This System provides best Cloud service for personalized user has been suggested. In this paper, the cloud services rating are based on Qos and individual users. Considering techniques that are available in the cloud e-marketplace context, we conducted a comparative examination depending on the said analysis conditions: 1) to elicit consumer's preferences, graphical user interface (GUI) was adopted. 2) Elicitation of the subjective preferences related to QoS with regard to consumer's level, ideal values, and priorities on the QoS parameters. 3) Efficiently rating several cloud services with respect to consumer's priorities. 4) For discovering services that are rated best which satisfy QoS priorities of consumers, a system of QoS aspects visualization may be adopted. To analyze best cloud service prediction mechanism, six separate approaches are compared. The first two methods are dynamic offering cloud services Selection Techniques are taken into consideration QoS values to discover cloud services, while the remaining three methods are best and quality cloud service Prediction Techniques.

Greedy: This technique selects the cloud service at the moment and does not consider updation of Qos values of the cloud services in the Service Level Agreement (SLA). The advantage of this technique is it provides security. The drawback of this technique does not consider Qos values that are dynamically offering in the SLA and it is not compatible with various Qos attributes.

Rough Set Theory: Important attributes, in combination with an Analytic hierarchy process is used for choosing suitable cloud services that might not satisfy QoS aspects. The disadvantage of this technique is less number of Qos values is considered and it selects the less number of cloud services.

Rating Based Technique: The RSBT identify the all Qos value of the cloud service and also takes the changing Qos values in SLA and discover the best and quality cloud service. The rating-based approach is to predict QoS values as accurate as possible. This technique provides best cloud service and considers the Qos values that are dynamically changing and reduce time complexity. It provide reliability and accuracy.

Active Lezi: This technique decides the similarity between the various Qos values from a set of cloud service and predicts the cloud service. The only advantage of this technique it processes fast. The drawback of this technique is it has no

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guarantee on quality of cloud service.

Apriori: it provides an optimal way for user to select cloud service among large amount of cloud services and measure the quality and prioritizes cloud service. The drawback of this technique is it is not compatible with various QoS attributes and performance is not good.

Hybrid: The advantage of this particular approach is that it offers unsupervised learning and proper security. The drawback, on the other hand, is that it could only offer low safety, low confidentiality, low scalability, and will not satisfy users' expectations and it predicts the unknown values for QoS-based selection. Ranking providers using such system might lead to errors.

Multi-Step Matching: In this technique the QoS (Quality-of-Service) attributes are taken into consideration. The similarity amidst users QoS requirement and the cloud service is computed by comparing the QoS values mentioned in SLC and takes the past cloud service user experience also. The services that are similar get removed and then rank the cloud service. The advantage of this technique is it reduces time cost in real world and also scalable, fast and efficient.

6. CONCLUSION

Multiple cloud services are being launched in the CC environment since the cloud users are growing in large numbers. With this, there is an increase in similar cloud services that makes the process of selecting the best cloud service amidst the available relevant/similar services and dynamically changing QoS values, extremely complex. For the benefit of the personalized users the techniques proposed are: cloud service recommendation, Multi step matching algorithm, rating based Technique and requirement base similarity ranking, in order to select the most appropriate cloud service. In this paper to achieve to Rating based service selection techniques for best cloud services selection processing and Multi-step matching algorithm for predict the best cloud service to be recommended personalized users. It's both are working efficiency and given to maximum accuracy points. Among all these, the cloud service recommendation system gives better performance compared to Apriori, Active_Lezi and Hybrid. The proposed approach yields in an accuracy of 95.2%depicting a remarkable hike than rest of the exiting approaches. The compared results assures that the proposed system is highly beneficial for the user producing effective output.

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