A Reputation Management Policy Based on the User Credibility for Cloud Services

Xiao-gang Cai, Qing-tao Wu, Ming-chuan Zhang

Abstract—**In order to ensure the high availability of the cloud service credit system, and for that there are some problems such as disloyal evaluation existed in the system, the lack of enthusiasm for evaluation and so on, a cloud service resource management strategy based on the credibility is proposed. This paper uses the "credibility" of the user nodes to modify reputation value of cloud services, which based on the distributed computing of cloud service reputation, introduces the dynamic incentive mechanism to improve the enthusiasm of user evaluating cloud services simultaneously, and combines calculation credibility, the modification reputation and evaluation incentives to build a distributed reputation evaluation model of high credibility. The simulation results verify its feasibility and effectiveness, and improve the enthusiasm of the user evaluating cloud services while improve the accuracy of the results is improved.**

***Index Terms*—cloud service; reputation rating; reputation revision; rating credibility; penalty incentive.**

I. Introduction

With the rapid development of cloud computing, more and more cloud services have been generated. . Users wish to get high-quality services from the cloud, while providers are looking to optimize the allocation of resources and wish that the users are honest to use the cloud service. Therefore, the reputation management for cloud service resources is particularly important.

Through the collection and analysis of the historical behavior of nodes, reputation management can predict their possible behavior in the future interaction, which will provide a certain basis for the choice of interactive objects and successfully avoid the risk. The reputation management has been widely used in the business evaluation of online trade, the upload node selection of p2p file transfer, grid computing and other fields[1,2].

For the open, dynamic cloud service environment, the introduction of reputation system provides the basis for the user to obtain accurate and reliable cloud services, which will improve the accuracy and reliability for cloud services push. How to build an effective reputation evaluation model for cloud services has become a hot research[3].

Paper [4] presented a reputation measurement approach of Cloud services based on cloud model and fuzzy logic for unstable feedback ratings of Cloud services and compute the unstability of feedback ratings and then employ fuzzy logic to calculate the reputation score of Cloud service. Paper [5] proposed a new model based on D-S evidence theory, which uses the fuzzy theory to deal with the customer's satisfaction with the related service. Paper [6] proposed a new method of filtering out inaccurate ratings based on departure degree, which is proposed to revise the negative and positive error evaluation. Paper [7] designed a kind of service selection model based on reputation perception, which is based on a reputation revision method. Paper [8] presented a new method which is used as a reference to identify and filter out the inaccurate ratings by evaluating the mean value of similarity with the priori knowledge.

The above research provides certain theoretical basis for cloud service resource reputation management, but there are some deficiencies. Literature [4, 5] more concerned reputation management of cloud service provider, which ignored trust evaluation of the cloud service users, this makes some users get their own personal interests to make incompatible with its reputation during evaluating cloud services, such as excessive exaggeration or malicious slander. Literature [6-8] proposed some amendment credit strategy, but without considering some users only using cloud services but not participating in the evaluation actively by reason of their selfishness, inert or other factors, which affects the reputation center get sufficient evaluate resources. These weaknesses make the difficult of acquiring real credit of cloud services, and then affect the availability of the credibility system.

Considering these problems, a reputation management policy has been proposed. Based on the direct experience between the evaluation nodes and the cloud service providers, the credibility of each evaluation node has been measured which will directly affect its weight in the reputation computing. Then the reputation result will be more accurate and more useful to respond to user changes in demand. At the same time, a dynamic incentive mechanism based on punishment has been introduced. The change for the participation degree of user node will “punish” or “reward” the credibility of the user node, and further affect the scope and quality of recommended cloud services the user node will get. Eventually, the user will be prompted to carry out the honest evaluation actively.

II. REPUTATION EVALUATION MODEL AND RELATED DEFINITIONS FOR CLOUD SERVICES

The figure 1 is the reputation evaluation model for cloud services. The initial republican is an initial value of the cloud service registered to the service reputation management center. The value of the global reputation is obtained by the calculation in the reputation center, to provide a reference for all users. The local reputation is stored as an evaluation set in the user side. As a historical evaluation information, the local reputation is saved and used for reference of the individual demands. There are many subjective factors such as malicious evaluation in user independent evaluation carried out by the experience of the users. So the reputation revision is necessary for the reputation evaluation. In order to encourage users to participate in the evaluation, the dynamic incentive mechanism based on punishment is introduced.

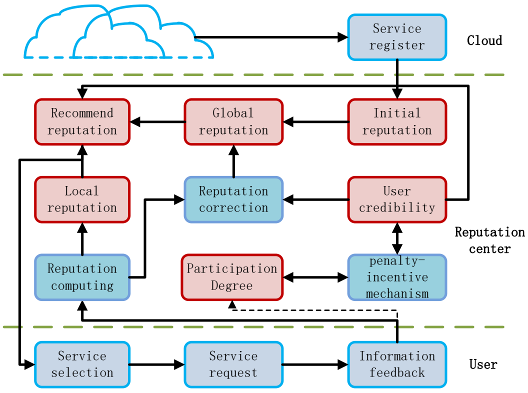

Fig 1 Reputation evaluation model for cloud services

The model manages the reputation of cloud services, service providers and users by the combination of reputation computing, reputation revision and evaluation incentive, which made the distributed reputation evaluation model more credible.

Definition 1. **Rating Period** (*RP*): it is defined as user's several trading stages which contain at least one transaction behavior.

Definition 2. **Rating Credibility** (*RC*): it reflects the authenticity or accuracy of the evaluation submitted by the user node. Its value is calculated based on the evaluation behaviors within a fixed number of trading stages in the rating period, the higher the value of reputation, the more creditable the evaluation.

Definition 3. **Participation Degree** (*Pd*): we define the Pd as follows:

$$Pd = \begin{cases} \frac{R}{E}, & if\ E \neq 0 \\ 0.5, & else \end{cases}$$

In the definition 3, R is the number of evaluation and E is the total number of cloud services users got within a fixed number of trading stages in the rating period.

III. REPUTATION COMPUTING, REVISION AND INCENTIVE POLICY

A. Reputation Computing of Cloud Service

The reputation computing for cloud services includes global reputation computing and local reputation computing. Massive user's local reputation were collected to the reputation center, which formed the global reputation. As each user's personal preference is different, the user's local reputation evaluation will be the basis for the recommendation when the reputation center were recommending the cloud services.

$$SR = \mu \times GR + (1-\mu) \times LR \quad \mu \in [0,1] \quad (1)$$

SR is the reference of the service recommendation, GR is the global reputation stored in the reputation center, LR is the local reputation stored in the user's local storage, μ is a weight parameter.

User will make the evaluation after having used the cloud service. The user give the objective quantitative score according to the quality of service parameters and give the subjective qualitative score according to their satisfaction. Then the objective evaluation and the subjective evaluation will gather to form the LR, which will be upload to the reputation center. (SID, S_i, F_i) is defined as the index for the registered cloud service. SID is a specific service, the S_i is the number of times the index i of this service has reached the specified level and F_i is the number of times the index i of this service has not reached the specified level. In the evaluation, the satisfaction is marked as $s_i = 1$, while the not satisfaction is marked as $f_i = 1$. And $s_i + f_i = 1$.

$$LR(SID) = F_o(q_1, q_2, \ldots, q_n) + F_s(user) \quad (2)$$

The F_o is a function which integrated related indicators q_i for *QoS*. The F_s is a function to handle user satisfaction. As is shown in formula (3).

$$F_o(q_1, q_2, \ldots, q_n) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{S_i + s_i}{S_i + F_i + 1}\right) \quad (3)$$

The global reputation are calculated by collecting all the evaluation of the same service. In order to reflect the timeliness of reputation and reduce the impact of historical reputation, we introduce the exponential decay factor to increase the influence of real time service. As is shown in formula (4):

$$GR = GR' \times e^{-\alpha\Delta t} + \frac{\sum_{i=1}^{n} f(LR_i)}{n} \quad (4).$$

B. Reputation Revision Based on the Credibility of Users

Due to the malicious bad review or deliberate good review, we revised the reputation evaluation by introducing the credibility of the evaluation node. Then the different user will have different credibility and the feedback information of different user will have different treat. The function f is shown in formula (5).

$$f(LR_i) = F_o(q_1, q_2, \cdots, q_n) + F_s(user) \times RC_i \quad (5)$$

The user's rating credibility is usually influenced by two factors: 1). subjective and objective rating similarity; 2). subjective and majority rating similarity.

1) The subjective and objective rating similarity (SORS)

The subjective evaluation and objective evaluation measure the performance of service from two angles, and the two groups should be consistent or have high similarity. Because the objective evaluation is calculated based on the actual monitoring value, with a high reference value, it can be used as the reference point to measure the subjective evaluation.

We regard the subjective evaluation sequence $Sr = (sr_1, sr_2, \cdots, sr_n)$ and objective evaluation sequence

$Or=(or_1,or_2,\cdots,or_n)$ as two points in n-dimensional apace. By calculating the *Euclidean distance* of the two points, we can measure the subjective and objective rating similarity. The smaller the distance, the greater the similarity and the higher the credibility of subjective evaluation. As is shown in the formula (6).

$$SORS=\sqrt{\sum_{1}^{n}(sr_i-or_i)^2} \qquad (6)$$

2) The subjective and majority rating similarity (SMRS).

It is generally considered that the subjective evaluation of most user nodes in the evaluation system is reasonable and reliable. Based on this, we use the *k-means* algorithm to cluster the evaluation information $R=\{r_i \mid i=1,2,\cdots,n\}$ in a period of time. $C_j\left(j=1,2,\cdots,k\right)$ indicates k class of clustering, $c_j\left(j=1,2,\cdots,k\right)$ indicates the initial clustering center, the *Euclidean distance* between two data objects is the formula (7):

$$d\left(x_i,x_j\right)=\sqrt{\sum_{1}^{n}\left(x_i-x_j\right)^2} \qquad (7)$$

The clustering center is the formula (8):

$$c_j=\frac{1}{n_j}\sum_{x\in C_j}x \qquad (8)$$

The core idea of k-means algorithm is to divide the data object into different clusters by iteration, so as to make the objective function (formula (9)) minimal and the generated clusters as compact and independent as possible.

$$E=\sum_{i=1}^{k}\sum_{j=1}^{n_j}d\left(x_j,\mathrm{c}_i\right) \qquad (9)$$

Then, we choose the center of the maximum cluster as the majority rating (*MR*) value of *R*.

$$MR=center\left(\max\left(C_j\right)\right) \qquad (10)$$

MR is used as a reference, and the Euclidean distance between the user subjective evaluation sequence *Sr* and *MR* is used to calculate the subjective and majority rating similarity *SMRS*. As is shown in the formula (11):

$$SMRS=\sqrt{\sum_{1}^{n}\left(sr_i-mr_i\right)^2} \qquad (11)$$

The smaller the value of *SMRS* which explains that the evaluation of this particular user is close to the evaluation of most users, the higher the credibility of users.

Finally, the calculation of the user's rating credibility is shown in the formula (12):

$$RC=\frac{2}{\pi}\arctan\left(\alpha\times SORS+\beta\times SMRS\right)^{-1} \qquad (12)$$

$0\le RC<1$, $0<\left(\alpha,\beta\right)<1$ is the weight factor , $\alpha+\beta=1$.

C. Dynamic Penalty-incentive Mechanism Based on User Credibility

In order to solve the problem that users only use cloud services but not give evaluation actively, we introduce the incentive mechanism based on penalty and construct the reputation evaluation incentive model, as is shown in figure 2.

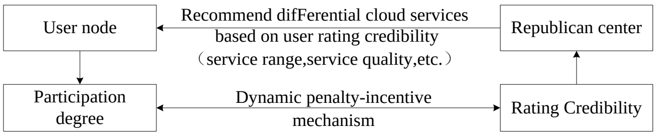

Fig.2. Reputation evaluation incentive model

The core idea of the model is that discovering the participation of user's evaluation and determining the punish degree of the rating credibility based on the evaluation behavior. The punishment dynamics will continue to adjust dynamically, according to the historical evaluation behavior and cumulative rating credibility of the user node. In order to obtain high quality recommended cloud service from reputation center, users will actively maintain their own evaluation credibility and actively participate in the evaluation.

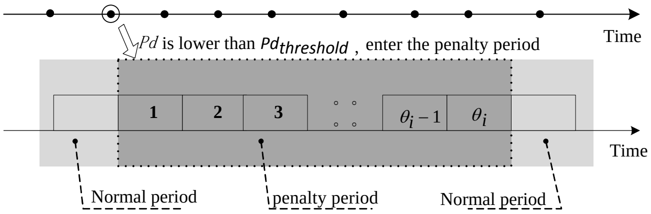

Fig.3.The incentive flow chart based on punishment

As is shown in Figure 3, when the participation degree of the user node is lower than a certain threshold, then entering the penalty period and will accept a certain amount of time and frequency of continuous punishment. In the penalty period, the user node must continuously and actively participate in the evaluation before the end of the penalty period to return to normal period. θ_i is a penalty count factor, which indicates the number of stages in the penalty period. The incentive mechanism determines the punishment dynamics of different evaluation behavior by adjusting θ_i .The value of θ_i is related to the historical behavior (participation degree, rating credibility, etc) of user node *i* in the time window of the fixed *w* transaction before this current transaction is evaluated. Its calculation method is shown in the formula (13).

$$\theta_i=\log_\tau\left(\sum_{k=1}^{w}N_k\times\left(\sum_{k=w}^{1}\sum_{l=1}^{N_k}\left[RC\left(i,k,l\right)\times Pd\left(i,k,l\right)\times\sigma^{\sum_{j=1}^{w-k}N_{w-j+1}+N_k-l}\right]\right)^{-1}\right) \qquad (13)$$

N_k represents the number of transactions produced in the k phase; $Pd\left(i,k,l\right)$ represents the participation degree that the user node i finished the l transaction in the k stage and $0\le Pd\le 1$; $RC\left(i,k,l\right)$ represents the rating credibility that the user node i finished the l transaction in the k stage and $0\le RC<1$; $\sigma\left(0<\sigma<1\right)$ represents the proportion distinguish factor; $\tau\left(\tau>1\right)$ is the punishment intensity factor, the smaller the value, the greater the penalty count factor.

The number n of remainder penalty phase in the penalty period will be calculated according to a certain rule based on the situation involved in the evaluation of the stage after the end of each phase, as is shown in formula 14. $n_i(t)$ is the number of current remainder penalty phase in the penalty period of user node *i*, $n_i(t+1)$ is the number of the new phase, $r(s)$ is a random function, λ is a reference factor and $0<\lambda<1$. Under normal circumstances, if the user node in the penalty period participates in evaluation continuously and actively, the number of remainder penalty phase will be reduced by 1. And the punishment will be end if $n=0$. On the contrary, if the user's evaluation behavior is negative during the penalty period, the penalty count factor will be recalculated as is shown in formula (13). Obviously, the negative evaluation behavior in the penalty period will inevitably lead to the extension of the penalty period. To end the penalty period, the user nodes must continue to participate in the evaluation more. And, even if the user node actively participates in the evaluation of the current stage, the probability of reducing remainder penalty phase is only λ. This makes the user nodes and cloud service providers can not conspire to quickly end the penalty.

$$n_i(t+1)=\begin{cases}\theta_i, & ifPd(i,k,l)<Pd_{threshold}, n_i(t)=0\\ \max\{\theta_i, n_i(t)+1\}, & ifPd(i,k,l)\le Pd(i,k,l-1), n_i(t)>0\\ n_i(t)-1, & ifPd(i,k,l)>Pd(i,k,l-1), n_i(t)>0, r(s)\le\lambda\\ n_i(t), & ifPd(i,k,l)>Pd(i,k,l-1), n_i(t)>0, r(s)>\lambda\\ 0, & otherwise\end{cases} \quad (14)$$

When $k>0$, $RC(i,k,l)$ indicates the credibility that the user node *i* finished the *l* transaction of the *k* stage in the penalty period. When $k=0$, the user node is in the normal period. $n_i(0)$ represents the initial number of stages for user nodes *i* in the penalty period, $n_i(t)$ represents the remainder number of stages for user nodes *i* in the penalty period. As the rules of $RC(i,k,l)$ are shown in the formula (15):

$$RC(i,k,l)=\begin{cases}\min(RC(i,k,l-1)+\eta,1), & ifPd(i,k,l)>Pd_{threshold}, k=0\\ RC(i,k,l-1)-RcD, & ifPd(i,k,l)\le Pd_{threshold}, k=0\\ RC(i,1,1)+RcA\times\dfrac{n_i(0)-n_i(t)}{n_i(0)}, & ifk>0\end{cases} \quad (15)$$

η is a very small credibility increment for user nodes in the normal period, *RcD* is a credibility penalty when the participation degree is lower than the threshold value $Pd_{threshold}$. *RcA* is a credibility bonus when the user node actively participated in evaluation in the penalty period. Usually, $RcA<RcD$. Obviously, if the evaluation behavior of the user node in the penalty period is negative, its rating credibility will be reduced by stages. If the behavior is positive, the rating credibility will be gradually restored. The pseudo code of the dynamic incentive mechanism based on punishment is as follows:

```
Begin
  // Get input parameters
  Get (Pd_threshokd, Pd(i,k,l), RC(i,k,l),k);
  While k=0   // update rating credibility in the normal period
    If Pd(i,k,l)>Pd_threshokd
    then RC(i,k,l)=min(RC(i,k,l-1)+n,1);
    Else if Pd(i,k,l)<=Pd_threshokd
    then RC(i,k,l)=RC(i,k,l-1)-RcD;
         k=1;        //the sign of the penalty period is 1
  End while
  While k=1        // Enter the penalty period
    // The dynamic calculation of the number of the remainder phases in the penalty
    If Pd(i,k,l)<Pd_threshokd and n_i(t)=0
    then n_i(t+1)=θ_i;
    Else if Pd(i,k,l)<=Pd(i,k,l-1) and n_i(t)>0 then
    n_i(t+1)=max(θ_i, n_i(t)+1);
    Else if Pd(i,k,l)>Pd(i,k,l-1) and n_i(t)>0
    then n_i(t+1)= random(n_i(t),n_i(t)-1);
    Else n_i(t+1)=0;
    End if
    If n_i(t+1)=0
    then k=0;        // the sign of the normal period is 0
    End if
    //update the rating credibility
    RC(i,k,l)=RC(i,1,l)+RcA*(n_i(0)- n_i(t))/n_i(0)
  End while
  //Submitted the rating credibility to the reputation center
  Send RC(i,k,l) to reputation center.
End
```

IV. EXPERIMENTS AND ANALYSIS

A. Reputation Evaluation Simulation Experiment

I We designed a 'java' simulation program to simulate the behavior of the user's evaluation in the cloud environment, which is used to verify our proposed reputation revision method. This system consists of 100 cloud services provided by cloud service providers and 60 different types of users. Cloud services are divided into many categories according to function and configuration. The S represents cloud services, and its reputation evaluation is divided into four categories: normal, good, bad, and excellent. The U represents users, and it is divided into three categories: preference evaluation, objective evaluation and deviation evaluation.

In order to reflect the user's type, the true quality of cloud services is known for each consumer in the process of evaluation. According to the type of user they belong to, they make different evaluation behavior. After each transaction, the user should make a score of the cloud service. In order to revise the abnormal reputation score, the reputation data were extracted from the data in the cluster and revised after each round.

In our experiments, the main validation of the two hypotheses: 1) Calculating the user's credibility of evaluation can improve the accuracy of the results of reputation computing. 2) Introducing the evaluation incentive model can effectively improve the enthusiasm of the user to participate in the evaluation.

Figure 4 shows the reputation value of each service after five round of the evaluation, and then these data are aggregated to test the effectiveness of our proposed method. Figure 5 shows the comparison for the accuracy of reputation value between having introduced the modified incentive and without introducing the modified incentive.

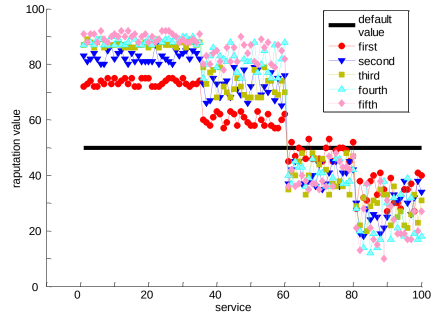

Figure 4 the reputation value of each service after five round of the evaluation

Figure 4 shows the distribution of reputation value for cloud service after five round of reputation evaluation. The initial value is set as 0.5. After a period of accumulation, it can clearly distinguish different cloud service quality level. As is shown clearly in Figure 4-2, the service has roughly four levels, but inaccurate reputation value is still exist, which is affected by the existence of the dishonest evaluation and subjective preferences of users. The deviation of reputation for cloud service will gradually decrease when the system has sufficient number of users.

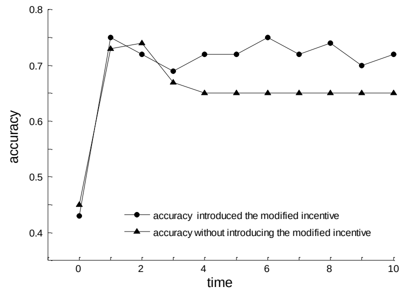

Figure 5 the accuracy of reputation evaluation for cloud service

As is shown in Figure 5, the initial accuracy is only 0.45 after the initial value of the cloud services is set. However the initial reputation value is often not able to characterize the true quality level. The accuracy of global reputation value remain at the level of 75% with continuous change after a round of reputation evaluation, which is higher than the accuracy without introducing the modified incentive. This also proves that the process of reputation calculation is dynamic and tends to be objective, and it can describe the quality level of service after a lot of reputation accumulation.

B. Simulation Test of Incentive Mechanism for Reputation Evaluation

In order to accurately verify the evaluation results with the introduction of incentives, we set that the proportion user had participated in evaluation at each round was λ in the general computing, the proportion user had participated in evaluation at each round was λ in the normal period after introducing the incentive mechanism and the proportion user had participated in evaluation at each round was ε in the punishing period after introducing the incentive mechanism. λ and ε randomly generated and $0 \le \lambda < \varepsilon \le 1$.

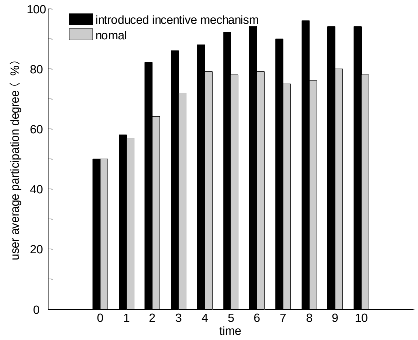

Fig 6.user participation degree after 10 rounds of reputation evaluation

As is shown in Figure 6, the user's initial average participation degree of 0.5, the same conditions, before introducing the incentive mechanism, the increase of the average participation degree tends to be gentle, and finally, it is about 80%. After introducing the incentive mechanism, the user's average participation degree improved rapidly after the second round evaluation. The overall average participation degree of the user will gradually be maintained at a higher level.

V. CONCLUSIONS

The emergence of massive cloud services forms a challenge for the user to identify and select the cloud services with high quality. 1) In this paper, we propose a reputation management policy based on the credibility of the user to provide some reference for the service selection. 2) We introduced the idea of the incentive mechanism to provide mentality for solving the negative pretermission in the evaluation participation. 3) The method we proposed is effective, but there is some deficiencies. Next step, we will consider the influence of computational complexity on the entire reputation system, which may improve the efficiency of the system.

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