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An Evaluation Approach of Subjective Trust Based on Cloud Model

Shouxin Wang[1], Li Zhang[1], Na Ma[2], Shuai Wang[1]

[1]Software Engineering Institute Beihang University Beijing, China, [2]Logistics R&D Center North China Institute of Computing Technology Beijing, China
Email: shouxin_wang@126.com; lily@buaa.edu.cn; wangshuai_911@sina.com; mana82@126.com

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ABSTRACT

As online trade and interactions on the internet are on the rise, a key issue is how to use simple and effective evaluation methods to accomplish trust decision-making for customers. It is well known that subjective trust holds uncertainty like randomness and fuzziness. However, existing approaches which are commonly based on probability or fuzzy set theory can not attach enough importance to uncertainty. To remedy this problem, a new quantifiable subjective trust evaluation approach is proposed based on the cloud model. Subjective trust is modeled with cloud model in the evaluation approach, and expected value and hyper-entropy of the subjective cloud is used to evaluate the reputation of trust objects. Our experimental data shows that the method can effectively support subjective trust decisions and provide a helpful exploitation for subjective trust evaluation.

Keywords*: *Subjective Trust, Cloud Model, Trust Decision-Making

1. Introduction

With the expansion of the Internet, applications based on the internet, such as electronic commerce, online trading and networked communities are going from a closed mode to open and open mode. People and services or services providers are interacting with each other independently. Because the parties are autonomous and potentially subject to different administrative and legal domains, traditional security mechanisms based on registry, authorization and authentication have not been able to satisfy numerous web applications [1,2]. A party might be authenticated and authorized, but this does not ensure that it exercises its authorizations in a way that is expected [3]. Therefore it is important that customers be able to identify trustworthy services or service providers with whom to interact and untrustworthy ones with whom to avoid interaction. Just like Sitkin points that it is widely agreed that electronic commerce can only become a broad success if the general public trusts the virtual environment, and this means that the subject of trust in e-commerce is an important area for research [4]. Trust between the participants involved has equal importance for the nonprofit network community. It is important that we research subjective trust evaluation based on trust relation in order to ensure the customers' satisfaction in the public-oriented distributed network environment.

At present, there are two trust relations in the area [5,6], namely objective trust and subjective trust. Hypothesis-based reasoning argumentation is a basic method in object trust research, such as BAN Logic [7] in security protocols. Subjective trust's principal component is an estimate of specific character or specific behavior level of trust objects, namely people. Trust from the principal part A to the object B means that A believes that B will definitely act in a predined or expected way under a specific circumstance [6]. This paper researches the trust decision-making of subjective trust relationships, and provides a quantitative evaluation method for subjective trust.

Many researchers have done studies on modeling and subjective trust reasoning. Papers [8,13] provide some trust evaluation and reasoning methods for probability models. Those methods don't consider fuzziness of trust itself, and their reasoning is based on pure probability models. As a result, they tend over formalize subjective trust quantification. Literatures [5,6] consider fuzziness of subjective trust, constructing subjective trust management models based on fuzzy set theory. Fuzzy set membership is a precise set description of the fuzziness but does not take the randomness into account. So, these methods lack flexibility [15]. Aiming at subjective uncertainty like randomness and fuzziness of subjective trust relationship, Beihang University advanced an approach to express trust based on a cloud model, which describes the fuzziness and uncertainty of trust [16].

Based on [16], we consider the impact of an object's reputation change with time to trust decision-making and

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exploited a subjective trust quantitative evaluation based on the subjective trust cloud, which preferably solves internet trust decision-making by means of analyzing historical reputation.

The remainder of this paper is organized as follows: Section 2 introduces the issue of internet trust decision-making. Section 3 describes the basic knowledge of cloud model involved in this paper. Section 4 specifies subjective trust evaluation based on cloud model and formalizes quantitatively the trust score. Section 5 shows a simulation experiment of the approach exploited in the paper and validates its validity and rationality. Finally we summarize the paper and discuss further research directions.

2. Trust Decision-making

The online trading and network communities need a set of entities providing services that they can trust. It is significant how users make a trust decision as presented in this paper. Here we call trust decision users trust subjects or subjects, entities evaluated trust objects or objects. Some large web application system, such as Amazon.com, eBay, AllExperts provide evaluation mechanisms for the reputation of subjects and objects. For objects, reputation is the evaluation of their capability, estimating intention, and capability of meeting subjects' services demands, also called objects' service satiability. In the context of this paper, we assume there is no difference in describing the trust relationship between objects trust or reputation and service satifaction capability.

A commonly used trust decision solution is based on ratings by users, including collaborative filtering [15,16], associative retrieval [19,20],association rules [21], and Horting graphs [22]. Of these methods, collaborative filtering is the most successful. It supposes that if users grade some items similarly, they will also grade the others similarly. The basic idea of the algorithm is that the score of un-graded items given by one user are similar to ones given by the nearest neighbors of that user [17].

Recommendation system of web application provides a valuable reference for subjects' trust decision. However, the general public prefers estimation based on an object's historical reputation. Even though supported by a recommendation system, subjects are still challenged by making trust decision(s) among many recommended objects. Because the essence of subjective trust is based on subjective belief [7,8], it is random and uncertain. In addition, reputation of trust objects changes with time, which should also be quantitatively taken into account. Therefore, it is essential that Web Application Systems provide subjects with objects to select from in order to improve subject satisfaction by analyzing subjective evaluation data of the objects' history reputation.

The paper suggests a subjective trust evaluation based on cloud model, which uses history grade of reputation from subjects to objects for selecting proper objects. Our hypothesis of business environment in the paper is listed below:

1) There are many subjects and objects in web application systems.

2) Web Application Systems provide rating mechanism for evaluating objects at least.

3) Web Application Systems provide mechanisms for avoiding vicious and illusive evaluation.

4) For convenience, we use rating mechanism of five levels to explain and validate trust decision approach proposed.

3. Introduction to Cloud Model

In the reasoning process, randomness and fuzziness are usually tightly related and hard to separate [23]. Based on random and fuzzy mathematics, a cloud model can uniformly describe randomness, fuzziness, and their relationship. This chapter introduces basic knowledge of the cloud model.

DEFINITION 1: Cloud and cloud drops [24]: Assume that U is a quantitative numerical universe of discourse and C is a qualitative concept in U. If $x \in U$ is a random implementation of concept C, and $\mu(x) \in [0,1]$, standing for certainty degree for which x belongs to C, is a random variable with stable tendency.

$$\mu: U \rightarrow [0,1] \quad \forall x \in U \quad x \rightarrow \mu(x)$$

Then distribution of x in universe of discourse U is called cloud and each x is called a cloud drop.

According to definition 1, cloud has the important qualities as follows.

1) Cloud is the distribution of random variable X in the quantitative universal set of U. But X is not a simple random variable in the term of probability, for any $x \in U$, x has a certainty degree and the certainty is also a random variable not a fixed number.

2) Cloud is composed of cloud drops, which are not necessarily in any order. A cloud drop is the singular implementation of the qualitative concept. The character of concept is expressed through all drops, the more drops there are, the better the overall feature of the concept is represented.

3) The certainty degree of cloud drop can be understood as the extent to which the drop can represent the concept accurately.

4) Qualitative concept described in cloud model is reflected by many quantitative concept values and binary pairs from $<x, \mu>$ of their certainty degree.

The general concept of a cloud model can be expressed by its three numerical characteristics: Expected value (*Ex*), Entropy (*En*) and Hyper-Entropy (*He*). In the discourse universe, *Ex* is the most representative for qualitative concept. *En* is a randomness measure of the qualitative concept, which indicates its dispersion on the cloud drops, and the measurement of "this and that" of the qualitative concept, which indicates how many elements could be accepted to the qualitative linguistic concept. *He* is a measure of the dispersion on the cloud drops, which can also be considered as the entropy of *En* and is determined by the randomness and fuzziness of *En*.

DEFINITION 2: One-dimension normal form cloud [24]: Assume that U is a quantitative numerical universe of discourse and C is a qualitative concept in U. If x∈U is a random implement of concept C, x satisfies: x～N(Ex,En'2), En'～N(En,He2), and certainty of x for C satisfies the following rule:

$$\mu = e^{-\frac{(x-Ex)^2}{2(En')^2}} \tag{1}$$

Then x can be called normal form cloud in the discourse U. The paper [25] thoroughly analyzes and discusses the universe of normal form cloud in applying uncertainty representation. The cloud models involved in this paper are one-dimension normal form cloud and Figure 1 shows the graph of one-dimension normal form cloud whose numerical characteristics are *Ex*= 3, *En*= 3, and *He* is 0.01.

As defined earlier, the quantitative value of cloud drops is determined by the standard normal form distribution function. Their certainty degree function adopts a bell-shaped membership function used broadly in fuzzy set theory. As a result, normal form cloud model is a brand new model based on probability theory and fuzzy set theory, and concurrently holds randomness in the former and fuzziness in the latter.

4. Subjective Trust Evaluation Based on Cloud Model

It is important to understand and distinguish the difference of alternative trust objects from which trust decisions are made. Trust decisions in the internet environment are a process where trust subjects can distinguish the difference of reputation of alternative objects using decision constraints. Subjects choose some objects from an object set Objs={obj_1,obj_2,…,obj_n}. It can generate a smaller alternative trust object set Objs'={obj_1,obj_2,…,obj_m} (m<n) and reduce the selection range. Decision constraints are the focus of the decision process and provide rules for distinguishing potential differences of objects' trust reputation. The formal description of trust decision process is given below as expression (2).

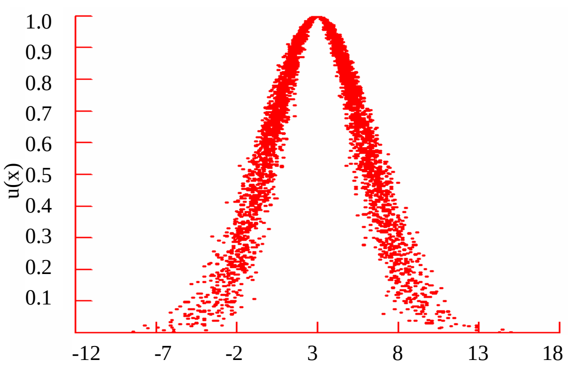

Figure 1. Cloud graph of one-dimension normal form cloud

$$Transform(Objs) \xrightarrow{constraint} Objs \tag{2}$$

A trust decision method means, subjects describe decision constraints qualitatively or quantitatively in the process of selecting objects based on analysis of potential differences in their trust reputation. In this paper, we use subjective trust cloud based on the cloud model to quantitatively describe decision constraints, and to distinguish the average level of trust reputation between multiple objects.

4.1 Subjective Trust Cloud

With a simple subjective grade mechanism and average value to calculate trust reputation, i.e., Amazon.com and OnSale and so on, evaluate a seller's trust reputation [26]. Table 1 displays five evaluation information of objects' trust reputation from Amazon.com which provides same services. Amazon provides the overall reputation of every object. The other four objects have the same overall evaluation value except A. Therefore, without other supporting information, it is difficult for subjects to make a trust decision reasonably and effectively. Statistical methods can effectively reflect randomness of subjective grade, but can't express the significance of subjective uncertainty, namely, fuzziness. As a result, it is rational to express the qualitative concept of subjective trust in a cloud model. In addition randomness and fuzziness are correlated in cloud model expression, which provides support for trust decisions more reasonably and effectively.

In this paper, we give definitions which are correlated with subjective trust cloud as follows:

DEFINITION 3: Subjective trust degree (STD) is an ordered set of number in an universal set [0, n], STD=[0, n]. STD is composed of sequential or discrete numbers which represent a trust object's reputation and n is any positive integer. 0 and n represent the lower and upper limit of the reputation.

DEFINITION 4: Subjective trust space (STS) is an ordered set of qualitative concepts which represent the qualitative degree of trust. There can be 0 or more than one trust level standard for one STS.

DEFINITION 5: Subjective trust cloud (STC) is a subjective trust concept represented by cloud model and composed of many cloud drops. STD=[0, n] is the universal set of STC, for any e ∈STS is a qualitative trust concept of STS, and any x ∈STD is a implement of e. The certainty degree of x for e, i.e., μ(x) ∈ [0, 1] is a random value with stabilization tendency.

Table 1. Reputation of objects from amazon.com

object	1	2	3	4	5	Aggregation
A	17	77	89	154	589	4
B	55	29	46	90	732	4.5
C	14	20	62	137	788	4.5
D	16	26	49	121	734	4.5
E	58	60	161	380	234	4.5

$$\mu:STD \to [0, n] \quad \forall \quad x \in STD \; x \to \mu(x)$$

Then the distribution of x on STD is defined as STC(x), and every x is called subjective trust cloud drops.

The subjective trust cloud is extensible, and when the discourse space of STD is [0, 1], it is equal to the trust cloud in [16]. Quantitative reputation of subjective trust cloud can be ordered value composed of any value of [0, n]. For STD, ordered value is composed of a set of sequential or discrete values reflecting reputation, which makes subjective trust evaluation based on cloud more pervasive. Firstly, without extra data processing, it is applicable to discrete or sequential value reputation grade mechanism. Secondly, it can effectively reflect qualitative-quantitative transformation of cloud and climbing-up of qualitative concepts. If reputation is continuous values, it reflects qualitative-quantitative transformation between subjective qualitative trust concepts and quantitative discourse. If reputation is discrete value space, it reflects climbing-up of fine granularity of concept, namely, qualitative concepts and values in discourse space form hierarchical construct of concepts.

The other characteristic of subjective trust cloud means that it doesn't necessarily require qualitative concept in trust space, namely, regulating trust grade. It evaluates overall objects' reputation by just comparing < *Ex*, *He* > which is called subjective trust character vector. It is necessary to endow its numerical characteristic with rational and significant physical meanings in the context when cloud model expresses qualitative knowledge. In this paper, we take *Ex* as typical value of objects' reputation, namely, average reputation level of objects. In addition, we use *He* to reflect decentralization degrees from objects' reputation to the average, namely, *He* reflects the stability of an objects' reputation. If *Ex* is big, then an object's ability to satisfy a subject's need is big and vice versa. If *He* is small, then the stability of reputation for an object is good and vice versa.

Subjective trust cloud design

The first step for a quantitative evaluation of an object's reputation is to design the STD, confirm the upper/lower limit of reputation space, and select discreteness or continuity of reputation. In this paper, we give a possible STD design, with five-grade-mechanism of Amazon.com serving as an example. When STD is a discrete space, every discrete reputation virtually can be considered as qualitative concept. STD is designed to be[1, 2, 3, 4, 5] in this paper.

Generation of numerical character value of STC

Object reputation varies with time, and it associates closely with its historical reputation and time [27]. Therefore, evaluation data of subjective reputation is only effective for a given period of time. This means the further away the evaluation time from the trust decision, the lower the effectiveness of its object reputation. In order to correctly evaluate that, we extend the cloud generation algorithm backward without certainty degree in [24], and design a weighted backward cloud generation algorithm. Based on the distance from reputation evaluation time to current trust decision time, this algorithm assigns different weights to reputation data of different times. The basic weight rule of this algorithm is, the newer the reputation data is, the bigger its weight and vice versa. We first explain the time model of reputation and basic rules for weighting.

Suppose the time model of reputation M=<X, t_c, t_b, T>.

1) X={x_1,x_2,…,x_n} is the full set of historical reputation data of an object. For any x_i, Time(x_i) denotes the time of reputation evaluated.

2) t_c denotes the current time of trust decision and serves as time origin. t_b denotes certain time of forward direction of time axis, and serves as time threshold for judging effectiveness of reputation.

3) T={t_1,t_2,…,t_{m-1}} is an ordered set composed of m-1 time values between t_c and t_b. For any t_i, $d_i=|t_i-t_c|$ is called time distance from t_i to t_c, and satisfies following constraint.

1) $\forall d_i (1 \le i \le m-1) \to d_i \le |t_c - t_b|$

2) $\forall d_i, d_j (1 \le i < j \le m-1) \to d_i < d_j$

Based on Time(x_i), t_b can separate X into two subsets, X_1' and X_2', and they satisfy the conditions below.

1) X= X_1' ∪ X_2',且 X_1'∩X_2'=Φ

2) $\forall_{x_i} \in X'1(1 \le i \le n) \to (|Time(x_i) - t_c| \le |t_c - t_b|)$

3) $\forall x_i \in X_2'(1 \le i \le n) \to (|Time(x_i) - t_c|) < |t_c - t_b|)$

As mentioned above, t_c serves as time origin, and $|t_c-t_b|$ serves as time threshold for judging effectiveness of reputation evaluation data. The set of X is separated based on the difference of $|Time(x_i)-t_c|$ and $|t_c-t_b|$. Time distance from any element in X_1' to t_c is less than or equal to the threshold, and that of X_2' is more than the threshold. Therefore, we consider evaluation time of reputation data in X_2', to be far away from current decision time, which can't correctly reflect the object reputation of current time. Evaluation data of object reputation is all included in X_1'.

The set T separates time interval between t_c and t_b into m sub-areas called temporal windows and marked as W_t. Temporal windows make X_1' m subsets of reputation evaluation data, Xt_1, Xt_2, …, Xt_m. They satisfy following conditions:

For any temporal window, $Win_{ti} = < t^i_{low}, t^i_{\sup} >$, t^i_{low}, is the lower time limit of W_{ti}, and $t^i_{\sup}$ is the upper time limit of Win_{ti} which satisfy $|t^i_{low} - t_c| < |t^i_{\sup} - t_c|$. $Win_{ti} = |t^i_{\sup} - t^i_{low}|$ is called window length of Win_{ti}

X_1'=Xt_1∪Xt_2∪,…,∪Xt_m, and

$$\forall Xt_i, Xt_j (1 \le i \le m, 1 \le j \le m) \to (Xt_i \cap Xt_j) = \phi$$

$$\forall y \in Xt_i, z \in Xt_j (1 \le i < j \le m) \to |Time(y) - t_c| < |Time(z) - t_c|$$

When we design the set of T, we should consider the time span of $|t_b\text{-}b_c|$, and quantity of reputation data in the span. T further separates X_1' into m subsets, and based on whose subject temporal windows, there is strict time sequence in Xt_1, Xt_2, …, Xt_m. There is equivalent weight of effectiveness for some reputation data whose time value is in the same temporal window. For any subset Xt_i (1<=i<=m) of X_1', we can assign a weight wt_i, which denotes the reputation influence extent from data in Xt_i to that of overall results of the objects. Weights should satisfy the constraints of expressions (3) and (4). Based on these expressions, we provide a simple weight assignment method satisfying the expression (5), which is based on that, as the time distance of t_i from t_c increases, its effectiveness for a period of time fades, and we express that fading trend in the mode of descent with the same difference which is indicated by the variable *inter*.

$$\forall x_i \in Xt_K, x_j \in Xt_l (1 \le k < l \le m) \rightarrow (wt_k < wt_l) \tag{3}$$

$$(\sum_{i=1}^{m} wt_i) = 1 \tag{4}$$

$$w_{ti+1} = w_{ti} - \mathrm{int}\,er(1 \le i \le m-1) \tag{5}$$

After calculating the weights we can apply the weighted backward generation cloud algorithm, to calculate the subjective trust cloud values of *Ex*, *En*, *He*. The weighted backward generation cloud algorithm is described as follows.

Input: a set of N cloud drops, X_1'={x_1,x_2,…,x_N}, and a set of cloud drops' weight, W_t={ w_{t1},w_{t2},…,w_{tm}}. m indicates the number of temporal windows.

Output: (*Ex*, *En*, and *He*) representative of qualitative concept of N cloud drops.

Steps:

1) Calculate the weight w_i of x_i with the equation i.e., $w_i = {w_{tj}}\Big/{numWin_j} \; (1 \le i \le N, 1 \le j \le m)$. Win_j is the jth temporal window and w_{tj} is the weight of it. num (Win_j) is a function which computes the number of drops in Win_j.

2) On the basis of x_i and its weight, calculate sample mean, first-order absolute central moment, and sample variance of x_i, i.e., $\overline{X} = \sum_{i=1}^{N} w_i x_i$, $\sum_{i=1}^{N} w_i \left| x_i - \overline{X} \right|$, and $S^2 = \sum_{i=1}^{N} w_i (x_i - \overline{X})^2$

3) $\hat{E}x = \overline{X}$

4) $\hat{E}n = \sqrt{\frac{\pi}{2}} \sum_{i=1}^{N} w_i \, | \, x_i - \hat{E}x \, |$

5) $\hat{H}e = \sqrt{|S^2 - \hat{H}e^2|}$

4.2 Trust Decision-making

After we compute three numerical values of the subjective trust cloud, we can make trust decisions based on the foundation of its character vector. For the physics meaning of < *Ex*, *He* >, we should pick objects whose *Ex* is big and *He* is small. A formal description of the trust decision, based on the subjective trust cloud, is expressed by equation (6).

$$Transform\,(Objs) \xrightarrow{<Ex, He>} Objs \tag{6}$$

But the character vectors may not accurately represent the things the trust subjects care about because they only pay attention to the result of selecting a trust objects based on some reasonable and simple rules. Therefore, similar to some existing methods [2, 28, 29, 30], it is very necessary to provide one certain approach, which can combine the *Ex* with *He* to obtain certain simple result of reputation, for trust subjects. Relying on the simple result, the most suitable object would be selected for trust subjects. Here we provide a reputation scoring method to address the issue.

As stated as above, *Ex* expresses the average reputation level, and *He* describes the decentralization degrees from reputation to the average, namely, stability of uncertainty of reputation. Hereby, for calculating quantitatively, we consider the *Ex* as the master value and *He* slave value. Reputation score is a function of *Ex* and *He* and increases with *Ex* and decreases with *He*. The formalized function of reputation score (hereafter RS) is described as $RS = Ex \times e^{-He}$ (7).

Expression 7 can represent the basic function relationship among RS, *Ex* and *He*. But in some special situations, expression 7 may have inaccurate results. To analyze these special situations, some typical cases of *Ex* and *He* are listed in Table 2.

According to expression 7, the RS is clearly better in case1 than case3. However, if there exists object A with high *Ex* and *He*, and object B with low *Ex* and *He*. Then the *Ex* of A may be higher than B's, but object A and B may have the same RS. In this situation, RS can not tell the fine difference of object A and B. To overcome the issue, expression 8 is introduced to amend the function of expression 7.

$$RS = Ex \times e^{-He} + \frac{b}{c} Ex (c = b + 1) \tag{8}$$

$\frac{b}{c}$ is an impact factor to adjust the computing result of RS. Expression 8 with the impact factor can distinguish the RSs among objects in case2 and case4. We can prove the validity of expression 8 as follows:

Proof: Suppose RS_a and RS_b are the reputation scores of objects A and B. $Rs_a = Ex_a \times e^{-He_a} + \frac{b}{c} Ex_a$, $Rs_b = Ex_b \times e^{-He_b} + \frac{b}{c} Ex_b$, and $Ex_a > Ex_b$.

Table 2. Table 1 four cases of *EX* and *HE*

	Ex	***He***
Case1	High	Low
Case2	High	High
Case3	Low	High
Case4	Low	Low

1) If $RS_a=RS_b$ then

$$Ex_a \times e^{-He_a} + \frac{b}{c} Ex_a = Ex_b \times e^{-He_b} + \frac{b}{c} Ex_b \quad \text{and} \quad \frac{Ex_b}{Ex_a} = \frac{e^{-He_a} + \frac{b}{c}}{e^{-He_b} + \frac{b}{c}} \tag{9}$$

2) Because 1<e<1 and *He*>0, so 0< e^{-He_a} <1 and 0<e^{-He_b} <1

3) As the result, $1 < \frac{Ex_b}{Ex_a} < c/b = \frac{b+1}{b}$

4) From the initial assumptions and the sequence of deduction steps, we can conclude that if $RS_a=RS_b$ then Ex_a approximately equals to Ex_b.

Similarly, let $\frac{Ex_b}{Ex_a} = \alpha$, then $\alpha e^{-He_b} + \alpha \frac{b}{c} = e^{-He_a} + \frac{b}{c}$ (10). Applying natural logarithm and equation transformation to equation 8, we can get a new equation $He_a - He_b = Ln(\frac{1}{\alpha^2})$ (11). Since α is close to 1, He_a is approximately equivalent to He_b.

Computing the RS of objects by the equation 8, can limit the error into acceptable range. $\frac{b}{c}$ is used to adjust the precision of reputation score. More small the inverse of $\frac{b}{c}$, more fine difference among reputation score of objects can be distinguished.

5. Experiment and Discussion

5.1 Maintaining the Integrity of the Specifications

Because most Web Sites can't provide time of reputation and the intention of the experiment is evaluating the effectiveness of the approach in the paper, we simulated the time of reputation based on real reputation data from Amazon.com. We collected 14 objects which provide a similar service, with ratings of each service greater than 700. Table 3 shows three typical original reputation data of objects.

The simulation steps are described as follows.

1) Assume the basic time unit is a week and all reputation data has been given in past ten weeks, this means t_b=10 weeks.

2) Designate several different ways to divide the temporal windows

3) Calculate time weight for each temporal window based on the equation (4) and (5)

Table 3. The original reputation data of three objects

objects	1	2	3	4	5
A	264	519	496	649	967
B	571	533	504	680	363
C	424	604	903	579	756

Firstly, we divide the ten weeks into three temporal windows. The number of weeks of each window is 1, 4, and 5 respectively. Applying the weighted backward generation cloud algorithm, we can obtain the numerical characteristics of the subjective trust cloud for objects A, B, and C depicted in Table 4.

From table 4, the *Ex* of B is lower than that of A and C. But the *Ex* of A is similar to C, and their difference is only 0.07. However, the *He* of A is smaller than that of C. Therefore, we can say that the basic level of reputation of B is lower than others, and the stability of reputation of A is higher than B. The result shows not only that the cloud model can express the uncertainty of subjective trust, but the numerical characteristics can be used as the decision constraints for subjective trust decision-making, and indicate fine differences among objects.

Next we validate the effect of temporal window on the result of reputation evaluation based on our approach. Actually, customers or owners of web site have many optional ways to define different temporal windows. They can choose two, three, or more temporal windows, and decide the number of basic time units of each one. Table 5 gives some possible methods to divide temporal windows.

Temporal windows depicts the number of temporal windows whereas the column of Basic time unit indcates the partition of each temporal window. For example, (1, 4, 5) means the first window should contain one week, and the second and third should contain four and five weeks. The curves of *Ex* and *He* of A, C under different partitions are shown in Figure 2 below.

The red curves represent object A, and blue ones represent object C. According to the partitions of Table 5, the *Ex* of A is always higher than that of C, and the *He* of

Table 4. Reputation ranking and the numbers of STC

objects	Ex	En	He
A	3.60	1.45	0.62
B	3.13	1.51	0.62
C	3.53	1.46	0.88

Table 5. The instances of temporal windows

Serial number	Temporal windows	The number of basic time unit
1	2	(10, 0)
2	2	(1, 9)
3	2	(2, 8)
4	2	(3, 7)
5	2	(4, 6)
6	2	(5, 5)
7	2	(6, 4)
8	2	(7, 3)
9	2	(8, 2)
10	2	(9, 1)
11	10	(1, 1, 1, 1, 1, 1, 1, 1, 1, 1)
12	3	(1, 4, 5)
13	3	(1, 2, 7)

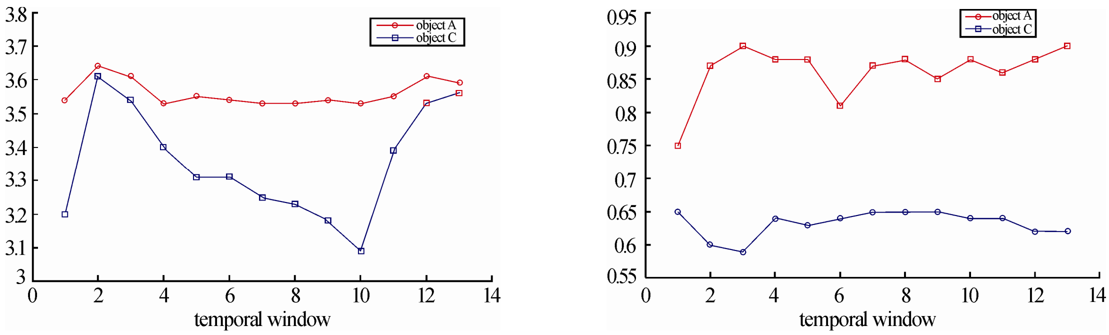

Figure 2. Ex and He curves of A and C

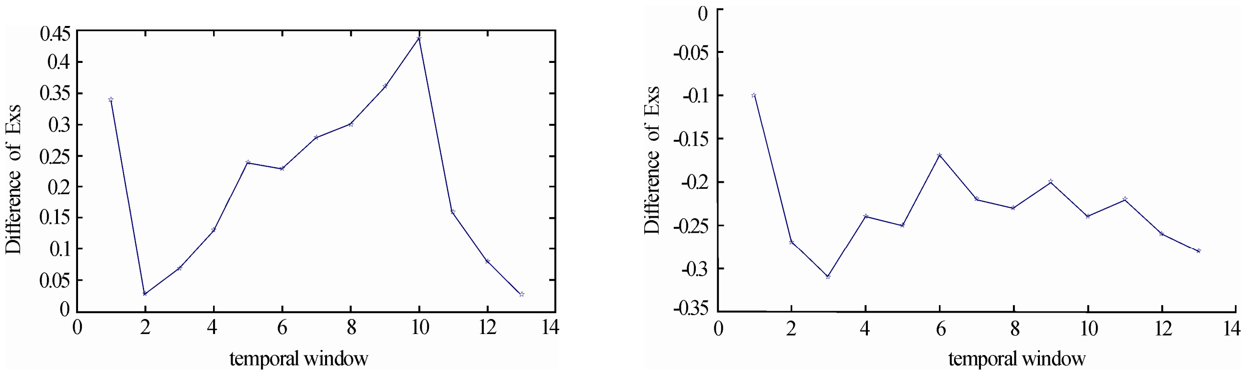

Figure 3. Curves of difference of Ex and He for A and C

A is smaller than C. Therefore, we can conclude that different partition methods don't change the result of reputation evaluation based on the subjective trust cloud. But different partitions can affect the precision of reputation evaluation. To exhibit this, the curves showing the difference of *Ex* and *He* of A, and C are depicted in Figure 3.

In Figure 3, the difference of *Ex* reaches the maximal value at the tenth partition, and the minimum at the second partition. However, the maximum and minimum of *He* are achieved at the first and third partition. So the trend of the two curves is not absolute consistent. We believe the distribution of reputation data may be what causes the difference under different partitions. Additionally, from Figure 2 and 3, the difference of *Ex* of A and C is more than zero, while their *He* difference is less than zero. Although different partitions may result in dissimilar evaluation, we can obtain the same conclusion which is consistent with that from Figure 2. That is the result of reputation evaluation does not change with the partition method.

5.2 Reputation Scoring Function

Based on the values of *Ex* and *He* in table 4, we apply the reputation scoring function mentioned in section 4.2 to compute the quantitative reputation scores of trust objects. Then the RSs can be calculated and the graphs of the RSs under different $\frac{b}{c}$ is shown in Figure 4.

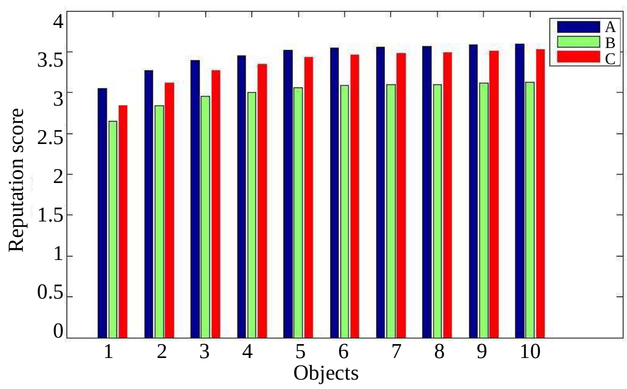

Figure 4. Reputation scores of trust objects A, B and C

There are ten groups of columniations in Figure 4. The value of c of each group from left to right is 3, 5, 8, 7, 21, 31, 41, 51, 101, 1001. The RS changes clearly from 3 to 21, but these ones between 31 and 1001 are very similar. So it is not necessary to give c a high value. On the other hand, $\frac{b}{c}$ can control the precision to tell difference of RSs. Actually RS of reputation may be in the range from $\frac{Ex}{c}$ to *Ex*. At the same time, we could find that different c would not affect the order of reputation scores for objects A, B, and C. From the view of reputation scores, object A may be the final one selected by trust subjects. The choice result based on reputation score is consistent with that one based on Figure 2 and 3, but more simple and suitable to trust subjects.

6. Conclusions

Cloud model overcomes the limit of fuzzy set theory which represent fuzzy concept with an accurate and sole membership degree. We proposed an evaluation approach of subjective trust based on subjective trust cloud. The approach combines *Ex* with *He* of subjective trust cloud to evaluate the randomness and fuzziness of subjective reputation. We validated our approach with a simulation experiment and showed the effectiveness of the approach. Our approach needs time of reputation. However, most Web Sites don't provide this data. But with development of business and cooperation on the Internet, especially with more attention put on satisfaction of general public, we believe that the evaluation of reputation change will be a novel and effective approach to assist end-users in trust decision-making. Furthermore there is still a need for significant research in this field, such as how to extend the approach to apply in the other related field, how to design and validate other weighting methods of reputation, how to combine subjective with objective trust data to make trust decisions, find the reasonable law and rules to design temporal windows and so on.

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