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Evaluation Model of Buyers' Dynamic Reputation in E-commerce

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Abstract

Members in electronic commerce often have no information about each other, thus, trust is one of the most important aspects in online transaction. In order to accurately display the buyers' trustworthiness. This paper constructs a mean model to compute reputation of buyers. The model is based on two aspects, successful trading and returned goods. We introduce two adaptive trust factors, transaction value factor and return rate factor, to improve the feedback rates of sellers. Contrasting reputation based solely on feedback from sellers, the reputation of buyers is eventually represented by a three-dimensional array in our model. Simulation experiments evaluated different buyers and a buyer's different period dynamic reputation. Compared with existing rating models, this model is more effective and can increase the ability to resist fraud.

Keywords: *C2C e-commerce; buyers' reputation; mean model; return rate factor*

1. Introduction

With the rapid development of information technology and increasing popularity of the Internet, style of traditional consumption is undergoing tremendous changes. A increasing number of people are choosing online shopping. The "33rd China Internet Development Survey Report "[1] pointed out that, in 2013, China's online shopping users reached 312 million, while in 2012 it was 2.47 million, (see an increasing of 26.3%). According to the "2013 Annual China online retail market data monitoring report "[2], the total transactions amount is up to 1.8851 trillion in 2013. Compared with the data of 2012, it increased 42.8%.

However, online transaction, to some extent, is still inadequate. Lacking of understanding and trust is caused by various network unknown entities. Such unknown entities are invisible and anonymous between each other, and participants are easy to entry, exit or change the identity of the characteristics between customers and businesses [3]. Thus, members in electronic commerce may have little information on each other's reputation, let alone they have knowledge about each others reputation. Mutual trust has been always influencing on e-commerce to move forward. With the developing of information technology, *Reputation System* [4] appeared and it provides an effective way to solve the crisis of trust in online shopping. The reputation assessment model is the core mechanism of *Reputation Management System*. Due to the characteristic of information asymmetry between buyers and sellers, buyers are vulnerable to risks. Previous researches about the evaluation model of reputation were mainly focused on how to accurately assess the seller's reputation [5]. Studies about computing model of reputation of buyers are relatively limited. However, in the process of the development of e-commerce, various mechanisms (*e.g.* "seven days unconditional return", "retreat cargo insurance fees") have effectively improved the vulnerable status of the buyer.

On the contrary, many phenomenons which are harmful to the seller or e-commerce platform have been increasingly appearing. First, many sellers disguise as buyers to deal low price goods, and then give a negative rate to their sellers, which is intend to damage the peer reputation. Second, since the “freight insurance” has appeared, there are even some buyers return goods deliberately in order to freight difference. Therefore, the study on how to evaluate different buyers’ credibility in e-commerce is meaningful either on theory and application. That could not only fill the hole of currents research, but have important significance of improving current’s Reputation Management System as well.

2. Evaluating of Reputation of buyers

C. Dellarocas holds that someone’s reputation originates public evaluation, and it reflects a person’s specific characteristics or properties. From the point view of trading, buyers’ or sellers’ credibility is overall impression leaving by each other after a transaction [6]. "Reputation Management System" provides an effective tool to generate and disseminate the buyer’s or seller’s reputation information on the electronic market. Reputation value can reflect the quality of products or services that sellers providing, or transaction information of a buyer. Assessment of reputation is one of the mechanisms of Reputation Management System, and assessing model is a critical component [7]. The task of computing reputation is normally achieved by collecting, aggregating, or publishing user’s history transaction information to encourage cooperative behavior between strange buyers and sellers, and thus to promote trust among the network [8]. As to assess reputation of buyers, the main idea of evaluation mechanism is that the seller gives feedbacks to the cooperative buyer after a successful transaction. The score are determined by various factors, including the attitude during deal, whether pay for goods in time, and even whether rate the goods or the cooperative seller objectively. Thus, the buyer will get a transaction reputation value after each successful transaction. By certain way, reputation scores of all transactions of one buyer can be aggregated, and the reputation of the buyer can be reflected using comprehensive performance indicators.

2.1. Existing evaluating models

From the existing C2C (Consumer to Consumer, C2C) e-commerce site, we observe that a number of C2C e-commerce sites, such as eBay or Taobao, are using the Reputation Management System to promote mutual trust in transactions. However, all of them are adopting a single cumulative score from sellers to rate the reputation of the buyer. For example, eBay or Taobao requires the seller to rate cooperative buyer after a transaction. The rating is divided into three classes, i.e. *Good reputation*, *Medium reputation* or *Bad reputation*. Such rating classes are replaced by +1, 0 or -1 respectively. Thus, the reputation performance indicator of a buyer *j* is calculated by a cumulative sum:

$$R_j = \sum_{i=1}^{m} r_i ,\ \ i = 1, 2, 3 \cdots, m, \tag{1}$$

R_j: reputation value of the buyer j;
r_i: the feedback score of the seller i;
m: the number of trading of buyer j [7].

It can be seen that the model is quite simple in calculation, but it cannot reflect to the buyer's reputation properly and objectively.

2.2. Problems of the Existing Models

To the best of our knowledge, problems of the existing models can be summarized as follow:

(1) The single cumulative scoring model merely uses the number of Good reputation subtract the number of Bad reputation. The computing method does not take full use of the number of comment times [7]. So it cannot properly capture the actual reputation of a

buyer. The reputation of one buyer in different periods cannot be compared as well, so it can not reflect the trend of the buyer's reputation.

(2) The single cumulative scoring model uses solely simple accumulation, and does not consider the price of goods in each transaction. Basing on this method, buyer may get the same reputation value in each transaction, which is one of the +1, 0 or -1, and have no relationship with the transaction value [9]. By this means, this model fails to describe the formation of the buyer's reputation effectively [10].

(3) The single cumulative scoring model only considers the impact of successful traded goods (ordering goods and receive it) and on reputation of buyers, without considering the returned goods (ordering goods and return it). This will result that when doing transaction online, part of buyers select only low-priced goods regardless of comparing the quality. If they dissatisfy with the goods they have ordered, they would return them to the seller. In addition, there exists many "professional fraudulent returns people ". These kinds of people return deliberately the goods in order to make the price difference of return. In the undergoing period, the return goods phenomenon in e-commerce is becoming serious. The phenomenon of high return rate not only harms the benefits of sellers and insurance companies, but also has a bad effect on the healthy development of e-commerce websites.

It is still an interesting research field in rating model of the credibility in e-commerce. Scholar, U. M. Dholakia *et al.*, improves the evaluation model on the basics of single cumulative scoring model to rate sellers' reputation objectively. They introduces several indicators (*e.g.* density of bidding, density of transaction etc.) to enhance historical trading record [11]. S. X. Ji *et al.* optimizes feedback system of buyer's reputation in the view of the e-commerce platform though introducing trading merchandise's value and time value. They selected two sellers of Taobao to validate the validity of the model and further analyze the positive role of improving system on promoting the trusted of the seller [12]. L. F. Xu *et al.* assess reputation value of the seller basing on buyers' reputation, and confirmed the validity of the model in the prevention of each fraud [13]. In their paper, they argue the rating accuracy is main factor in influencing buyers' reputation, and the more accuracy of buyer rating is, the higher he/she reputation is. J. B. Hu *et al.* construct evaluating model of sellers' reputation. They utilize entropy method to calculate weights. Their model allows buyer to select trading seller in the view of protecting the buyer [14]. Y. L. Zheng *et al.* propose a model to calculate the seller's reputation, which only standardize the reputation of the seller [15]. C. Li *et al.* propose multidimensional scoring models to calculate sellers' reputation, while the credibility of the buyers be calculated only using the seller's feedback [16]. Scholars' research on assessing the credibility in e-commerce has been focusing mostly on the seller. Most of studies are focused on preventing buyers from suffering deception. While study about evaluating model of buyers reputation are rarely limited. In addition, all these papers only consider traded goods, but ignore return goods.

In order to improve the Reputation Management System's deficiencies of C2C e-commerce and reflect objective the buyer' reputation, and construct a good trading platform, this paper suggests that, when evaluating a buyer reputation, both traded goods dimension and returned goods dimension should be taken into account. Each dimension should also involve multi-indexes.

Base on the analysis above, this paper argues that evaluating model of buyers' reputation should include the following steps:

(1) Recognize and identify main indexes, which have an impact on buyers' reputation and the scoring rules of it.

(2) Determine performance indicators of reputation and its calculation method.

3. Building Evaluation Model

3.1. Evaluation indexes

When a buyer conducts a deal online, there can be two results in the end. He/She accepts the goods, or returns it. Therefore, online transactions can be divided into two kinds: successful trading and unsuccessful trading. According to the results of online shopping transactions and the characteristics of e-commerce trades, buyers' reputation should include two aspects of successful traded goods and returned goods.

The buyer's reputation of traded goods is oriented from successful transactions, which includes three factors: the number of successful deals, seller's feedback rating, and transaction price. Buyers' reputation of returned goods is obtained from the fail transactions, which includes two factors, the number of fail transactions and the number of successful transactions.

3.1.1. Sellers' Feedback Score e_{ij}: In C2C e-commerce, sellers' feedback score is an assessment that one seller give to the cooperative buyer in a transaction. We let e_{ij} represents buyer i get feedback rating from seller j ($j = 1、2、3、4 \cdots m \cdots$). The feedback score scale can be defined to many scales, such as (Ⅰ) $e_{ij} \in (-1, 0, 1)$; (Ⅱ) $e_{ij} \in (1,2,3,4,5)$; (Ⅲ) $e_{ij} \in (-2, -1, 0, 1, 2)$; (Ⅳ) $e_{ij} \in (1,2,3 \ldots 8,9,10)$ and so on [6]. After a successful transaction, the seller can give a rating to the buyer only once, and it can not be modified again.

3.1.2. Transaction Value factor ω_1 : The single cumulative scoring model does not take the price of each transaction into account. As describe above, a buyer's reputation updates by pulsing one of them (+1, 0, -1) after a successful transaction, which has nothing to do with the price of goods. However, there are billions of goods in e-commerce trading platform, and their prices are different from each other. Even the same kind of goods have different price.

Commodity prices can be divided into two kinds: high-priced goods and low-priced goods, at the same time, the transactions in e-commerce website can be divided into two kinds basing on the goods price. When a buyer makes a deal with a seller on high-priced goods and gives positive feedback to the seller, the buyer is most likely a high reputation person. His or her reputation value in this transaction should be awarded basing on the seller's feedback score. Further, comparing with low-priced goods, a buyer usually has higher expectations on high-priced goods. If a buyer wants to buy high-priced goods, he or she may do careful evaluation before determine to make a deal. Despite people in e-commerce platform hold different attitude toward risk, there still exists different risk between high-priced goods and low-priced goods. The success of transaction of high-priced goods should have greater utility for buyers' reputation value. So, this paper argues that transaction value of each transaction should consider when evaluating a reputation of a buyer.

Base on price of transaction goods, we set a dynamic weight to adjust sellers' feedback rating, and then to influence transaction reputation of the buyer. By the following equations (2), (3), and (4), the price of trading goods is converted to transaction value factor to improve sellers' feedback rating. The effect of it depends on the trading price.

$$\omega_1 = f_1(\theta_1) \quad ; \qquad (2)$$

$$\theta_1 = \frac{P_j - C}{C} \quad ; \qquad (3)$$

$$\omega_1 = \begin{cases} 1 & \theta_1 \le 0; \\ f_1^{(1)}(\theta_1) & 0 < \theta_1 \le \theta_1^{(1)}; \\ f_1^{(2)}(\theta_1) & \theta_1^{(1)} < \theta_1 \le \theta_1^{(2)}; \\ a & \theta_1 \ge \theta_1^{(2)}; \end{cases} \quad (4)$$

Where,

P_j: the price of a commodity for the j-th transaction;

C: fixed constant, which can be defined as nationwide average price of online goods or some areas' average price of online transaction and so on;

θ_1 **:** Relative deviation between P_j and C, which is a random variable;

We let transaction value factor ω_1 is a function of θ_1, and $f_1^{(1)}(\theta_1)$, $f_1^{(2)}(\theta_1)$ should make $f_1(\theta_1)$ both smooth and continuous.

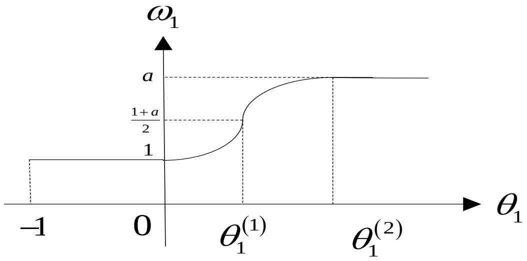

Figure 1. Relationship of ω_1 with θ_1

It can be seen from Figure 1 that ω_1 and θ_1 the following relationship.

(1) If $-1 \le \theta_1 \le 0$, then we let $\omega_1 = 1$ .That means while a buyer conducts low goods transaction, there is no incentive effect for the transaction price to the seller feedback score. His or her transaction reputation by the trading is set as the seller feedback score;

(2) If $0 < \theta_1 \le \theta_1^{(1)}$, then we let $1 < \omega_1 \le \frac{1+a}{2}$ (a>1). The rate of the change of ω_1 or the value increases with the increasing of θ_1. That means while a buyer conducts relatively high price transactions, the transaction price has reward utility for the seller feedback score, and the greater of trading price is, the greater of the utility value.

(3) If $\theta_1^{(1)} < \theta_1 \le \theta_1^{(2)}$, then we let $\frac{1+a}{2} < \omega_1 \le a$. The value of ω_1 increases with the increase of θ_1, but the rate of change decreases. That means while the buyer make a deal of goods price between this phase, the transaction price has rewarded utility to the seller feedback score, and the greater the commodity exchange price is, the greater the incentive effect is , but the reward rate is smaller.

(4) If $\theta_1 \ge \theta_1^{(2)}$, then we let $\omega_1 = a$ .That means while a buyer conducts high price transaction, the transaction price has rewarded utility to the seller feedback score, but it is value no longer increases with the transaction price increasing.

3.1.3. Return Rate Factor ω_2 : In current's online reputation assessment system of C2C e-commerce, only the seller's return rate is calculated. The seller's return rate provides reference information for buyers' whether make a deal with the seller. Since Taobao or other websites launched freight insurance of refund, buyers could return goods with a very low cost with the help of freight insurance. In order to attract customers, there are even a larger amount of sellers giving freight insurance. Therefore, freight insurance becoming popular in C2C e-commerce, and the use of freight insurance has been increasing significantly since it launched. Although part of return owe to quality of goods, there still a larger number of buyers order goods without carefully evaluating the nature of products. Because they subconsciously think if the goods they received is not as good as they expected, they can return it with almost no cost. What's more, some of buyers seize the loopholes of mechanism of freight insurance. They order a large number of goods with freight insurance, and then return deliberately all of them to earn freight difference.

The return rate has been changing markedly in C2C e-commerce. Newspaper *Hangzhou Daily* reported that, more than 50% buyers choose to return goods in C2C e-commerce since the freight insurance of return launched. Deliberate return of goods not only damages interests of sellers and insurance company, but is harmful to e-commence platform as well. Some sellers offering free freight insurance aim to protect buyers' interest from being harmed, but they receive high return goods as a result. Similarity, facing unexpected return rate, the insurance company has to undertake huge freight of returning goods. What's more, the phenomenon of malicious return has bad influence on developing of e-commence platform.

Considering malicious returning goods, this paper argues that the return rate of buyers should be considered as one of the factors when evaluating buyer's reputation. If this factor is introduced in evaluating model, it can increase the ability to resist fraud of malicious returning goods and encourage buyers to evaluate the goods carefully before order. On the other hand, for buyers of high return rate, it can provide an early warning mechanism for the seller and C2C e-commerce platform, therefore to protect the legitimate interests of the seller and the C2C e-commerce platform. Further, it can provide basic date for insurance to set a price on fee of freight insurance.

Base on the number of buyers' return goods, a mean model can compute buyers' return rate, and set dynamic weight to influence the transaction reputation of the buyer. By the following equations (5), (6), and (7), the number of returned goods is converted to return rate factor to influence the reputation of traded goods buyers. Based on the different return rate, the model sets different weight.

$$\omega_2 = f_2(\theta_2) \tag{5}$$

$$\theta_2 = \frac{N_t}{N_m + N_t} \tag{6}$$

$$\omega_2 = \begin{cases} f_2^{(1)}(\theta_2) & 0 \le \theta_2 \le \theta_2^{(1)}; \\ 1 & \theta_2^{(1)} < \theta_2 \le \theta_2^{(2)}; \\ f_2^{(2)}(\theta_2) & \theta_2^{(2)} < \theta_2 \le \theta_2^{(3)}; \\ 0 & \theta_2^{(3)} < \theta_2 \le 1; \end{cases} \tag{7}$$

Where,

N_m : The total number of successful transactions;

N_t : Total number of unsuccessful transactions (a commodity counted once);

θ_2 : Return rate of some buyer;

$\theta_2^{(1)}$: The highest return rate of providing incentives for a buyer's reputation. The value can be set according different conditions. (*e.g.* average return rate of all kinds of goods or other number);

$\theta_2^{(2)}$: The lowest return rate which begins to punish a buyer's reputation. The value can be set according different conditions as well. (*e.g.* keep the premium unchanged that insurance company)；

$\theta_2^{(3)}$: The highest return rate that the e-commerce platform allow. (e. g. the max return rate of insurance company provides freight insurance. If some buyer's return rate is higher than it, insurance company or seller has right to cancel freight insurance, even don't make a deal with he/she)；

We let return rate factor ω_2 is a function of return rate θ_2 , and $f_2^{(1)}(\theta_2)$ and $f_2^{(2)}(\theta_2)$ should make the $f_2(\theta_2)$ both smooth and continuous.

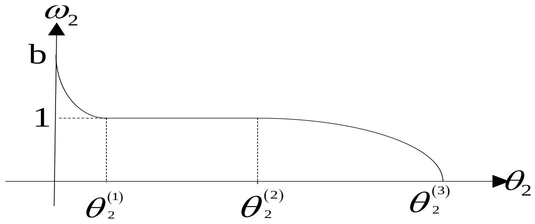

Figure 2. Relationship of ω_2 with θ_2

It can be seen from the figure that ω_2 and θ_2 should have the following relationship.

(1) If $0 \le \theta_2 \le \theta_2^{(1)}$, then we let $1 < \omega_2 \le b$ （b>1） . The value of ω_2 and the changing rate of it decreases with increase of the value of θ_2 .That means while buyers return rate is below $\theta_2^{(1)}$, the return rate factor has awarded utility for buyers reputation, the lower of return rate is, the greater the awarded effect is.

(2) If $\theta_2^{(1)} < \theta_2 \le \theta_2^{(2)}$, then we let $\omega_2 = 1$. The value of ω_2 does not change with the change of θ_2 . That means while buyers return rates is in the range of $\left[\theta_2^{(1)}, \theta_2^{(2)}\right]$, the return rate factor has no effect on buyers traded reputation.

(3) If $\theta_2^{(2)} < \theta_2 \le \theta_2^{(3)}$, then we let $0 \le \omega_2 \le 1$, and the value of ω_2 decreases with the increase of θ_2 , but its changing rate increases. That means while buyers return rates is in the range of $\left[\theta_2^{(2)}, \theta_2^{(3)}\right]$, the return rate has punitive effect for buyers traded reputation, and the higher the return rate is, the greater the effectiveness of punishment is.

(4) If $\theta_2^{(3)} < \theta_2 \le 1$, then we let $\omega_2 = 0$, and the value of ω_2 does not change with change of θ_2 . That means while the buyer's return rate is higher than $\theta_2^{(3)}$, he or she may be a malicious buyer, so the return rate factor should increase the punitive effect for buyer's reputation.

3.2. Performance Indicators of Reputation

In order to compensate for deficiencies of single reputation indication, this paper use a three-dimension array $M_i = (D_i, T_i, Z_i)$ to represent buyers' reputation. The performance indicators are as follows.

$$D_i = (\sum_{j=1}^{m} e_{ij} * \omega_{1j}) / \mathrm{m} \tag{8}$$

$$T_i = \theta_2 \tag{9}$$

$$Z_i = D_i * \omega_{2i} \tag{10}$$

Where,

ω_{1j} : ω_1 of *j*-th successful transaction

D_i: reputation of successful traded goods of buyer *i*. It can be aggregated by sellers' a feedback scores, the number of successful transactions and transaction value factor;

T_i: return rate of buyer *i*;

ω_{2i} : ω_2 of buyer *i*;

Z_i: comprehensive reputation of buyer *i* and it can be aggregated by reputation of traded goods and the buyer's return rate factor.

4. Simulation and Analysis

We design a simulating environment to simulate online transactions, and then use the mean model to assess the reputation of the buyer. According to different trading behavior of buyers, the buyer's dynamic reputation would be calculated by the mean model. Contrasting value of buyer's different reputation verify the effectiveness of the model.

4.1. Experimental Assumptions

Referring to the model of eBay or Taobao Reputation Management System, in this paper, we let $e_{ij} \in$ (- 1, 0, 1). That is when a seller rating a buyer, he or she can choose any of one in set of *e= {+1, 0,-1}* as the feedback rate.

In this experiment, buyers of the online transaction are divided into two kinds. Initial value of buyers' reputation is set to zero. For one kind of buyers, their return rate is not higher than 10%, and the transaction price distribution is uniform. For the other kind of buyers, either their return is higher than 10% or tend to buy low-price goods.

A survey report released by *PricewaterhouseCoopers* suggested that the mean annual online shopping times are 80 times. According to this, we calculated out that the mean purchase price of per transaction was about 75 Yuan [16], so in this paper, we set the value of C=75. Else $a = 2$, $\theta_1^{(1)} = 0.5$, $\theta_1^{(2)} = 1$.

Based on this actual situation, the relationship between ω_1 and θ_1 is set as following.

$$\omega_1 = \begin{cases} 1 & \theta_1 \le 0; \\ 2*(\theta_1)^2 + 1 & 0 < \theta_1 \le 0.5; \\ -2*(\theta_1)^2 + 4*\theta_1 & 0.5 < \theta_1 \le 1; \\ 2 & \theta_1 \ge 1; \end{cases}$$

According to the "China Electronic Commerce Research Center" report, experiment sets $\theta_2^{(1)}$ as 5%. It is the value that insurance company keeping premium unchanged. $\theta_2^{(2)}$ is set as 30%, which is the highest return rates that the insurance companies will provide freight insurance for a transaction. We set $\theta_2^{(3)}$ = 50% and *b* = 2.

The relationship of ω_2 with θ_2 is set as following in simulation experiment.

$$\omega_2 = \begin{cases} 400*(\theta_2)^2 - 40*\theta_2 + 2 & 0 \le \theta_2 \le 0.05; \\ 1 & 0.05 < \theta_2 \le 0.3; \\ -25*(\theta_2)^2 + 15*\theta_2 - 1.25 & 0.3 < \theta_2 \le 0.5; \\ 0 & 0.5 < \theta_2 \le 1; \end{cases}$$

4.2. Experiment

4.2.1: Experiment 1: Evaluation of Buyers' Dynamic Reputation

Assuming that there is a buyer of each kind, and both of them conducted 60 times online transactions. Their trading properties are showed in Table 1

Table 1. Different Buyers Property Sheet

Attribute \ Buyer	First	Second
The percentage of sellers negative feedback	0	5%
Relatively deviation distribution of price	N(0,1)	N(-0.3,1)
Return rate	0.06	0.3
Dynamic reputation	Figure 3	Figure 4

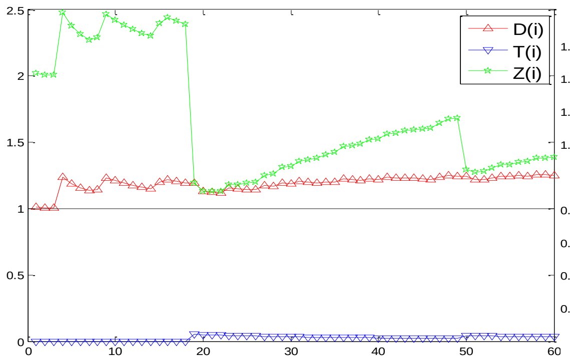

Figure 3. Buyers Dynamic Reputation Indications

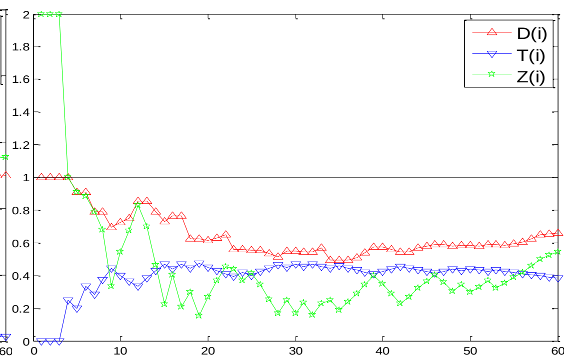

Figure 4. Buyers Dynamic Reputation Indications

Seeing from Figure 3 and Figure 4, it can be learned that the evaluation model calculated the value of three-dimension array $M_i = (D_i, T_i, Z_i)$. That is to say, the mean model proposed in the paper can assess buyers' reputation accurately according to their trading behaviors. For the 60 times online transactions of the first buyer, the reputation of traded goods is higher than sellers' feedback rating. Because of lower return rate, his/her comprehensive reputation is also higher than the reputation of traded goods after added returned rate factor. For the 60 times online transactions of second buyer, either he/she is often tend to purchase low-price or much likely to return goods. Because he/she receives negative feedbacks from sellers sometimes, the reputation of traded goods is lower than sellers' feedback rating. At the same time, owing to their high return rate, the comprehensive reputation is also lower than the reputation of traded goods after added return rate factor. Therefore, the information presented in Figure 3 and Figure 4 can effectively validity hypothesis.

Compared with the single cumulative scoring model, this model can reflect properly dynamic reputation changes according to buyers' transaction behaviors. One buyer's reputation can also be compared in different periods. From this point of view, the model is feasible for evaluating buyers' reputation in C2C e-commerce.

4.2.1. Experiment 2: Comparison of different buyers: Assuming that there are five buyers, and all of them conducted 60 times online transitions. Their trading behaviors properties are showed in Table 2.

Table 2. Five Different Buyers Transaction Attribute

Attribute \ Buyer	Buyer 1	Buyer 2	Buyer 3	Buyer 4	Buyer 5
The percentage of seller negative feedback	0	0	5%	10%	0
Relatively deviation distribution of price	N(0,1)	N(-0.3,1)	N(0,1)	N(-0.3,1)	N(0,1)
Return rate	0.03	0.03	0.15	0.35	0.55
Z_i Dynamic value	Figure 5	Figure 5	Figure 5	Figure 5	Figure 5

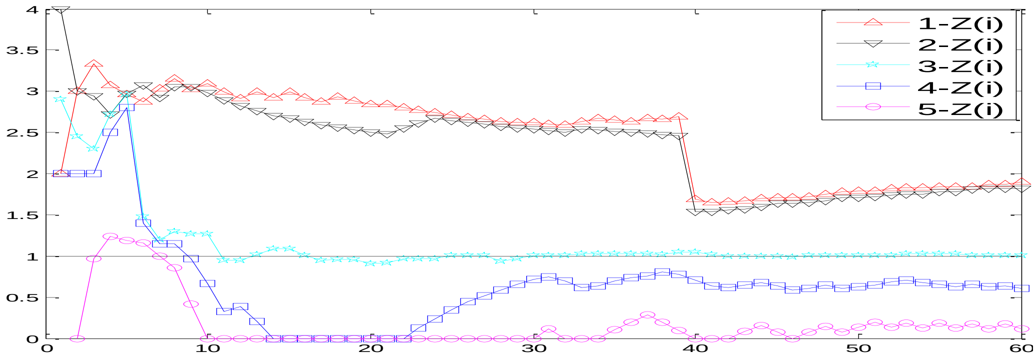

Figure 5. Contrasting Figure of Comprehensive Reputation of Different Buyers'

Seeing from Figure 5, the five curves display dynamic comprehensive reputation of five buyers in 60 times online transitions respectively. Comparing curve 1 and curve 2, comprehensive reputation of first buyer is slightly larger than second buyer's. It suggests that although they have different relatively deviation distribution of trading goods, the same return rate lead to their comprehensive reputation almost the same. Contrasting curve 1, curve 3 and curve 5, we can learn that their comprehensive reputations are quite different from each other. It suggests that although they have different relatively deviation distribution of trading goods, the different return rate leads to that their comprehensive reputations are quite different from each other. From this point, the return rate of buyers plays an important role in evaluating the reputation of buyers.

According to the experimental hypothesis, the third buyer is a person of medium reputation. With increasing number of online transactions, curve 3 is almost equals to 1. Similarity, Curve 1 and curve 2 are on top of curve 3, and curves 4 and 5 are under curve 3.It suggests that the first or second buyer has good reputation, and fourth or fifth has bad reputation. From these views, the value of these buyers' reputation matches with the assumption we had set above. Therefore the mean model has ability to evaluate accurately reputation of buyers, and it is in line with the actual situation.

Because of high return rate, the fifth buyer might be a "professional return goods person", and he/she has behaviors of malicious return, so his/her reputation should be low. Seeing from curve 5, his or her comprehensive reputation is nearly equal to zero. Therefore, when this kind of people appeared in C2C e-economic trading platform, they can be easy identified through their comprehensive reputation, which evaluated by their trading behaviors.

5. Conclusions

Single cumulative scoring evaluating model of current Reputation Management System cannot meet the development of C2C e-commerce, and more and more people seize flaws of C2C e-commerce platform, and buyer's reputation evaluation has become a weak point of current research. We identified, in this paper, that both the successful trading dimension and return goods dimension should be considered when evaluating a buyer's reputation, and return rate of a buyer plays an vital role in his/her reputation of online transaction. We also repented a mean model to evaluate reputation of buyers. In the model, we deeply analyzed dynamic effect of transaction value factor and return rate factor in evaluating buyers' reputation. Instead of single scoring, performance indicators of the buyer's reputation are represented by three-dimension array: reputation value of successful trading, return rates, comprehensive reputation value. We reported two initial experimental to demonstrating the feasibility, effectiveness, and benefits of our evaluating model as well.

(1) Our mean model takes advantage of times of online transaction; therefore buyers' reputation can be evaluated objectively. Rather than the more number of successful transactions you conduct, the better you reputation is;

(2) Not only different buyers' reputation can be evaluated, but a buyer's reputation can be compared as well. This can show dynamic changing of buyers' reputation, and predicting the future behavior of buyers.

(3) The mean model can increase the ability to resist fraud. For vicious buyer, their comprehensive reputation value can provide an prior warning to sellers or insurance company.

Owing to buyers' transaction information is difficult to collect, this model just considers the transaction value and the return rate to improve the seller's feedback score. While how to build a sophisticated buyer credit assessment index system can be as future research.

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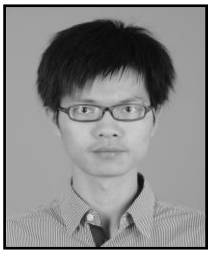

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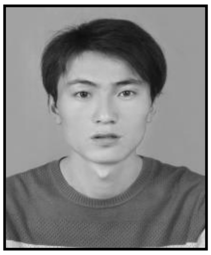

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