Trust and Risk Evaluation of Transactions with Different Amounts in Peer-to-Peer E-commerce Environments

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Abstract

As Peer-to-Peer (P2P) e-commerce environments lack central management, prior to new transactions with an unknown peer, the trust evaluation becomes a very important concern, which relies on the transaction history data. Traditionally the evaluation process is based on other peers' recommendations neglecting transaction amounts. This may lead to the bias to the transaction trust evaluation and risk the new transaction, which may occur between unknown peers. This paper presents a novel model for transaction trust evaluation, which distinguishes transaction amounts and thus computes different impact factors when analyzing old transactions and computing trust values. As a result, the trust evaluation becomes more accurate, which is dependant on transaction history, the amounts of old transactions, the amount of the new transaction, and the temporal dimension. Therefore the obtained trust value can be taken as the risk indication of the forthcoming transaction.

1 Introduction

Peer-to-Peer (P2P) network is an infrastructure where each peer can play the role of a client and a service provider at the same time. Meanwhile, P2P e-commerce systems are drawing more and more attention [4, 1, 9], which let P2P networks go beyond the scope of information sharing systems like Napster [3] and GNutella [2].

However, as it lacks the central management in most P2P systems, the dynamic status of each peer and the network causes trust evaluation a very important issue. Before interacting with an unknown peer, it is rational to doubt its trustworthiness. Therefore, it makes the new transaction securer by enabling trust evaluation prior to interacting with an unknown peer.

Generally, in Peer-to-Peer (P2P) environments, the trust evaluation on an unknown peer relies on the recommendations of other peers, which have transaction history with the target peer that is being investigated. If the unknown target peer is one of potential sellers, the end-peer (requesting peer) can enquire other peers about the target peer's transaction trust. After having collected the feedback from a set of responding peers, the requesting peer can analyze the data and evaluate the trust status of the target peer [7, 8, 13].

To evaluate a peer's service quality, some attributes can be considered, such as the price, warranty, and delivery etc. From the point of view of an end-peer, other peers' recommendations outline the transaction history of the target peer providing an indication of the transaction trust status of the target peer, which in some sense indicates the risk level of the new transaction. However the possible new transaction may be different from some previous transactions in terms of transaction amount, which implies these old transactions should not be taken as references equally when analyzing the transaction trust of the target peer. Otherwise, it may lead to a result with bias. This is especially risky for an end-peer, if it has no transaction previously with the target peer.

In this paper, we propose a novel model for evaluating the transaction trust of a target peer taking into account of the transaction amount property. The new method is based on other peers' transaction experience but distinguishes different categories of transaction amounts and determines different impact factors according to the amount of the new transaction. Meanwhile, the new method also considers the temporal dimension weighing more to fresh transactions. This results in more accurate trust values, which can be taken as the risk indication of the new transaction. With our model, when targeting at a set of potential service providers (peers), the end-peer can investigate their transaction history, analyze the transaction risk, and thus make the decision of selecting the most suitable seller.

This paper is organized as follows. In section 2, we review some existing studies. Section 3 presents our approach for peer trust evaluation taking transaction amount into account. An example is presented in section 4 for further illustrating our model. Finally Section 5 concludes our work.

2 Related Work

eBay [1] is typical Customer-to-Customer (C2C) e-commerce system *with* central management, where peers - buyers or sellers - can evaluate each other based on the service quality or behaviors during transactions. [4] presents a P2P e-commerce system in pervasive environments, where each peer can interact with other peers directly by mobile and handheld devices with wireless network access and Internet access.

Due to the special infrastructure of P2P networks, trust evaluation remains a challengeable issue which draws much attention in the research community.

In [5], Damiani et al proposed $XRep$: a reputation-based approach for evaluating the reputation of peers through distributed polling algorithm before downloading any information. The approach adopts a binary rating system and it is based on GNutella [2] query broadcasting method using TTL limit.

EigenTrust [7] collects the *local trust values* of all peers to calculate the *global trust value* of a given peer. Additionally, EigenTrust [7] adopts a binary rating function, interpreted as positive one (representing satisfactory), or zero or negative one (representing unsatisfactory or complaint).

In [8], Marti and Garcia-Molina proposed a voting reputation system aiming at e-commerce applications that collects responses from other peers on a given peer. The final reputation value is calculated combining the values returned by responding peers and the requesting peer's experience with the given peer. This seems more reasonable than the model in [5]. However, this work and the work in [7] didn't explicitly distinguish transaction reputation and recommendation reputation. This may cause severe bias in reputation evaluation as a peer with good transaction reputation may have a bad recommendation reputation especially when recommending competitors.

In [10], Wang et al proposed several trust metrics for the trust evaluation in a decentralized environments (e.g. P2P network) where a trust value is a probabilistic value in the scope of $[0, 1]$. Prior to the interaction with an unknown peer P_x, the end-peer collects other peers' trust evaluations over P_x. A method has been proposed for trust modification after a series of interactions with P_x that a good value results from the cumulation of constant good behaviors leading to a series of constant good trust values. In [11] the temporal dimension is taken into account in the trust evaluation wherein fresh interactions are weighted more than old ones.

In [14], Yu el al proposed the method of exponential averaging taking into account a series of interactions of the requesting peer itself. It is similar to the work in [11]. In [12], Wang et al presented $Trust^2$, a model for trust evaluation taking recommendation trust into account. $Trust^2$ also includes a method to measure the recommendation trust, based on the requesting peer's interaction experience with the target peer and the recommendations of responding peers in multiple rounds. For the sake of simplicity, in this paper, recommendation trust is not taken into account. Readers can refer to our work in [12] for the method.

[6] presented a method for analyzing the gain and lose for different transactions and related them with transaction success probability and decisions which are represented as reliability trust and decision trust.

However, in most existing trust evaluation models, the evaluation is based on transaction history. But the amount of transactions is not taken into account. That implies that all previous transactions are equally evaluated. This may lead to some attacks that may be easily successful in e-commerce environments as different transaction amounts imply different risk levels. For example, buyer A has many successful transactions with seller B. So the trust value of B given by A is always very good. But each time the transaction amount is up to \$100 only. Assume for the next round, the transaction amount is \$1 million. As the new amount is so different from old transactions, previous trust evaluations may not be important references any more. This is because the nature and the risk of the new transaction are definitely different. It is similar to another case, where a new buyer C, to whom seller B is unknown, is going to have a transaction for about \$1 million with B provided the amount of most transactions that B had is around \$100. In this situation, other buyers' experience with the transaction amount around \$100 should not be taken as an important reference to C's new transaction.

In this paper, we proposed a novel trust evaluation model taking both the transaction history, transaction amount, and the temporal dimension into account. As the trust evaluation is based on both old transactions and the new one, the obtained trust value can be taken as an indication of the risk level of the new transaction.

3 Trust Evaluation

Now let's assume a requesting peer P_r would like to have a new transaction with a target peer P_x, wherein the transaction amount is about \$10K. If P_r has no transaction with P_x, it can enquire other peers about their previous transactions with P_x and their trust evaluations over P_x. However, if P_x has a lot of transactions with different transaction amounts, and P_r can collect some of them, as we have analyzed above, the trust evaluation done by P_r should identify different transactions with different transaction amounts. If an old transaction has the same transaction amount with the new one, or the two amounts are quite similar to each other, the old transaction information (collected from a responding peer) can be a direct reference for the trust evaluation. However, if the amount of the old transaction is different from the new one, it cannot be taken as a direct reference but is still useful for evaluating the transaction trust.

Different situations can be further analyzed into 3 cases as follows.

1. The amount of an old transaction is the same as the new one. In this case, the old experience and corresponding trust evaluation can be taken as a *direct reference* for the new transaction.

2. The amount of the old transaction is larger than that of the new one. In this case, the old transaction can be taken as the reference with less impact.

   For instance, assume seller P_x has a lot transactions with some peers, wherein each transaction amount is basically around \$1-2K. Assume the service is good each time. Let C denote the set of corresponding customers. Now P_r is going to buy a product for \$100. If P_r knows that the trust evaluations over P_x done by most peers in C are quite positive, P_r may not worry about the trust of the new transaction as the product to buy is cheaper. However, on the other hand, a situation exists. The gain for selling a cheap product is probably less. Therefore, the seller may not take it seriously. This leads to a worse service quality. Thus in this case, the old transaction cannot be taken as a direct reference when evaluating the transaction trust relevant to the new transaction. But good trust evaluations from this kind of old transactions should be helpful to give a new and positive trust evaluation relevant to the new transaction.

3. The amount of the old transaction is less than that of the new one. In this case, the old transaction cannot be taken as a direct reference either because it is risky.

   For instance, a seller may be always honest when selling cheap items (say for \$50). However if the new product is quite expensive (say \$10k or more), a fraud is more likely to happen. Due to this reason, after having collected trust evaluations based on transactions with lower transaction amounts, a factor should be determined to scale down the impact of these trust values. The final trust evaluation result should also reflect the risk of the new transaction, wherein the transaction amount is different from most old transactions.

3.1 Impact Factor

To summarize the above analysis, some principles can be listed as follows:

Principle 1 Any old transaction can be taken as a direct reference to a new transaction provided that the old transaction amount is the same as the new one.

Principle 2 Any old transaction with less transaction amount has minor impact to a new transaction with a larger transaction amount. The larger the difference is, the less the impact is.

Principle 3 Any old transaction with larger transaction amount can not be taken as a direct reference to a new transaction with less transaction amount. But it is more important than an old transaction wherein the transaction amount is relatively less than the new one.

To calculate the impact factor, let's first denote the transaction amount difference as:

$$\Delta = Amount_{new} - Amount_{old}$$

where $Amount_{old}$ denotes the amount of the old transaction and $Amount_{new}$ denotes the amount of the new transaction.

Next, let's design a formula to calculate impact factor θ, which results from Δ.

According to the above analysis, when Δ is 0, θ should be exactly 1 (Principle 1). When Δ is greater than 0, θ should be less than 1 (Principle 2). Therefore, to be consistent to Principle 2, we tentatively design a formula as follows using Hyperbolic Secant.

$$\theta = \frac{2}{e^{\Delta * \alpha} + e^{-\Delta * \alpha}} \quad if\ \Delta \geq 0 \tag{1}$$

where $\alpha \in (0, 1]$ is the *scale control factor*.

Formula (1) is plotted in Figure 1 where $\alpha = 1.0,\ 0.5,\ 0.2$ and 0.05 respectively. From Figure 1, it is easy to see that with more and more Δ, θ drops but its value is in the scope of $(0, 1]$. When $\Delta = 0$ and $\theta = 1$, with more and more Δ, θ approaches 0, namely, $lim_{\Delta \to \infty} = 0$. In addition, α is used to control the decrement trend. A smaller α (e.g. $\alpha = 0.05$) is more suitable for applications with a large transaction amount scope as θ approaches 0 very slowly. In contrast, a larger α (e.g. $\alpha = 0.5$) is suitable for applications with a smaller transaction amount scope.

Likewise, according to Principle 3, when $\Delta < 0$, the corresponding impact factor θ should be less than 1. Meanwhile, different from case 2, with more and more transaction amount difference Δ, the impact factor θ should be reaching a value greater than a threshold in (0,1) (e.g. 0.8). Therefore, a formula is designed as follows.

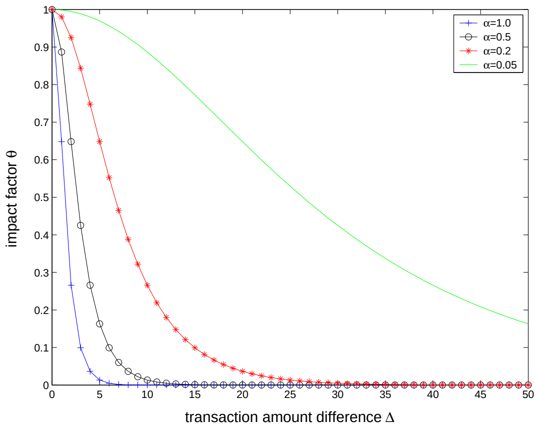

Figure 1. Impact Factor with Positive Δ

$$\theta = \frac{2}{e^{\Delta*\alpha} + e^{-\Delta*\alpha}} * (1-\beta) + \beta \quad if\ \Delta < 0 \qquad (2)$$

where $\alpha \in (0, 1]$ and $\beta \in (0,\ 1)$.

Formula (2) is plotted in Figure 2 where threshold $\beta = 0.8$. With more and more $|\Delta|$, θ drops from 1 and approaches β, namely, $lim_{\Delta \to \infty} = \beta$. In formula (2), α is the scale control factor - the same role as in formula (1).

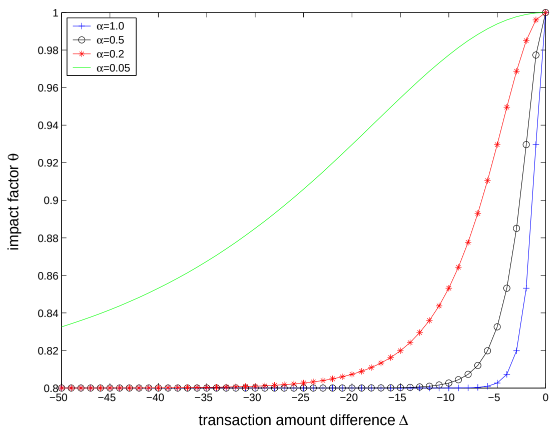

Figure 2. Impact Factor with Negative Δ ($\beta = 0.8$)

Definition 1: Let $Amount_{old}$ denote the amount of the old transaction and $Amount_{new}$ denote the amount of the new transaction. Let Δ denote the *transaction amount difference* i.e. $\Delta = Amount_{new} - Amount_{old}$. With Δ, the *impact factor* θ is defined as follows:

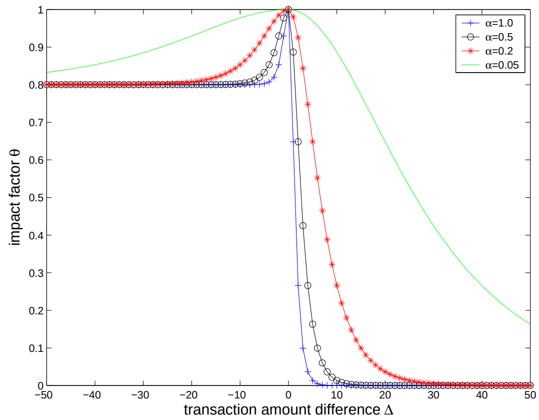

Figure 3. The Impact Factor Function

$$\theta = \begin{cases} 1 & \text{if } \Delta = 0 \\ \frac{2}{e^{\Delta*\alpha} + e^{-\Delta*\alpha}} & \text{if } \Delta > 0 \\ \frac{2}{e^{\Delta*\alpha} + e^{-\Delta*\alpha}} * (1-\beta) + \beta & \text{if } \Delta < 0 \end{cases} \qquad (3)$$

Formula (3) is plotted in Figure 3.

3.2 Transaction Amount Category

In the above discussion in section 3.1, impact factor θ results from transaction amount difference Δ. However, how to calculate the transaction amount difference? Is it to directly calculate it as $\Delta = Amount_{new} - Amount_{old}$? That means a transaction for $10 is definitely different from the one for $20. But in terms of the nature of transactions, they may be the same.

A more realistic method is to categorize the transaction amount. Transaction amounts in the same category are considered the same.

Here we list an example of transaction amount category as follows where $Amount$ denotes the *transaction amount*.

1. ***small-* transaction amount category:** In this category, $Amount \in [1, 10]$;

2. ***small* transaction amount category:** In this category, $Amount \in [11, 50]$;

3. ***small+* transaction amount category:** In this category, $Amount \in [51, 100]$;

4. ***medium-* transaction amount category:** In this category, $Amount \in [101, 500]$;

5. ***medium* transaction amount category:** In this category, $Amount \in [501, 1000]$;

6. ***medium+* transaction amount category:** In this category, $Amount \in [1001, 5000]$;

7. ***large-* transaction amount category:** In this category, $Amount \in [5001, 10000]$;

8. ***large* transaction amount category:** In this category, $Amount \in [10001, 30000]$;

9. ***large+* transaction amount category:** In this category, $Amount \in [30001, 100000]$;

10. ***huge* transaction amount category:** In this category, $Amount > 10K$.

Given a transaction amount $Amount$, if $Amount \in$ category $i \in [1, 10]$, it is denoted as $C(Amount) = i$. For example, if $Amount = 100$, it belongs to category 2 (i.e. $C(100) = 2$).

Based on the above category, when computing the impact factor θ, the transaction amount difference should be replaced with the transaction amount category difference.

Definition 2: If $Amount_{old}$ is the amount of an old transaction, and $Amount_{new}$ is the amount of the new transaction, the *transaction amount category difference* is:

$$\Delta_C = C(Amount_{new}) - C(Amount_{old})$$

With Δ_C, the *impact factor* θ is defined as follows:

$$\theta = \begin{cases} 1 & if \Delta_C = 0 \\ \frac{2}{e^{\Delta_C * \alpha} + e^{-\Delta_C * \alpha}} & \text{if } \Delta_C > 0 \\ \frac{2}{e^{\Delta_C * \alpha} + e^{-\Delta_C * \alpha}} * (1 - \beta) + \beta & \text{if } \Delta_C < 0 \end{cases} \quad (4)$$

where $\alpha \in (0, 1]$ and $\beta \in (0, 1)$.

Formula (4) is plotted in Figure 4 where we chose $\alpha = 0.5$ as the transaction amount category difference is $|\Delta_C| \in [0, 9]$.

Moreover, the transaction amount category is domain-dependant. For example, in the property market, a transaction for \$10K is in the "*small+*" transaction amount category as a house is generally worth about \$300K or more. With different transaction amount categories, we can choose different arguments α and β.

3.3 Transaction Trust and Transaction Risk Evaluation

In P2P e-commerce environments, as there is no central management mechanism, to obtain the transaction trust status of the target peer P_x, a requesting peer P_r has to enquire other peers who have transactions with P_x.

Definition 3: Assume P_r has collected a set of trust values from a set of intermediate peers $IP = \{P_1, P_2, \ldots, P_n\}$.

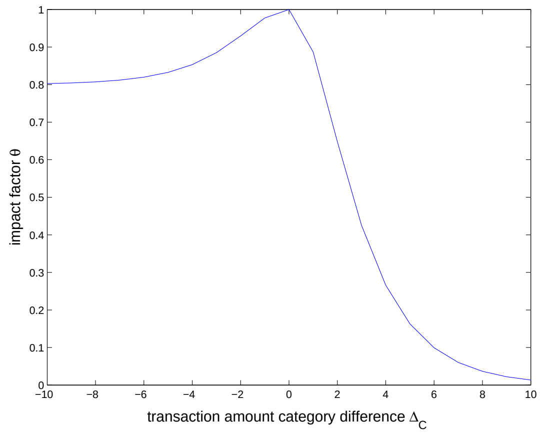

Figure 4. The Impact Factor Function ($\alpha = 0.5$ $\beta = 0.8$)

Let $T_{i \to x} \in [0, 1]$ denote the transaction trust given by a responding peer P_i over target peer P_x. Let $Amount_{old_i}$ denote the old transaction amount between P_x and P_i, and let $Amount_{new}$ denote the amount of the new transaction. θ_i is the impact factor resulting from $\Delta_{C_i} = C(Amount_{new}) - C(Amount_{old_i})$. The *trust value of the new transaction with* P_x is:

$$T_{new_x} = \frac{1}{n} \sum_{i=1}^{n} (\theta_i \cdot T_{i \to x}) \quad (5)$$

According to Definition 3, some features of the new transaction trust value T_{new_x} are as follows.

1. The new trust value T_{new_x} is based on the transaction history between P_x and other (responding) peers, and the new transaction amount $Amount_{new}$;

2. If each $Amount_{old_i}$ and $Amount_{new}$ are in the same category, and T_i is high, T_{new_x} will be a high value;

3. If most $Amount_{old_i}$ values and $Amount_{new}$ are in different categories, it leads to low θ_i values and thus a low new trust value T_{new_x} though each $T_{i \to x}$ may be a high value.

For each peer P_r, if it can collect the transaction history data from some intermediate peers, the risk of the new transaction can be analyzed as T_{new_x} can be taken as a direct risk indication. The relationship between the trust value and the risk value of the new transaction is:

1. If the trust value of the new transaction is high, the corresponding risk is low;

2. If the trust value of the new transaction is low, the corresponding risk is high.

According to the above properties, we can simply define the computation of risk value r_{new_x} as follows.

Definition 4: If the trust value of a new transaction with peer P_x is T_{new_x}, the *risk value* r_{new_x} of the new transaction is:

$$r_{new_x} = 1 - T_{new_x} \tag{6}$$

Therefore, if a peer P_r has a set of potential target peers $TP = \{P_{x_1},\ P_{x_2},\ \ldots,\ P_{x_m}\}$ to have a new transaction with, it can collect the transaction history data from other peers. Hereafter, P_r can evaluate the risk of the new transaction based on the the new transaction amount, the transaction history of each target peer, and old transaction amounts. The best target peer is the peer P_{best} with which the corresponding risk value of the new transaction is the minimal.

$$P_{best} = P_i \in TP = \{P_i :\ i = 1, \ldots,\ m\} \tag{7}$$

$$where\ r_{new_i} = min(r_{new_1} : r_{new_m})$$

3.4 Adding Temporal Dimension to Trust and Risk Evaluations

In the above discussion, we have proposed an approach relating the new transaction trust evaluation with the new transaction risk evaluation. However, in the proposed approach, the temporal property of a transaction is not taken into account. That means all transactions occurred in different periods are equally evaluated. Nevertheless, this may lead to inaccurate trust and risk values. To reflect more accurate trust situation of a target peer, transactions occurred in different periods should be given different weights, wherein very old transactions should be ignored and fresh transactions should be weighted more as they are more important.

Thus when broadcasting the request, the requesting peer P_r should specify that it is interested in transactions occurred during the period $[t_{start},\ t_{end}]$=$\{t_1,\ t_2,\ \ldots,\ t_l\}$ where $t_k < t_{k+1}$ $(1 \leq k \leq l-1)$ and t_l is the latest period. When calculating the trust value based on the collected data, P_r should also specify a set of weights:

$$W = \{w_k :\ k = 1,\ \ldots,\ l\} \tag{8}$$

where $w_k \leq w_{k+1}\ and\ \sum_{k=1}^{l} w_k = 1$

With W, the new trust value can be calculated as follows.

Definition 5: Let $T_{i \to x}^{(t_k)}$ denote the trust value given by peer P_i over peer P_x for the transaction with the transaction $Amount_{old_i}$ occurred at period t_k. The new trust value of peer P_x is:

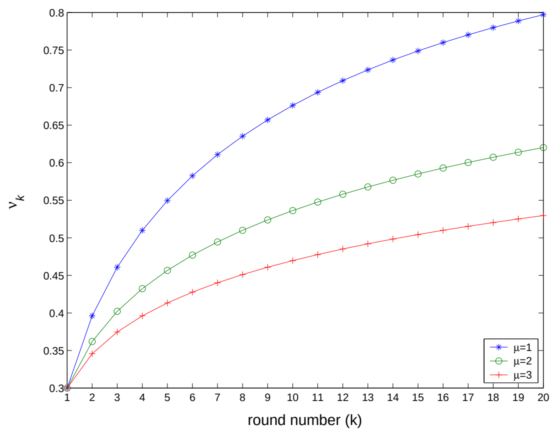

Figure 5. ν_k **(**$\lambda = 0.7$**)**

$$T_{new_x} = \sum_{i=1}^{l} (\theta_i \cdot w_k \cdot T_{i \to x}^{(t_k)}) \tag{9}$$

where $w_k \leq w_{k+1}\ and\ \sum_{k=1}^{l} w_k = 1$

Furthermore, to ease the trouble of assigning a set of weights, we propose a formula with 2 parameters only, which can be employed to generate l weights for period $[t_{start}, t_{end}]$=$\{t_1,\ t_2,\ \ldots,\ t_l\}$ where $t_k < t_{k+1}$ $(1 \leq k \leq l-1)$.

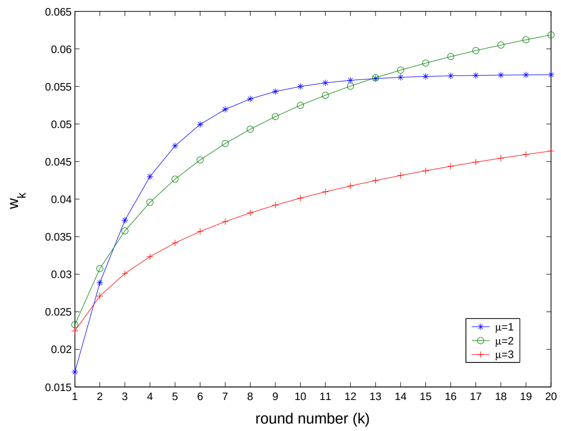

Figure 6. w_k **(**$\lambda = 0.7,\ l = 20$**)**

Definition 6: Given parameters λ $(0.5 < \lambda < 1)$ and μ $(\mu \in \{1,\ 2,\ 3, \ldots\})$, *the weight of period* t_k can be calculated as follows:

$$w_k = \frac{\nu_k}{\sum_{i=1}^{l} \nu_i} \tag{10}$$

where

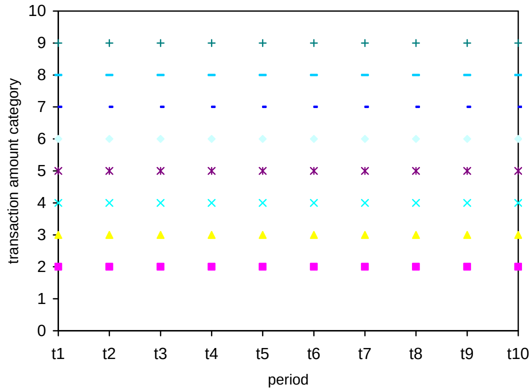

Figure 7. Transaction History of P_{x_1}

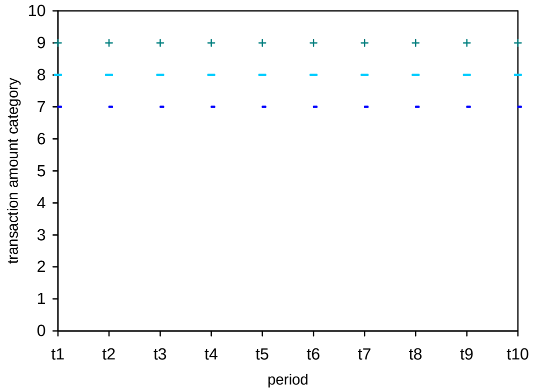

Figure 8. Transaction History of P_{x_2}

$$\nu_k = 1 - \lambda^{k^{\frac{1}{\mu}}}, \; 0.5 < \lambda < 1 \; and \; \mu \in \{1, \; 2, \; 3, \ldots\} \quad (11)$$

According to Definition 6, given round number l, parameters λ and μ, $W = \{w_k\}$ and each weight factor ν_k can be generated. Hereafter each weight w_k can be calculated. For example, if $l = 10$, $\lambda = 0.7$ and $\mu = 2$, then $W = \{0.038797, \; 0.065955, \; 0.084965, \; 0.098273, \; 0.10759, \; 0.11411, \; 0.11867, \; 0.12187, \; 0.1241, \; 0.12567\}$

In formula (11), $\nu_1 = 1 - \lambda$ is the minimal weight factor for period t_1 where $k = 1$. k corresponds to period t_k. Given the same λ and μ, the larger k is, the larger ν_k is. This ensures the property $w_k < w_{k+1}$. In addition, the valuation of μ is dependant on applications. For certain applications, 10 or 20 may mean a high quantity of interactions. In this case, $\mu = 1$ is suitable. For other applications, where 100 means high quantity of interactions, $\mu = 2$ or $\mu = 3$ is more suitable.

ν_k is depicted in Figure 5 where $\lambda = 0.7$ and $l = 20$. w_k is plotted in Figure 6.

4 An Example

In this section, we compare 3 seller peers (say P_{x_1}, P_{x_2} and P_{x_3}) wherein P_r has collected the transaction trust values for $[t_{statrt}, \; t_{end}] = [t_1, t_2, \ldots, t_{10}]$. The transaction history data is plotted in Figures 7, 8 and 9. It is easy to see that peer P_{x_1}'s transaction amounts are in the category scope of $[2, 9]$ (see Figure 7). Peer P_{x_2}'s transaction amounts are in the category scope of $[7, 9]$ (see Figure 8) while P_{x_3}'s are in $[2, 4]$ (see Figure 9). To compare their transaction trust values and risk values, we assume $C(Amount_{new})$ is 3, 8 or 10 respectively. For the sake of simplicity, the trust value of each transaction is assumed to be 0.95. In the experiment, we set $\alpha = 0.5$, $\beta = 0.8$, $\mu = 1$.

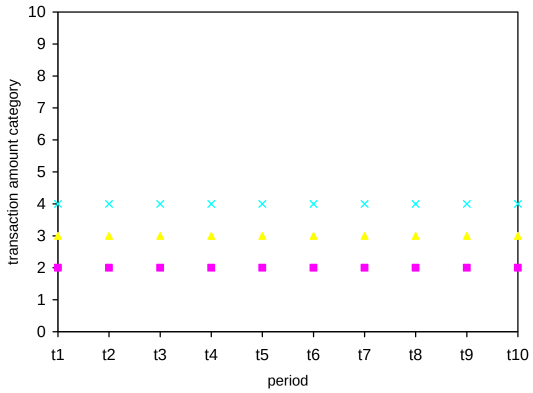

Figure 9. Transaction History of P_{x_3}

According to the results listed in Table 1, as P_{x_3}'s transactions cover *categories* 2 to 4, when $C(Amount_{new}) = 3$, its trust value is the maximum. P_{x_1}'s trust value is good too as its transactions cross categories 2 to 9, most of which are higher than category 3. But P_{x_2} has no transaction history in category 3. This results in a trust value lower than those of P_{x_1} and P_{x_3}.

Similarly, when $C(Amount_{new}) = 8$, P_{x_2} becomes the best peer as $C = 8$ is among the category of its transactions. But P_{x_1} is not as good as peer P_{x_2} because it has many transactions in $Categories$ 2 to 7. This results in a lower trust value as in the above case θ is as low as $\beta = 0.8$. Meanwhile, P_{x_3} is in the worst case as its transaction amounts are lower than $Amount_{new} \in Category$ 3. This results in that impact factors are as low as 0.

When $C(Amount_{new}) = 10$, no peer has a transaction in the category. Finally P_{x_2} becomes the best peer as its transactions are in *categories* 7 to 9, very close to $Category$ 10. P_{x_1} also has transactions in $Categories$ 7 to 9. But it also has transactions in $Categories$ 2 to 6, which are lower than *Category* 8. Thus its trust value is lower than P_{x_2}. P_{x_3}

T_i=0.95	C=3	C=8	C=10
P_{x_1}	0.852	0.522	0.301
P_{x_2}	0.777	*0.870*	*0.596*
P_{x_3}	*0.907*	0.167	0.062

Table 1. Trust Values T_{new}

T_i=0.95	C=3	C=8	C=10
P_{x_1}	0.148	0.478	0.699
P_{x_2}	0.223	*0.130*	*0.404*
P_{x_3}	*0.093*	0.833	0.938

Table 2. Risk Values r_{new}

is the worst one as its transactions belong to $Categories$ 2 to 4, which are far away from $Category$ 10.

Risk values are listed in Table 2. It is easy to see that when $C_{Amount_{new}} = 3$, the risk of the new transaction with P_{x_3} is the minimum. When $C_{Amount_{new}} = 8$, it is P_{x_2}. And the risk with P_{x_3} is the maximum. When $C_{Amount_{new}} = 10$, P_{x_2} is better than P_{x_1}, which is better than P_{x_3}.

5 Conclusions

In this paper, we proposed a novel model of transaction trust evaluation taking the transaction amount into account. The trust value results from the transaction history, other peers' evaluation, old transaction amounts and the new transaction amount. This model can depict the trust value of a new transaction and thus indicates the risk level of it, which is especially useful for a buyer peer who intends to have a new transaction with an unknown peer, or useful for the case where the seller peer is known but the new transaction amount is different from some old transactions. In this paper, a method is also proposed to take the temporal dimension into account, which weights more to recent transactions. This results in more objective trust evaluations and risk evaluations.

Additionally, the proposed approach can be applied to both decentralized e-commerce environments without a central management server (e.g P2P) and centralized e-commerce environments with a central management server (e.g. eBay [1]). The difference is that if there is no central server, it needs intensive communication between peers and it is not feasible to collect all evaluations for a target peer. If the central server exists, these problems will not exist. The server will be in charge of collecting all evaluations and calculate the current trust value and risk value of a new transaction.

For future work, some directions can be further explored. As the evaluation is based on other peers' experience and recommendations, how to verify the accuracy and the objectivity of recommendations remains a problem. It relies on either security mechanisms or a mechanism checking the deviation of recommendations [12]. Another direction is to take other factors into account when evaluating the transaction trust and the transaction risk so that results can reflect more aspects of the nature of transactions.

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