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Trust model based on individual experience

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Abstract: To improve the accuracy of node trust evaluation in a distributed network, a trust model based on the experience of individuals is proposed, which establishes a new trust assessment system by introducing the experience factor and the comparative experience factor. The new evaluation system considers the differences between individuals and interactive histories between nodes, which solves the problem that nodes have inaccurate assessments due to the asymmetry of nodes to a certain extent. The algorithm analysis indicates that the new model uses different deviating values of tolerance evaluation for different individuals and uses different updating values embodying node individuation when updating feedback credibility of individuals, which evaluates the trust value more reasonably and more accurately. In addition, the proposed algorithm can be used in various trust models and has a good scalability.

Key words: trust model; individual experience; feedback trust value

The complication of distributed networks along with the lack of integrity and symmetry of node information has led to the outcome of many trust related questions. How to predict the credibility of these nodes in order to maximize the success trading rate or avoid unnecessary losses when facing myriad distant and unfamiliar nodes, how to punish cheaters when hostile cheating on nodes occurs, and how to measure the reliability of information passed by different nodes: these are the hotspots of the research on the trust model.

In networks, individual differences of evaluation standards, experiences and interests might lead to a problem of different nodes giving out different evaluations to the same service which means that present trust models do not regard individual recommended node differences to be a considerable problem.

A new trust model based on individual experience is proposed in this paper, so the above problem of node asymmetry is solved to some extent.

1 Related Work

The current work concerning the model includes: the trust evaluation method brought out by Beth[1], the distributed trust model of Abdul-Rahman[2], and the subjective logic of Jøsang[3-5]. P2P used two different trust calculation methods, which are the classical trust model[6] as part trust calculation and the PeerTrust [7-8] as whole trust calculation.

Although PeerTrust, DyTrust[9] and many other models have rendered doable calculation methods on feedback trust value, none of them takes the following problems into consideration:

On the one hand, recommender nodes have fewer direct interactive experiences than accessing nodes, and they easily make different evaluations based on their own experiences to some extent. These do not match actual situations and are easily treated as malicious nodes. On the other hand, if accessing nodes have fewer direct interactive experiences than recommenders, they also easily make different evaluations, which easily treat some experienced well-meaning nodes as malicious nodes. The main reason causing these problems is that different nodes have asymmetric experiences. To solve the above problems, this paper proposes an appraisal analysis model based on the individual experience trust.

2 Trust Model Based on Individual Experience

2.1 Arithmetic of trust evaluation

This paper supposes that node j is capable of providing a particular service in a particular field, k_v ($v = 1, 2, \ldots, n$) is recommender node, and has direct exchange with node j; i_u ($u = 1, 2, \ldots, t$) are accessing nodes. Node i_u' s trust value on node j is $R_{i_u j}$, which can be achieved through direct trust and recommended trust. $R_{i_u j}$ can be defined by the following function:

$$R_{i_u j} = h_{i_u j} D_{i_u j} + (1 - h_{i_u j}) \sum_{v=1}^{n} \frac{C_{k_v j} D_{k_v j}}{\sum_{v=1}^{n} C_{k_v j}} \tag{1}$$

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where D_{i_uj} is the direct trust value of node i_u made on node j and D_{k_vj} is the direct trust value of node k_v made on node j; C_{k_vj} is the feedback trust value of node k_v evaluating node j's trust value; $h_{i_uj}(0 \leqslant h_{i_uj} < 1)$ is the experience factor of node i_u based on the service of node j, the bigger h_{i_uj} is, the more direct experience the node i_u takes into account (h_{i_uj} is defined in section 2.2).

The satisfaction evaluations are made after interactive connections. The satisfaction evaluation of node k_v made on node j is marked as e_{k_vj}, $0 \leqslant e_{k_vj} \leqslant 1$. When $e_{k_vj} = 1$, it implies that node k_v is completely satisfied with node j, and 0 means node k_v is completely not satisfied. The greater the sum e_{k_vj} is, the more satisfied the node k_v is.

In a certain amount of time, supposing that the number of direct interactive connections between node k_v and serving node j is m_{k_vj}, the direct interactive satisfaction D_{k_vj} can be achieved in an average method:

$$D_{k_vj} = \frac{1}{m_{k_vj}} \sum e_{k_vj} \tag{2}$$

2.2 Arithmetic of feedback trust value

Definition 1 (experience factor) In a certain amount of time, suppose that the times of direct exchange made between node i_u and service node j is m_{i_uj}. This paper makes $h_{i_uj} = 2^{-(m_o/m_{i_uj})}$, and calls h_{i_uj} the experience factor of node i_u made on node j. If $m_{i_uj} < m_o$, which means $h_{i_uj} < 1/2$, then node i_u has a lack of direct experience on the service provided by node j.

h_{i_uj} is a monotonically increasing function and its value is defined in $[0, 1)$; $m_o(m_o > 0)$ is the minimum value that the feedback evaluation will use, which can be set by users and is an integer.

Definition 2 (comparative experience factor) In a certain amount of time, suppose that the times of direct exchange made between node i_u, k_v and service node j are m_{i_uj} and m_{k_vj}. This paper makes $\Phi^j_{i_u,k_v} = h_{i_uj}/h_{k_vj}$ and calls $\Phi^j_{i_u,k_v}$ the comparative experience factor of node i_u made on node j compared with node k_v. If $\Phi^j_{i_u,k_v} > 1$, node k_v has a lack of experience compared with node i_u; if $\Phi^j_{i_u,k_v} < 1$, node i_u has a lack of experience compared with node k_v.

In a certain amount of time, the differences among evaluations $\mathrm{diff}^j_{i_u,k_v}$ made by node i_u and node k_v on public node j can be defined by the following function:

$$\mathrm{diff}^j_{i_u,k_v} = \left| \phi^j_{i_u,k_v}(D_{i_uj} - D_{k_vj}) \right| \tag{3}$$

When $h_{k_vj} \geqslant 1/2$, supposing the maximum evaluation deviation that node i_u can endure to node k_v is θ, when $\mathrm{diff}^j_{i_u,k_v} < \theta$, number of times $\mathrm{SC}^j_{i_u,k_v}$ adds 1; when $\mathrm{diff}^j_{i_u,k_v} > \theta$, defeat number of times $\mathrm{FC}^j_{i_u,k_v}$ adds 1. The reliability of i_u to k_v, marked as $C^j_{i_u,k_v}$, can be refreshed under two different conditions:

① When $\Phi^j_{i_u,k_v} \leqslant 1$,

$$C^j_{i_u,k_v} = \begin{cases} C^j_{i_u,k_v} + \alpha\phi^j_{i_u,k_v} \left| 1 - \dfrac{\mathrm{diff}^j_{i_u,k_v}}{\theta} \right| & \mathrm{diff}^j_{i_u,k_v} < \theta \\ C^j_{i_u,k_v} - \beta\phi^j_{i_u,k_v} \left| 1 - \dfrac{\theta}{\mathrm{diff}^j_{i_u,k_v}} \right| & \text{others} \end{cases} \tag{4}$$

② When $\Phi^j_{i_u,k_v} > 1$,

$$C^j_{i_u,k_v} = \begin{cases} C^j_{i_u,k_v} + \dfrac{\alpha}{\phi^j_{i_u,k_v}} \left| 1 - \dfrac{\mathrm{diff}^j_{i_u,k_v}}{\theta} \right| & \mathrm{diff}^j_{i_u,k_v} < \theta \\ C^j_{i_u,k_v} - \dfrac{\beta}{\phi^j_{i_u,k_v}} \left| 1 - \dfrac{\theta}{\mathrm{diff}^j_{i_u,k_v}} \right| & \text{others} \end{cases} \tag{5}$$

In the functions above, α and β are the values of increase or decrease of the feedback trust value, and fit the condition of $0 < \alpha < \beta < 1$. In this way, when recommender is friendly, his feedback trust value increases rather slowly. The feedback trust value of hostile nodes decreases sharply. $C^j_{i_u,k_v}$ is defined in a range of $[0, 1]$, and $C^j_{i_u,k_v} = 0$ when $C^j_{i_u,k_v} < 0$, $C^j_{i_u,k_v} = 1$ when $C^j_{i_u,k_v} > 1$.

Node k_v recommends its trust value when node $i_1, \ldots, i_u, \ldots, i_t$ are accessing j's services, and these accessing nodes will have a whole recommender evaluation of k_v as

$$C_{k_vj} = \sum_{u=1}^{t} \left(\frac{(\mathrm{SC}^j_{i_u,k_v} - \mathrm{FC}^j_{i_u,k_v}) C^j_{i_u,k_v}}{\sum_{u=1}^{t} \mathrm{SC}^j_{i_u,k_v}} \right) \tag{6}$$

2.3 Trust value deposition

Every service evaluation storage spot d includes a data structure as shown in Fig. 1(a). Node d is the record storage spot on node j; its ID_j is the only sign of node j; $\mathrm{ID}_{k_1}, \ldots, \mathrm{ID}_{k_v}, \ldots, \mathrm{ID}_{k_n}$ are the signs of the nodes which have directly traded with node j; T_j is j's reputation value; $D_{k_1j}, \ldots, D_{k_vj}, \ldots, D_{k_nj}$ are the trust values made through every trade with j; $C_{k_1j}, \ldots, C_{k_vj}, \ldots, C_{k_nj}$ are the whole feedback trust value of $k_1, \ldots, k_v, \ldots, k_n$.

Every valuation storage spot includes at least one data structure as shown in Fig. 1(b). Node b is the record storage spot of node k_v; $m_{k_1j}, \ldots, m_{k_vj}, \ldots, m_{knj}$ are the total deals one node has made with j; $\mathrm{SC}^j_{i_u,k_v}$ and $\mathrm{FC}^j_{i_u,k_v}$ are the reports sent by nodes which have received the recommendation from node k_v to show how many recommendations are successful and how many are failed, ID_{k_v} is the sign of node k_v.

ID_j	ID_{k_1}	ID_{k_2}	…	ID_{k_v}	…	ID_{k_n}
T_j	$D_{k_1 j}$	$D_{k_2 j}$	…	$D_{k_v j}$	…	$D_{k_n j}$
	$C_{k_1 j}$	$C_{k_2 j}$	…	$C_{k_v j}$	…	$C_{k_n j}$

(a)

ID_{k_v}	$m_{k_v j}$	$D_{k_v j}$	$C_{k_v j}$		
ID_{i_1}	$m_{i_1 j}$	$D_{i_1 j}$	$SC^j_{i_1,k_v}$	$FC^j_{i_1,k_v}$	$C^j_{i_1,k_v}$
ID_{i_2}	$m_{i_1 j}$	$D_{i_2 j}$	$SC^j_{i_2,k_v}$	$FC^j_{i_2,k_v}$	$C^j_{i_2,k_v}$
⋮	⋮	⋮	⋮	⋮	⋮
ID_{i_u}	$m_{i_u j}$	$D_{i_u j}$	$SC^j_{i_u,k_v}$	$FC^j_{i_u,k_v}$	$C^j_{i_u,k_v}$
⋮	⋮	⋮	⋮	⋮	⋮
ID_{i_t}	$m_{i_t j}$	$D_{i_t j}$	$SC^j_{i_t,k_v}$	$FC^j_{i_t,k_v}$	$C^j_{i_t,k_v}$

(b)

Fig. 1 Construction of data. (a) Service appraised spot; (b) Recommendation appraised spot

3 Arithmetic Analysis

This paper marks the difference of evaluation on public node j between node i_u and node k_v as

$$\mathrm{diff}_{i_u,k_v,j} = |D_{i_u j} - D_{k_v j}| \tag{7}$$

Suppose that the maximum bearable evaluation error that node i_u can take from node k_v is θ. After we introduce the comparative experience factor, then $\mathrm{diff}^j_{i_u,k_v} = \Phi^j_{i_u,k_v}\mathrm{diff}_{i_u,k_v,j} < \theta$. Next we will discuss how to solve problems caused by individual experience differences.

3.1 Visitor lacks of experience

If accessing node i_u lacks of exchange experience or comparative experience to node j, then $\Phi^j_{i_u,k_v} < 1$ and $h_{k_v j} \geqslant 1/2$. Now, when $\mathrm{diff}_{i_u,k_v,j} < (1/\Phi^j_{i_u,k_v})\theta$, it is inferred from Fig. 2.

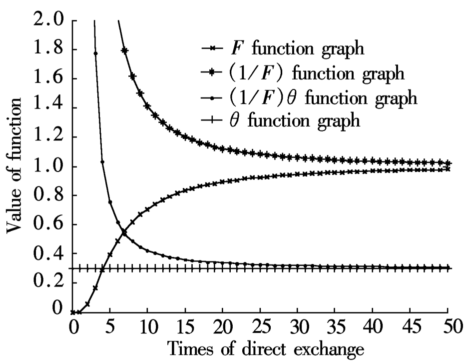

Fig. 2 Relative experience factor $\Phi^j_{i_u,k_v} < 1$ graph ($F = \Phi^j_{i_u,k_v}$)

1) When $(1/\Phi^j_{i_u,k_v})\theta \gg \theta$, node i_u has few direct exchange times with j and the deviation allowance of node i_u to node k_v tends to be large.

2) When $(1/\Phi^j_{i_u,k_v})\theta \approx \theta$, node i_u and node k_v should have similar activities, with the experience growing of node i_u, the value of $(1/\Phi^j_{i_u,k_v})$ is decreased to 1, the value of $(1/\Phi^j_{i_u,k_v})\theta$ inclines to θ, and the maximum evaluation deviation range shrinks.

After importing comparative experience factor, the value of $\mathrm{diff}^j_{i_u,k_v}$ tends to be more reasonable. The affection of importing the comparative experience factor on the feedback trust value is discussed as follows:

1) When $\mathrm{diff}^j_{i_u,k_v} < \theta$, the smaller $\Phi^j_{i_u,k}$ is, the fewer experience nodes i_u has, and the feedback trust value of node i_u to k_v increases, but with a slow progress; the bigger the value $\Phi^j_{i_u,k_v}$ has, the more experience nodes i_u has, and the feedback trust value of k_v increases at a greater pace.

2) When $\mathrm{diff}^j_{i_u,k_v} \geqslant \theta$, the smaller $\Phi^j_{i_u,k_v}$ is, the fewer nodes i_u has, and now the feedback trust value of node i_u on node k_v decreases, but with slow progress; the bigger $\Phi^j_{i_u,k_v}$ is, the more experience nodes i_u has, and the feedback trust value of k_v decreases at a greater pace.

3.2 Recommender lacks of experience

When node i_u needs to get the evaluation of j, i_u only adopts recommendations from those nodes which have made direct exchange times that fit the following conditions: $m_{k_v j} \geqslant m_o$, $h_{k_v j} \geqslant 1/2$. If $m_{k_v j} < m_o$, node i_u will not refresh the recommendatory trust value of k_v. This method may prevent the nodes lacking of recommending experience from being punished.

If k_v has comparatively fewer experiences than node i_u, then $\Phi^j_{i_u,k_v} > 1$ and $h_{k_v j} > 1/2$. Now, $\mathrm{diff}_{i_u,k_v,j} < (1/\Phi^j_{i_u,k_v})\theta$ is implied in Fig. 3.

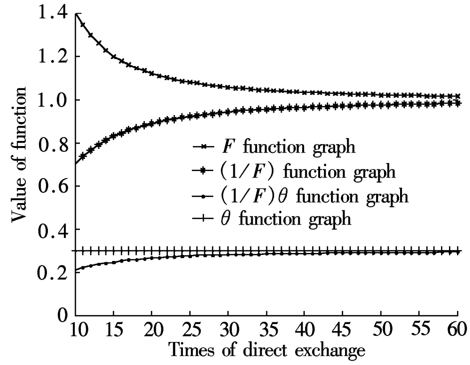

Fig. 3 Relative experience factor $\Phi^j_{i_u,k_v} > 1$ graph ($F = \Phi^j_{i_u,k_v}$)

At this time, $(1/\Phi^j_{i_u,k_v})\theta < \theta$, node i_u has more direct exchanges with node j than with node k_v, so node i_u has a lower deviation request to node θ.

1) When $\mathrm{diff}^j_{i_u,k_v} < \theta$, the smaller $(1/\Phi^j_{i_u,k_v})$ is, the fewer experiences nodes k_v has. At this point, the feed-

back trust value of node i_u to node k_v increases slowly; the greater $(1/\Phi^j_{i_u,k_v})$ is, the more exchange experiences node k_v has. At this point, the feedback trust value of node i_u to node k_v increases sharply.

2) When $\mathrm{diff}^j_{i_u,k_v} \geqslant \theta$, the smaller $(1/\Phi^j_{i_u,k_v})$ is, the fewer comparative experiences node k_v has. At this point, the feedback trust value of node i_u to node k_v decreases at a small pace; the greater $(1/\Phi^j_{i_u,k_v})$ is, the more comparative experiences node k_v has. At this point, the feedback trust experience of node i_u to node k_v decreases at a greater pace.

All the analyses come to one conclusion: this new model can solve the problems which are caused by differences in individual experience. Those nodes which offer false feedbacks will be punished; the more untrue information they offer, the more severe punishment they will receive.

4 Conclusion

In this paper, a new trust model is proposed based on individual experience by importing the concepts of the experience factor and the comparative experience factor. This paper solves the problems that different nodes have asymmetric experiences. The analysis implies that the arithmetic of feedback trust values has been improved to a certain extent. The comparative experience the arithmetic brings out in this paper has a very good expandability and can be used in many trust models.

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基于个体经验的信任模型研究

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摘要:为了提高分布式网络中各节点信任评价的准确度,提出了一种基于个体经验的信任模型. 该模型通过引入经验因子和相对经验因子的方法,建立了新的信任评价体系. 这种新的信任评价体系考虑了个体节点的差异问题,在计算节点的信任值时考虑了节点间的交互历史,这在一定程度上解决了由于节点的非对称性而导致的信任评价不准确的问题. 算法分析表明:新模型能够针对不同的个体节点,采用不同的最大容忍评价偏差,并且对个体节点的反馈可信度进行更新时,采用不同的更新值,体现了节点的个性化特征,使信任评价更加准确合理. 此外,所提出的新算法能够运用到多种信任模型中,具有很好的可扩展性.

关键词:信任模型;个体经验;反馈可信度

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