Trust Network and Small World Trust Community Clustering for E-Commerce

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Abstract

Trust in e-commerce has become one of the most important issues in online applications. Constantly, a user will only search for the most credible of goods and service providers and then take on their transactions. How to confirm which service providers are the most trusted for a user has become the most critical problems. This paper presents a trust network and small world trust community clustering for the analysis of the users most trusted relationship. It uses the nodes to represent the various subjects involved in the trust and use the connection links to denote relationships. The weight of the links indicates the strength of the relationships. First, it construct a trust network diagram which has the weight value of links, and then to analyze the clustering properties of the relationship according to the weights and the path length. At last, it classifies the most trusted subjects to the same cluster for a user. Local trust recommendation degree and global trust recommendation degree are used to evaluate trust relations among subjects and it gives an improved shortest path algorithm to construct trust network. A clustering algorithm based on coefficient and path length is presented for e-commerce trust network community. Experiments show that the method of building trust through the network model can well describe the main indirect e-commerce trust and the algorithm has obvious advantages in accuracy and time cost.

Keywords: *E-commerce, Small world network, shortest path algorithm, trust community clustering*

1. Introduction

We can use the complex, interactive network node and network connections to represent the interests of the subjects and the interactions or relationship between them in e-commerce trust [1]. A notion of trust is described for estimating the economic value of trust [2]. Reputation and trust have also been used in many fields such as economics, e-commerce and wireless sensor networks [3]. The description of trust can be come from different factors [4]. Trust relationship between subjects to another can be regulated by trust network model and support the function of other's trust or credibility [5, 6, 7]. Trust network in e-commerce is one of social network. We can use the tool of social network analysis to study the theory and methods. Many scientists have studied the structure and properties of the large and complex network [8, 9, 10], such as small-world networks, collaboration networks, multi-scale networks and community networks in their attributes analysis of the structure and the topology [11, 12, 13]. These networks and have very similar characteristics and properties with e-commerce trust networks.

Most studies in the past have focused on the study of a single subject, or trust in the credibility of the establishment of the issue. There is little in the network relationships of trust issues between subjects in e-commerce applications of real confidence. For example, in the trust evaluation model of subject, the majority of researches focus on the trust and credibility of the subject, and by the characteristics of the individual to establish trust and credibility for impact on the surrounding association to determine the subject. This kind of trust and credibility is unchanged in the network. For any subject in the network, its trust degree is the same. However, it is difficult to trust a credibility which establish by unilateral confidence due to the uncertainty of the sources of information and breadth of the subject in e-commerce environment. Trust relationship between subjects is different in reality trust network. That is trust degree, which is different from a subject to another subject compare to the subject to others. In addition, a direct trust degree between a subject and another does not mean that the degree of global one between them. One could decide whether to buy a product by some passed the evaluation of other users though he has not interact with the merchant when he brows products in e-commerce. These users may have the same characteristics or properties with the user. The user may trust these users which are in the trust network and then trust their review and purchase the goods. Therefore, a trust relationship of the trust and credibility in e-commerce environment needs an evaluation model which is established on self-trust relationship.

1.1 Small World Network

The research of relationship of social network can be traced back to the 1960s in the field of sociology. Milgram found the characteristics of small world in social network analysis [14]. Since then, many researchers made an extensive research on social network structure and their characteristics. With the development of computer science and network technology, it is growing in popularity in computer science. In the related research in the small world network, the graph model is a very important modeling tool. It has been abstracted an individual into a node and the relation between the individuals into the link. The study of this particular graph can analysis and mining the internal pattern and information that be implied. Graph model can be applied in sociology, human behavior, transmission of disease and information and communication aspects of the Internet and other online communities. Recently, some researches of data mining and structure mining technical have proved that these networks have the small world properties and characteristics. In order to improve the efficiency and scalability of SA-Cluster, Zhou proposes an efficient algorithm Inc-Cluster to incrementally update the random walk distances given the edge weight increments [15]. And Wu proposes a framework of an exact solution and an approximate solution for computing ranking on a subgraph. He proved that the ideal-rank scores for pages in the subgraph converge and analyzed the distance between Ideal-rank scores and approx-rank scores of the subgraph [16].

1.2. Trust Network for E-commerce

In e-commerce environment, Business subjects, including consumer and business, their trust and credibility has become an important issue which affects the development of e-commerce. There are trust relationships exists between consumers to consumers, businesses to businesses, and consumers to businesses. Golbeck proposed a trust inference mechanism for trust relation establishment between a source participant and the target one based on averaging trust values along the social trust paths [17]. G. Liu put forward a framework of trust propagation to study the complex social network by the path selection problem and a new concept Quality of Trust is used to guarantee a certain level of trust worthiness in trust propagation along a social trust path [18]. R. James examined the role of trust from various aspects within telemedicine, with particular emphasis on the role that trust plays in the adoption and adaptation of a telemedicine system [19]. These relationships directly affect a user whether to trust quality review of another user of a certain goods, business or service. They directly impact on the user's determination for the quality of business, goods or services, and deeply affect the user's choice of goods and services.

The paper establishes a trust network model for e-commerce by small world network analysis. Local trust information degree and global trust recommendation degree are used to build trust relationship among the subjects in trust network. An improved shortest path algorithm PFS (Path First Search) is used to build trust network model. It implements trust community clustering analysis through the clustering coefficient and global trust recommendation degree and presents an improved clustering analysis algorithm for trust community.

2. Construction of Trust Networks

Small-world-network is a kind of undirected and no-weighted network and edges in it have two kinds of circumstances: 0 to represent there is no edge between two nodes, and 1 mean the opposite situation. However in real network you cannot simply tell whether there exists or not exists relationship between nodes. In commerce related location service relevance among location resource nodes are usually difficult to be depicted by undirected and no-weighted graph of small-world-network model, because discrepancy of commerce information nodes in a certain location or within a location may vary greatly. To describe connection degree of location resource more precisely, we combine the recommendation degree method with small world network model to construct weight value of edges and location resource network. In the paper, we use local trust recommendation degree and globe trust recommendation degree to depict the correlation degree of the node in small world network.

2.1. Correlation Degree between Two Nodes

A vector space model is used to calculate comparability between two nodes. The model of vector space is a classical statistical algorithm in the area of information collection, which treats the node as a vector. It matches their attribute based on comparing the comparability degree of two crunodes vectors. Each embranchment of the vectors expresses various characteristics of the corresponding node. These characteristics usually consist of several meaningful name or attribute of the node. It can identify semantic implication for different nodes by turning the characteristics to vectors.

The paper gives a hypothesis that the merchandise node set in whole resource network is P , and the set P is consist of different merchandise of n . That is:

$$P = \{p_1, p_2, p_3, ..., p_n\} \tag{1}$$

The characteristics of all goods nodes in P build up the characteristic set of F . There are k characteristics in set F , that is:

$$p_i = (v_{i,1}, ..., v_{i,j}, ..., v_{i,k}) \tag{2}$$

Where $v_{i,j}$ is the j th characteristic of p_i

We supposes that the vectors of two merchandise are p_i and p_j respectively. And there are:

$p_i = (v_{i,1}, v_{i,2}, ..., v_{i,k})$ And $p_j = (v_{j,1}, v_{j,2}, ..., v_{j,k})$

Then the cosine value between p_i and p_j is $\beta_{i,j}$. There is:

$$\cos(\beta_{i,j}) = \frac{\sum(v_{i,k}, v_{j,k})}{\sqrt{\sum v_{i,k}^2}\sqrt{\sum v_{j,k}^2}} \qquad (3)$$

The correlation degree between two nodes can be denoted by formula (3). From the above we know that if the angle of the two vectors is zero then the cosine value is the maximum 1. If the two vectors are orthogonal then the cosine value is zero, which indicates there is no comparability between them. Cosine value is used to present path weight between modes and used to construct merchandise resources network in this paper. Distance between node p_i and p_j is denoted by $D_{i,j}(p_i, p_j)$.

2.2. Local Trust Recommendation Degree

Assume the whole location resource network is N, and all the resource nodes set in N is O, which is composed of many different resource nodes. The resource node set O can be represented by the following formula:

$$O = \{o_1, o_2, o_3, ..., o_n\} \qquad (4)$$

The trust degree method used in P2P network in references [15] can be adapted to define local recommendation trust degree and globe recommendation trust degree.

Definition 1(Local recommendation trust degree): Let $p_{i,j}$ represents the recommendation trust degree of node i to node j, $p_{i,j}$ is determined by interaction history between the two nodes, and

$$p_{i,j} = \frac{S_{i,j}}{I_{i,j}} \qquad (5)$$

In formula 5, $I_{i,j}$ denotes direct interaction times between node i and node j within a certain time τ, which can be the frequency of changing the position of node i to; $S_{i,j}$ denotes the successful trading times from the view of node i, while $I_{i,j} = 0$, $p_{i,j} = 0$

2.3. Globe Trust Recommendation Degree

Definition 2(Globe recommendation trust degree): In a network N, globe trust recommendation degree of node i to node j is denoted by T_j, let

$$T_j = \begin{cases} \dfrac{\sum_{i \in K_j} N^{T_j} P_{i,j}}{\sum_{i \in K_j} N^{T_j}} & \textit{while} \quad K_j \neq 0 \\ 0, & \textit{while} \quad K_j = 0 \end{cases} \tag{6}$$

In the formula N denotes network scale, $p_{i,j}$ stands for local trust recommendation degree, K_j denote a node set of nodes which have interaction with node j. When $K_j = \emptyset$, which means there is no interaction between node j and the others, globe recommendation trust degree of node j is 0.

Theorem 1: Solution of trust recommendation degree of all nodes in definition 2 exists.

Proof: Let Γ be a set of trust recommendation degree in structure solution space, $\Gamma = \{T_i\}$, and $0 \leq T_i \leq 0$, $i = 1,...,n$,

$$\Gamma_0 = \{(T_1, T_2, T_3, ..., T_n)\}, \qquad 0 \leq \mathrm{T}_i \leq 1, i = 1,...,n \tag{7}$$

Let Γ^* denotes the transposed matrix of T_i, $\Gamma^* = \{T_1, T_2, T_3 ... T_n\}$ and globe trust recommendation degree of Γ^* can be represented as fellow:

$$g_j(\Gamma^*) = \begin{cases} \dfrac{\sum_{i \in K_j} (N^{T_j}, P_{i,j})}{\sum_{i \in K_j} N^{T_j}} & K_j \neq \phi \\ 0 & \mathrm{K_j} = \phi \end{cases} \tag{8}$$

The mapping of solution space $\Gamma \subset P^N \to P^N$ can be defined as:

$$G(\Gamma^*) = (g_1(\Gamma^*), ... g_n(\Gamma^*))^{\Gamma^*} \tag{9}$$

Γ_0 is obviously a closed convex set; $g_j(\Gamma^*)$ has continuity in Γ_0, so G is also continuous in Γ_0.

While $K_j \neq \phi$, the following inequality is true.

$$\min_{i \in K_j} P_{i,j} = \frac{\sum_{i \in K_j} (N^{T_j}, \min_{i \in K_j} P_{i,j})}{\sum_{i \in K_j} N^{T_j}} \leq \frac{\sum_{i \in K_j} (N^{T_j}, P_{i,j})}{\sum_{i \in K_j} N^{T_j}} \leq \frac{\sum_{i \in K_j} (N^{T_j}, \max_{i \in K_j} P_{i,j})}{\sum_{i \in K_j} N^{T_j}} = \max_{i \in K_j} P_{i,j} \tag{10}$$

Namely, in solution space exists a solution $g_j(\Gamma^*)$, and $\min_{i \in K_j} P_{i,j} \leq g_j(T^*) \max_{i \in K_j} P_{i,j}$.

In the case $K_j = \phi$, then $\min_{i \in K_j} P_{i,j} = 0$, the inequality $\min_{i \in K_j} P_{i,j} \leq g_j(\Gamma^*) \max_{i \in K_j} P_{i,j}$ is still true;

According to the fixed point theorem, G exists fixed points in Γ_0 and there exists at least point $\Gamma^* \in \Gamma_0$ where the equation $\Gamma^* = G(T^*)$ is true. So theorem 1 is true.

In location resource network set, nodes are used to represent location resource, edges are adapted to represent similarity between the resource and the attributes of the edges are represented by globe trust recommendation degree. Great globe trust recommendation degree between two adjacent nodes means a strong similarity of them. Recommendation degrees are treated as path weight between nodes to describe their distance, and the modified PFS algorithm is used to construct the location resource network structure.

2.4. Modified PFS Algorithm

The PFS algorithm is a variation of the classical Dijkstra algorithm. The algorithm works by maintaining a shortest-path tree T rooted at a source node s, T contains nodes whose shortest distances from s are already known. Each node u in T has a parent, which is represented by p_u. A set of labels, d_u is used to record the distances from the node u to node s. Initially, T contains only s. At each step, I select from the candidate set Q a node with the minimum distance to s and add this node to T. Once T includes all nodes in the graph, the shortest paths from the source nod s to all the other nodes have been found. PFS differs from the Dijkstra algorithm because it uses an efficient priority queue for the candidate set Q.

With modifications, PFS can be used to compute the shortest paths from a single source node to a set of specified nodes in the graph. That is, given a set of nodes $K \subseteq N, |K| = k \geq 2$ and a source node $s \in K$, the modified PFS algorithm can compute the shortest paths from s to all $u \in K$, and $u \neq s$. We therefore modify the algorithm so that it stops as soon as all $u \in K$ are included in the shortest-path tree T. The modified PFS algorithm pseudo-code is presented as follow:

Modified PFS algorithm

//This modified PFS algorithm computes the shortest paths from the first node in K to every other node in K

Begin

Initialize:

s= the 1*th* element of *K*; $d_s = 0, p_s = s; d_i = \infty$

$p_i = 0$ for all $i \in N, i \neq s$

$T = \{s\}; Q = \{s\}$.

While $K \neq \{\phi\}$ *// Search Q for the node with minimum distance to s*

$u = \{i; d_i \leq d_j, i, j \in Q, i \neq j\}$;

$Q = Q - \{u\}$;

//the shortest path between u and s has been found and added to T

$T = T \bigcup \{u\};$

for each $(u,v) \in Out(u)$ **such that** $d_u + l_{uv} < d_v$ do

//Update the distance label of v

$d_v = d_u + l_{uv}$

$p_v = u;$

if $v \in Q$ **then** $Q = Q \bigcup \{v\};$

end

if $u \in K$ then $K = K - \{u\};$

endwhile;

End

3. Clustering Trust Community

The purpose of the trust community clustering in the trust network is divided into a high degree of mutual trust community from the trust subjects. In these communities, the main body of each trust subjects has a high degree of global trust information. They can share evaluation of the goods or services among the subject in a same community and share the experience in trading, which will help people to remove interfering factors in e-commerce environment and extract the most valuable information.

3.1. Clustering Coefficient

Watts and Strogatz used clustering coefficient to describe the network node connection degree in small-world network analysis. In fact, that the clustering coefficient can also be used in the terms of small-world network or multi-scale network. We can use it to describe the characteristics of network structure in other complex network analysis. Clustering coefficient represents the closeness of a node with other nodes on behalf of the network. It denotes the degree of trust in e-commerce network between the business subjects. For node v with a k degree (k denotes there are k connected edges), its clustering coefficient can be defined as:

Clustering coefficient C : it is a measurement parameters of the closely degree of neighbor nodes. C_v denotes the ratio of actual number of edges of subgraph to that with the largest number of edges:

$$C_v = \frac{2t_v}{k_v(k_v - 1)} \tag{11}$$

k_v is the number of neighbor nodes. Let C denotes the mathematical expectation of C_v of all nodes, and then the expectation is the clustering coefficient:

$$C = \frac{\sum_{n=1}^{\infty} C_v}{n} \tag{12}$$

Clustering coefficient describes tightness hold together of the nodes on the network. It is the local features of a network. Among them, n denote the number of edge that the node v connected neighbor nodes.

3.2. Clustering Algorithm for Trust Community

The value of certain node in the process of the network inference is called evidence. The nodes which is within a set distance to a new user node can be denoted as F **,** the possibility of a unknown user x choosing a certain product β can be calculated by $p(x=\beta \mid F)$, where $p(x=\beta \mid F)=\dfrac{p(F,x=\beta)}{p(F)}$.

In this paper the recommendation algorithm is designed as fellow:

Input: Hybrid model $G=(V_{user},V_{produce},E,\theta)$, V_{user} denotes a set of all users, $V_{produce}$ denotes a set of all product nodes, G stands for the hybrid model, θ is a parameter of the model, E is an edge set and x is a set of the new user and its properties.

Output: Recommendations set for x.

Step 1: Cluster and reconnection for the new user node to get the user clustering and path length set.

$$V_{user}^{''} \leftarrow \{v_i \mid v_i \in V_{user}^{'} \wedge \| x-D_a \| = \min_{i \in V_{user}} \| x-D_i \| \} ;$$

Step 2: calculate the path length of x to all user nodes to form a set $D=\{D_1,D_2,...D_i,\}$, and find out $\min \| x-D_i \|$.

Step 3: if $\min \| x-D_i \| \leq \eta$ **,** add the node to the evidence set:

$$F \leftarrow \{v_i \mid v_i \in V_{user}^{'} \wedge \min \| x-D_i \leq \eta \| \} ;$$

Step 4: Calculate conditional probability distribution of evidence nodes against all product nodes, according to:

$$P(x=v_i \mid F)=\prod_{v_i \in V_{produce}} P(x=v_i \mid Pa(v_i))|_F$$

Step 5: Merge all the product nodes, which meet a certain probability threshold value,to form a recommended product set: if $P(x=v_i \mid F)>\mu$ then let $R=\{v_i\} \cup R$, $v_i \in V_{produce}$;

Step 6: repeat step4 and step 5 until all the product user nodes are visited.

The optimum matching trust community, which a node belongs to, can be obtained by calculating distance of the node and trust communities. The algorithm can be described as fellow:

First of all, calculate the distances from a new user node to all exists networks, and find the shortest path length. The community which has the shortest distance from the node to it is the optimum matching trust community.

Second, adjust distance of the node to others nodes in the optimum matching trust community.

Finally, take the neighbor nodes within a certain path length as evidence-nodes, and conditional probability of arriving these nodes can be figured out by the Bayesian-network-inference calculation.

Take a new user node x ($D_i(x,v_i)$ denotes distances between the node and other user nodes, $v_i \in V_{user}$) as an example, the Clustering algorithm described above can be expressed in Figure 1.

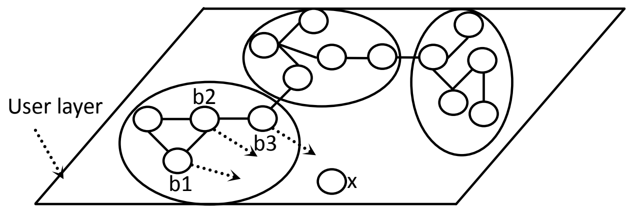

Figure 1. Clustering of New User and Adjustment of Structure

Pseudo-code of the clustering for trust community is listed as follow:

Small world trust community clustering algorithm

Begin

Step 1:

Calculate the distances $D_i(x,v_i)$ from an input user node x to other nodes. If the shortest path D_a between x and a certain node a exits, the cluster, which a belongs to, is the optimum matching trust community, the process can be described as:

$$\| x - D_a \| = \min_{i \in V_{user}} \| x - D_i \|$$

Step 2:

Adjust the path length D and direct topology structure of a according to the formula below:

$$D_i = \left\{ \begin{array}{l} D_i + \varepsilon_a (x - D_i), \text{if} \quad i = a \\ D_i + \varepsilon_n (x - D_i), \text{if} \quad i \in N_a \\ D_i, \text{otherwise} \end{array} \right\}$$

//in the formula, N_a denotes direct neighbor nodes of a (such as b_1, b_2, b_3 in Figure 1); ε_a and ε_n denote learning rate of a and its neighbor nodes, and generally, $\varepsilon_a \in [0.05\ 0.1]$, $\varepsilon_n \in [0.002\ 0.01]$.

End

4. Experiment and Analysis

Massa [20] used online community Epinions data sets to evaluate the trust relationship. We also use the data set to analysis the performance of clustering trust community. Epinions data is a who-trust-whom online social network of a general consumer reviewed site Epinions.com. Members of the site can decide whether to trust each other. All the trust relationships interact and form the Web of Trust which is then combined with review ratings to determine which reviews are shown to the user [21]. The data set consists of two parts, the rating_data sets and trust_data sets. Rating_data sets include three items, the user_id, item_id, rating_value, and comprising about 49,290 user's nodes, rating of 139,738 items. Trust_data sets consist of source_user_id, target_user_id, trust_statement_value, and comprising 49,290 user nodes trust status. We let the rating data set as training data and use algorithms 1 to 3 to build trust communities. The trust_data sets trust looked as a test set to assess the accuracy of the results.

In order to test our algorithms we use other two different algorithms to compare them. The first algorithm is a standard Collaborating Filtering one and the second is Mole Trust [20]. The validity of community clustering of trust network can be evaluated by the accuracy and time efficiency. When the trust community cluster that node included is in the consistency with higher confidence of trust_data sets, it indicates that the nodes in the community cluster have close relationship of trust with other nodes in the same community and the trust community clustering is correct. When there is low confidence in the consistency of trust_data sets, it shows the trust community clustering is incorrect. In this case, nodes in the same trust community cluster will not exist a highly trust relationship. The Accuracy is defined as:

$$Accuracy = \frac{N_c}{N_c + N_i} \tag{13}$$

Where N_c denotes the number of correct nodes and N_i denotes the number of incorrect nodes. The results show in Figure 2 to 3. The horizontal lines represent the number of nodes in the test samples set; the vertical line represents the accuracy of clustering community. The comparison results of three methods are shown in Figure 2.

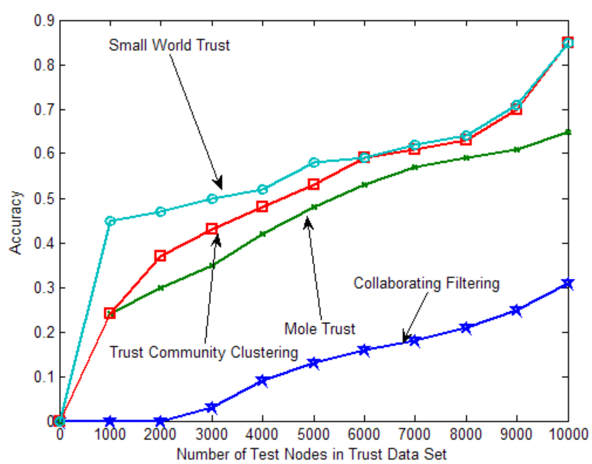

Figure 2. Compare the Precision of Small-world Trust Network with Other Three Trust Models

It can be easily find from Figure 2 that the precision of CF (Collaborating Filtering) is rather low. When training sample number reach to 10000, the precision of CF is less than 40%, which is difficult to meet the requirement of e-commerce trust recommendation. Precisions of other three recommendation model are relatively higher, and the accuracy of small-world trust model and trust community clustering model is generally the same. While, training sample number get to about 6000, their precision can reach to about 60%. Recommendation accuracy of the small-world trust model can come to more than 80% when raining sample number reach to about 10000, which can satisfy most trust recommend demand.

The Mean Absolute Error is also used to analysis accuracy also. The horizontal line indicates the number of sample nodes; vertical line represents the MAE, a comparison of the three methods shown in Figure 3.

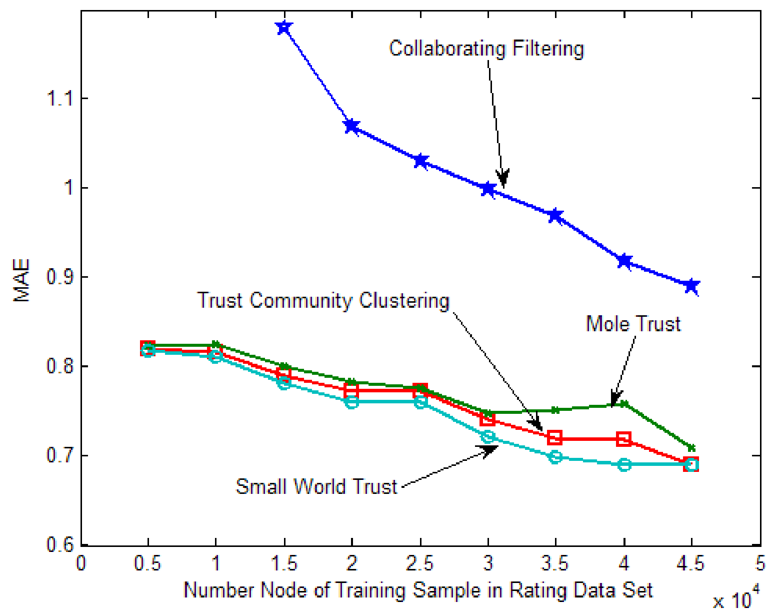

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Figure 3. MAE Comparisons of Four Models in Different Training Sample Data Set

As can be seen from Figure 3, MAE of CF model is relatively high, but basically similar for the other three models. While training sample number come to more than 35000, MAE of the three models seem to the same, which prove good precision of the three recommendation models.

The convergence of getting the shortest path length testing is conducted by selecting the different parameter (ε_a). Take 0.01, 0.05 and 0.1, respectively, which to analyze the algorithm's execution time. The results are shown in Figure 4.

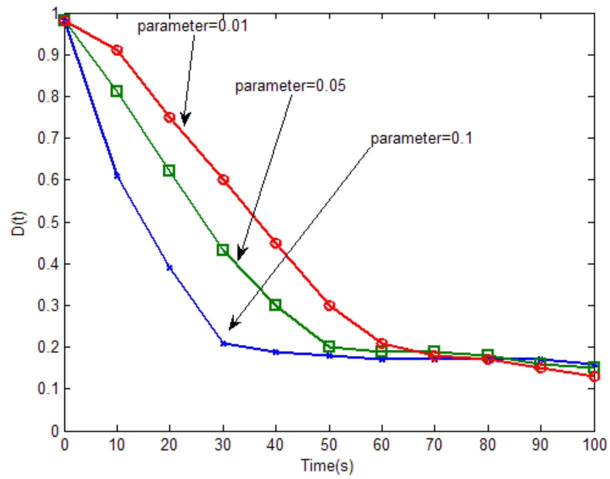

Figure 4. Comparison of the Shortest Path with Different Parameter (ε_a) Value

In Figure 4, the parameter is ε_a, which reflect study speed of a certain node a, and $D(t)$ denotes the shortest path length. The figure shows the result of different ε_a value (ε_a=0.01, 0.05, 0.1). Larger ε_a value means faster learn and convergent speed, which can get the shortest path in a short period. There overlap part in the figure. There are some points where convergence speed is very slow, but recommendation precision is rather high while ε_a is assigned with a small value. Also, there are some points where convergence speed is very fast, but recommendation precision is rather bad, while ε_a is set to be large. So ε_a value can be assigned with a proper value to get the best recommendation accuracy under different application environment.

The convergence of getting the shortest path length testing is conducted by selecting the different parameter (ε_a). Take 0.002, 0.05 and 0.01, respectively, which to analyze the algorithm's execution time. The results are shown in Figure 4.

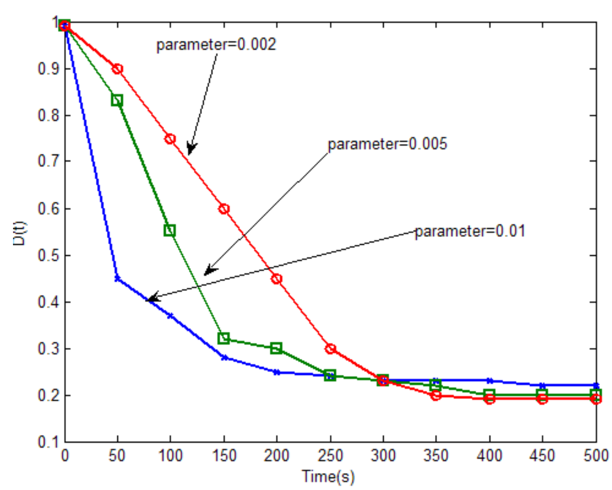

Figure 5. Shortest Path Comparison with Different Parameter (ε_n) Value

In Figure 5 the parameter is ε_n, which reflects learn speed of node a's direct neighbor nodes, and $D(t)$ denotes the shortest path length. While ε_n is assigned to 0.01, which means a fast learn speed, convergence speed is rather fast, and it can get the shortest path within 250 seconds. And when ε_n is set to 0.002, the shortest path can obtained within about 350 seconds. From Figure 5 we can come to a conclusion: high accuracy can be obtained with relatively low convergence speed, the faster convergence speed, the lower recommendation precision.

5. Conclusion

A trust network model in e-commerce by small world network analysis is established in this paper. This model combines local trust recommendation degree and global trust recommendation degree, which has an advantage of building a trust relationship network between the subjects. It proposes an improved shortest path algorithm to build trust network model. It proposed the concept of trust community networks and through community clustering analysis to construct trust relationship. It also gives the algorithms for the global trust information degree and trust community clustering in e-commerce. The experiments show that the method of building trust network model can well describe the main indirect trust in e-commerce and the algorithms has obvious advantages in accuracy and in time cost.

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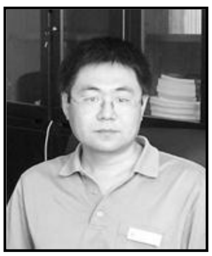
Authors



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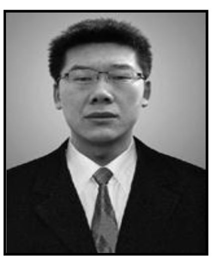

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