A Novel Community-Based Trust Model for P2P Networks

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Abstract In a heterogeneous peer-to-peer network, different peers may provide different qualities of service, so it is very important and helpful to identify those peers that can provide better services than others. A trust model is thus needed to provide a way for building trust through social control without trusted third parties. In this paper, we propose a new community-based trust model for P2P networks. There are three main features of this model. First, referral trust information is given to communities for each requestor, and in this sense, the prior knowledge of requestors about the environment is used to promote the collaboration. Second, the method to update referral trust value of each community is given, and thus, peers can learn from experiences about the environment. Third, the time aging factors of the both direct experience and indirect experience are taken into account. In order to justify the proposed model, we compare it with the existing models. The experiment results show that the use of community structure indeed improves the performance of the P2P networks.

Keywords P2P networks · Trust model · P2P community

1 Introduction

The emergence of decentralized and dynamic applications draws a lot of attention to P2P system. In a heterogeneous ubiquitous peer-to-peer network, different peers may provide different qualities of service, so it is very important and helpful to identify those peers that can provide better services than others. A trust model is

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thus needed to provide a way for building trust through social control without trusted third parties.

In many applications, peers sharing same interests construct communities. These communities are implicitly formed, self-organizing structures that depend on the declared interests of peers. The different communities within which a peer can participate due to its claimed interest constitute the roles of the peer. Every peer belongs to at least one predetermined community, and in many cases, it belongs to more than one possibly overlapping community. Rather than being a single, homogeneous community, they become a collection of communities of users as P2P system becomes more and more heterogeneous as their scale increases. For every peer, there are many communities that it is familiar with, and when searching for a service, it can ask for those community members about their opinion about the performance of service provider. How to utilize this community structure, especially how the prior knowledge of requestor about the environment evolved, is then a changeling question for P2P networks.

Referral trust [1, 2] is trust in recommendatory, which is user's belief about the trustworthiness of other users' referral knowledge, while functional trust is trust in target agent about its ability for providing good service. In real applications, peers usually have prior knowledge of communities about how reliable the referral trust coming from community is and it can then place different trust values to different communities. Many works have been present to build trust model in P2P networks, and in these works, function trust information is often used to assist peer to find a suitable service provider, and however, referral trust information that comes from different communities is seldom considered.

This paper extends our previous work [3] and presents a new community-based trust model for P2P networks. In this work, referral trust information is given to communities for each requestor, and in this sense, the prior knowledge of requestors about the environment is used to promote the collaboration. The method to update referral trust value of each community is then given, and thus, peers can learn from experiences about the environment. Furthermore, the time aging factors of the both direct and indirect experience are taken into account. We finally compare it with the existing models. The experiment results show that the use of community structure indeed improves the performance of the P2P networks.

The remainder of the paper is organized as follows: In the following section, we compare our work with related works. Then, in Sect. 3, the community-based trust model is given, and this is followed by a simulation and analysis of the proposed model in Sect. 4. And finally, the conclusion and future work are discussed in Sect. 5.

2 Related Works

In our previous work (Wang [3]), we give a model of community-based trust model for P2P networks; however, the time aging factor was not considered in that paper. Furthermore, a new Euclidean distance, which is a more accurate metric

than the one used there, is used to update the referral trust to communities in this work.

Sabater [4] proposes a reputation system that takes advantage of social relations between agents to overcome the problem that direct interactions are not always available, and however, the cooperation relation of witness and the service provider must be provided to obtain a reliable degree, and there are many cases that this information is not available either.

Khambatti et al. [5] present an optimistic-role-based model for trust among peers and show that it is scalable, dynamic, revocable, secure, and transitive. A new metric is defined to calculate peer links among communities, which is then used as trust value of a peer; however, the referral trust value of the agent to a community is not considered at all in this work, so the model cannot deal with the prior knowledge of requestors about the environment.

Singh [6] proposes a method to rate authentication information by a level of trust, which describes the strength of an authentication method, and gives a mathematical model to calculate the trust level when combining two authentication methods. However, the trust coming from the community cannot be used to help a peer to make the right decision.

Tian et al. [7] give a group-based reputation system GroupRep to establish the trust relationship in large-scale P2P networks. The trust relationship in GroupRep can be viewed as many tiers and can be used to assist the collaboration. This work has similarity with ours in that the trust relationship between group and peer is considered, but only the members of the group where the requestor belonging to are used to calculate the overall evaluation, and in our model, however, any group that the requestor is familiar can be an information source to find a service provider.

3 Community-Based Trust Model

In this section, we give a novel community-based trust model in which direct trust value and indirect trust value are combined to get overall evaluation. Community structure is used when calculating indirect trust value. The method to update referral trust value of communities after each interaction is given and the time aging factor are considered as well.

3.1 Direct Trust Calculation

Experience is one of the most important information that could influence the choice of the service requestor. In our model, an aggregation of a peer's experience to a special service provider is defined as its trust to that provider.

A peer r gets its direct trust value from its direct experience, it come from interaction history: With service provider p, let $S_{r,p}$ be the satisfaction of r to p, then direct trust value is calculated as follows:

$$\mathrm{DT}'_{r,p} = \sum_{i \in k} S_{r,p} \times f_w(i) \tag{1}$$

Note that $\mathrm{DT}_{r,p}$ is equal to zero, if there is no interaction between r and p at all.

Without further interaction, direct trust decreases over time according to a time-based aging factor Y. The closer the Y is to 1, the lower the value of Y, and the value of previous direct trust decreases with the decrease in Y. For static environments, where very few number of interactions take place within a particular time period, the value of Y might be chosen close to 0. Then, we get

$$\mathrm{DT}_{r,p} = \mathrm{DT}'_{r,p} \times \left(1 - \frac{(t - t_0)\Upsilon}{t}\right) \tag{2}$$

3.2 Indirect Trust Calculation Using Community Structure

It is less likely that repeat interactions will occur between same peers for the asymmetric interests between them. In many cases, it is difficult to establish the direct trust relationship between peers. Although interactions with someone in the past are of course the most reliable source of information about the agent's trustworthiness, however, relying only on direct experience is inefficient.

In community-based model, indirect trust value is used to get the overall evaluation. A requestor places different referral trust to different communities in prior, and this referral trust information is combined with functional trust of members of communities to get the overall evaluation; in this sense, the prior knowledge of requestor about the environment is used to promote the collaboration.

For an agent r, the set of all communities that it can interact with is denoted as N_r. The trust value to different communities is also different. We associate every $G_r \in \mathrm{N}_r$ with a $h_r \in [0, 1]$, which is the referral trust value of r to community G_r.

The evaluation of service provider is the aggregation of all evaluations of the different communities. Note that the weight to each community is just the referral trust value of the community.

$$\mathrm{IT}'_{r,p} = \sum\nolimits_{G_i \in N_r} \omega_i \times T_{G_i,p} \tag{3}$$

where $\omega_i = h_i$.

Just like direct trust, indirect trust value decreases over time according to a time-based aging factor Y also. Then, we get

$$\mathrm{IT}_{r,p} = \mathrm{IT}'_{r,p} \times (1 - \frac{(t - t_0)\Upsilon}{t}) \tag{4}$$

In the above formula, $T_{G_i,p}$ is used to denote the trust value to service provider by each community, and in the next part of this section, the method to calculate $T_{G_i,p}$ is given.

Let G_i be a community and $a_1^i \ldots a_j^i$ be all members of G_i, the trust value of G_i to p, which is denoted as $T_{G_i,p}$, is

$$T_{\mathrm{G}_i,p} = \mathrm{aggr}(T_{a_1^i,p}, \ldots T_{a_j^i,p}) \tag{5}$$

Much kind of operators can be used as *aggr* operator, and in this study, we choose OWA operator. OWA operators were originally introduced by Yager [8] to provide a means for aggregating scores associated with the satisfaction of multiple criteria, which unifies in one operator the conjunctive and disjunctive behaviors:

$$\mathrm{OWA}(x_1, x_2, \ldots, x_n) = \sum_{j=1}^{n} w_j * x_{\sigma(j)} \tag{6}$$

where σ is a permutation that orders the elements under consideration: $x_{\sigma 1} \leq x_{\sigma 2} \leq \ldots \leq x_{\sigma n}$. While ω_j is given as

$$w_j = Q\left(\frac{j}{n}\right) - Q\left(\frac{j-1}{n}\right) = \frac{j}{n} - \frac{j-1}{n} \tag{7}$$

3.3 Putting it Together: The Overall Evaluation

Using just direct trust value or just indirect trust value for a given requestor is only useful in extreme situations, and in most situations, it is preferable to consider both direct experience and indirect experience. Therefore, in our trust model, we adopt the combined degree as follows:

$$T_{r,p} = \kappa T_{r,p} + (1 - \kappa)\mathrm{IT}_{r,p} \tag{8}$$

where κ is a parameter reflecting the weight given to DT and IT, respectively.

3.4 Updating the Referral Trust to Communities

It is necessary to feedback the experience of following a particular recommendation into the trust relationship in order to enable the agent to learn from their experience. This is done as follows: After each interaction, a peer r who has acted

on the advice of its neighbor groups updates its referral trust value to each community.

Note that each neighbor community as a whole instead of individual member is updated.

Let $T'_{r,p}$ be the real satisfaction degree of peer r to service provider p, and let

$$r_k = \frac{1}{|G_i|}\sqrt{\sum\nolimits_{a_j \in G_i} \left| T_{a_j} - T'_{r,p} \right|^2} \tag{9}$$

Note that Euclidean distance is used here, which is a more accurate metric than the metric used in Wang [3].

It is convenient to define the update of $h_i(T+1)$ in terms of an intermediate variable $\tilde{h}_i(T+1)$:

$$\tilde{h}_i(T+1) = \begin{cases} r_k h_i(T) + (1-\gamma) r_k & \text{for } r_k \geq 0 \\ (1-\gamma) h_i(T) + \gamma r_k & \text{for } r_k < 0 \end{cases} \tag{10}$$

We then map it back to the interval [0,1]:

$$h_i(T+1) = \frac{1 + \tilde{h}_i(T+1)}{2} \tag{11}$$

4 Evaluations

The method given in this study is implemented based on Query-Cycle Simulator [9]. At the same time, we also implement RMS-PDN [10] and a conventional reputation system with shared information noted as RSSI [7]. The data are collected after 100th query cycle, and the results are averaged 5 runs.

The efficiency of the networks describes how good peers can efficiently get reliable files. They are as follows:

Satisfaction level (SAT): If the size of authentic contents downloaded by i is authentic_i, and the size of inauthentic contents downloaded by i is inauthentic_i, let

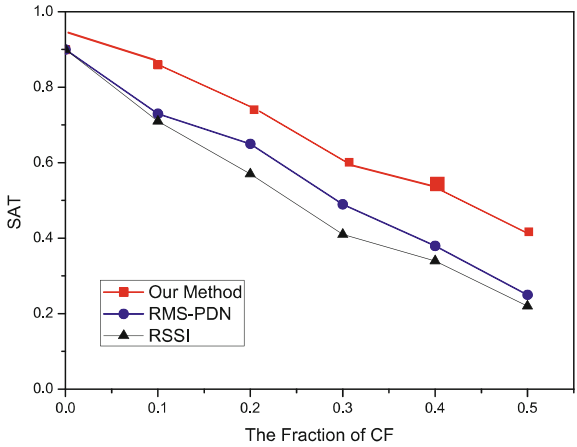
$$\text{Sat}_i = \frac{\text{authentic}_i - \text{inauthentic}}{\text{authentic}_i + \text{inauthentic}} \tag{12}$$

And then Sat is defined as

$$\frac{\sum_{i \in V_g} \text{Sat}_i}{|V_g|} \tag{13}$$

In order to compare with RMS-PDN, the simulated network is partially decentralized with 700 peers. Peers are constructed as 10 groups.

As shown in the below figure, SAT always changes with the same trend as RSQ does, so we can concluded that our method is also more efficient in this situation.



5 Summary and Outlook

In large-scale P2P networks, it is less likely that repeat interactions will occur between same peers for the asymmetric interests between them. So it is difficult to establish the direct trust relationship between peers.

This paper proposes a new community-based trust model for P2P networks. There are three main features of our model. First, referral trust information is given to communities for each requestor, and in this sense, the prior knowledge of requestors about the environment is used to promote the collaboration. Second, the method to update referral trust value of each community is given, and thus, peers can learn from experiences about the environment. Third, the time aging factors of the both direct experience and indirect experience are taken into account. Experiment results show that the use of community structure indeed improves the performance of the P2P networks.

In the future, we plan to add voting mechanism to the model so that the trust value given by the community can be more accurate.

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