A_020

A Measure of Reputation for More Precise Representation

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May 1, 2006

Abstract

Recently many studies on trust and reputation networks have been done, and several ways to measure degrees of trust and reputation have been proposed. However, it seems difficult to make comparisons in order to judge which is the most appropriate for the representation of these. This paper shows a novel measure based on principles of statistics that enables us to produce more sensitive representations of trust and reputation. Moreover, through several experiments, we show that with our measure, even simple algorithms are capable of maintaining the network well.

1 Introduction

As e-businesses become more popular, the notions of trust and reputation have grown in significance. In fact, many systems on trust and reputation (see [2] for example) have been proposed for distributed environments, where each agent works independently of others. For this purpose, it is necessary to consider how to represent the degree of trust and reputation. For example, Liu and Issarny [1] treat the degree as a scalar and present a recommendation mechanism. Mui *et al.* [3] consider the reputation score a vector containing two parameters that represent the amount of positive and negative ratings where the agent that received the vector computes the beta probability distribution function and the agent regards the distribution as one of reputation. This measure has produced several results (see [4, 5]).

This paper demonstrates a novel measure of reputation. Our idea comes from the following intuition: we may refer to things with some kind of "confidence", for example, "I'm sure that it works well", or, "it probably works well but I'm not sure." Thus, the principle of statistics enable us to represent such confidence. A reputation is denoted by a tuple (μ, σ^2), where μ denotes the average of the reputation and σ^2 denotes its variance. Intuitively, the smaller σ^2 is, more confident about its own opinion the agent is. Note that unlike [3], it is not assumed that the performance of an agent that is observed by a number of other agents is either cooperative or defective. Therefore, our measure can be applied in a variety of environments.

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This is aided by 21COE Program in Information, Electrics, and Electronics at Hokkaido University.

2 Our model and measure

Many models for representing decentralized environments have been proposed. In this paper, we discuss our measure using the model below.

Consider a situation in which agent A is observing agent B, and A wants to evaluate how trustworthy B is. Agents $C_1, C_2, \ldots, C_k$ are also observing B, and A and $C_1, \ldots, C_k$ have their own opinions about B.

2.1 Reputation measure

As mentioned in Section 1, we introduce notions used in statistics for representing reputation. We regard reputation as a combination of an average μ and a variance σ^2. In a sense, μ refers to the opinion and σ^2 refers to the degree of the confidence in that opinion.

When agent A asks C_j its opinion of B, the answer of C_j at round t is of the form $(\mu_{C_j \to B}(t), \sigma^2_{C_j \to B}(t))$, where $\mu_{C_j \to B}(t)$ and $\sigma^2_{C_j \to B}$ respectively denote the average and the variance of B's reputation in the eyes of C_j. (We use the notations $(\mu_{A \to B}(t), \sigma^2_{A \to B}(t))$ and $(\mu_{A \to C_j}(t), \sigma^2_{A \to C_j}(t))$ in the same sense.)

2.2 Calculation of (μ, σ^2)

First, at each round, agent A can ask C_j its opinion of B in order to update its own opinion of B. Then, agent B executes its task once and A evaluates how satisfied it is with B. (Its satisfaction is denoted by $s(t)$, which is in $[0, 1]$.) Next, A updates its own opinions of C_j, where $j = 1, \ldots, k$, according to gaps between $(\mu_{C_j \to B}(i-1), \sigma^2_{C_j \to B}(i-1))$ and $s(0), s(1), \ldots, s(t-1)$, A's satisfactions to B, as follows:

$$g_j(t) = \frac{\sum_{i=1}^{t} |s(i) - \mu_{C_j \to B}(i-1)|^2 / t}{\sum_{i=1}^{t} \sigma^2_{C_j \to B}(i-1)/t}.$$

That is, $g_j(t)$ is the ratio between the variance of the gap $|s(i) - \mu_{C_j \to B}(i)|$ and the average of $\sigma^2_{C_j \to B}$. Let $g'_j(t) = \min\{g_j(t), 1/g_j(t)\}$, then $g'_j(t) \leq 1$ always holds and $g'_j(t)$ becomes larger when $|s(t) - \mu_{C_j \to B}(t)|^2/t$ is close to the average of $\sigma^2_{C_j \to B}$. Then A updates its reputation of C_j as follows:

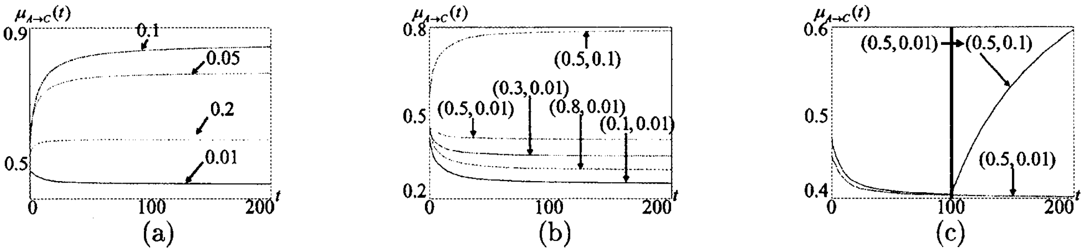

Figure 1: Relation between round t and $\mu_{A\to C}(t)$ (a) when C's opinion of B is each of $(0.5, 0.01)$, $(0.5, 0.05)$, $(0.5, 0.1)$, and $(0.5, 0.2)$, (b) when it is each of $(0.1, 0.01)$, $(0.3, 0.01)$, $(0.5, 0.01)$, and $(0.8, 0.01)$ (compared with the relation when C's opinion is $(0.5, 0.1)$), and (c) when agent C improves its opinion of B from $(0.5, 0.01)$ to $(0.5, 0.1)$ at $t = 100$, compared with the relation when C does not change its opinion.

$$\mu_{A\to C_j}(t) = \frac{1}{t}\sum_{i=1}^{t} g'_j(i),$$

$$\sigma^2_{A\to C_j}(t) = \frac{1}{t}\sum_{i-1}^{t} |g'_j(i) - \mu_{A\to C_j}(i)|^2.$$

After that, agent A calculates B's reputation in the view of A as follows:

$$\mu_{A\to B}(t) = \frac{1}{|\mathcal{C}|}\frac{\sum_{C\in\mathcal{C}} \mu_{C\to B}(t-1)\cdot\mu_{A\to C}(t)}{\sum_{C\in\mathcal{C}} \mu_{A\to C}(t)},$$

$$\sigma^2_{A\to B}(t) = \frac{1}{|\mathcal{C}|}\frac{\sum_{C\in\mathcal{C}} \sigma^2_{C\to B}(t-1)\cdot\sigma^2_{A\to C}(t)}{\sum_{C\in\mathcal{C}} \sigma^2_{A\to C}(t)},$$

where $\mathcal{C}$ denotes the set of $\{C_1, \ldots, C_k\}$. These formulas can be regarded as weighted averages of $\mu_{C\to B}$ and $\sigma^2_{C\to B}$ according to agent C's reputation.

Here, we should note that the above calculations require $O(n)$ time at round t.

3 Experiments

In this section, we show several results that show that even the simple algorithm can fulfill our needs. In our setting, only agents A and C are observing agent B, and C tells A the same opinion during all rounds. A's opinion of C at first, $(\mu_{A\to C}(0), \sigma^2_{A\to C}(0))$, is $(0.5, 0.01)$. We assume that A's satisfaction with B obeys uniform distribution between 0 and 1. (We have confirmed that the degree of satisfaction obeys uniform distribution for other ranges, for example $[0.5, 1]$, but have omitted the details.) Namely, the average of A's satisfaction is 0.5 and the variance is $1/12 \approx 0.0833$. Also, we set the number of agents $k = 10,000$.

In this paper, we have focused on relations between agent C's opinion of B and its reputation in the eyes of A, that is, how good are the results that the feedback yields. Figure 1(a) shows the relation between the number of rounds t and the average of C's reputation in the eyes of A, $\mu_{A\to C}(t)$, when C's opinion of B is any of $(0.5, 0.01)$, $(0.5, 0.05)$, $(0.5, 0.1)$, and $(0.5, 0.2)$. With this figure, we can see that as $\sigma^2_{C\to B}$ is closer to the actual variance of $s(t)$, C can gain a better reputation in A's view. Figure 1(b) shows the same relation when C's opinion is any of $(0.1, 0.01)$, $(0.3, 0.01)$, $(0.5, 0.01)$, and $(0.8, 0.01)$. We can see that it can gain a better reputation when C's opinion is nearer to the average of A's satisfaction, but in each case $\mu_{A\to C}$ becomes worse than the initial state. Thus we can conclude that C can gain A's good reputation when both $\mu_{C\to B}$ and $\sigma^2_{C\to B}$ are close to the actual satisfaction of A.

Next, we consider the situation in which agent C improves its own opinion of B closer to the actual satisfaction after the 100th round. Namely, C changes its opinion from $(0.5, 0.01)$ to $(0.5, 0.1)$. The results under the above conditions are shown in Figure 1(c). Compared with the lower broken line, i.e., the one where C does not improve its opinion, we can see that the reputation of C in the eyes of A becomes clearly higher after that change.

As these experiments demonstrate, even using an algorithm as simple as the one above, with our proposed measure it is possible to maintain a whole network stable. However, the results could probably be improved with better algorithms, which will be the aim of future work.

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