iCLUB: An Integrated Clustering-Based Approach to Improve the Robustness of Reputation Systems

(Extended Abstract)

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ABSTRACT

The problem of unfair testimonies has to be addressed effectively to improve the robustness of reputation systems. We propose an **i**ntegrated **CLU**stering-**B**ased approach called **iCLUB** to filter unfair testimonies for reputation systems using multi-nominal testimonies, in multiagent-based electronic commerce. It adopts clustering and considers buying agents' local and global knowledge about selling agents. Experimental evaluation demonstrates promising results of our approach in filtering various types of unfair testimonies.

Categories and Subject Descriptors

I.2.11 [**ARTIFICIAL INTELLIGENCE**]: Distributed Artificial Intelligence – Intelligent agents, Multiagent systems

General Terms

Algorithms, Experimentation

Keywords

Reputation System, Unfair Testimony, Clustering

1. INTRODUCTION

With respect to the the problem of "unfair testimonies" in reputation systems, most existing work focuses on the reputation systems accepting only binary testimonies [3]. In this paper, we propose an **i**ntegrated **CLU**stering-**B**ased approach called **iCLUB** to tackle this problem for reputation systems using multi-nominal testimonies. Our approach adopts clustering methods and integrates two components, Local (only buyers' knowledge about the sellers being currently evaluated) and Global (also buyers' knowledge about other sellers that the buyers have previously encountered).

2. THE PROPOSED iCLUB APPROACH

Suppose that in a reputation system, there are M selling agents $\{S_1, S_2, \ldots, S_M\}$, and N buying agents $\{B_1, B_2, \ldots, B_N\}$. K rating levels are adopted ($K \geq 2$). The ratings from a buyer B_n ($1 \leq n \leq N$) for a seller S_m ($1 \leq m \leq M$) can be expressed as a row vector:

$$R^{B_n}_{S_m} = [R^{B_n}_{S_m}(1), \ldots, R^{B_n}_{S_m}(i), \ldots, R^{B_n}_{S_m}(K)]$$

where $R^{B_n}_{S_m}(i)$ is number of transactions between B_n and S_m rated as rating level i. When B_n is evaluating S_m's reputation, it can collect rating vectors from other buyers to facilitate its evaluation. Then the set of these buyers that provide rating vectors to B_n regarding S_m are expressed as:

$$W^{B_n}_{S_m} = \{B_j \mid j \neq n \wedge \parallel R^{B_j}_{S_m} \parallel \neq 0\}$$

From B_n's point of view, $W^{B_n}_{S_m}$ is called the set of witness agents regarding S_m (each buyer in $W^{B_n}_{S_m}$ is a witness), and the rating vector provided by each witness is called testimonies from this witness. Then the local information $L^{B_n}_{S_m}$ regarding S_m can be expressed as:

$$L^{B_n}_{S_m} = \begin{cases} \{R^{B_j}_{S_m} | B_j \in W^{B_n}_{S_m}\} & \text{if } \|R^{B_n}_{S_m}\| = 0 \\ \{R^{B_j}_{S_m} | B_j \in W^{B_n}_{S_m} \cup \{B_n\}\} & \text{if } \|R^{B_n}_{S_m}\| \neq 0 \end{cases}$$

And the global information can be expressed as $G^{B_n} = \bigcup_{m=1}^{M} L^{B_n}_{S_m}$, which in fact contains the local information of B_n about S_m. The Local and Global components integrated in our iCLUB approach make use of the local information (Algorithm 1) and global information (Algorithm 2) to filter unfair testimonies, respectively.

Procedure: Local(S_t, B)
Input : S_t, seller whose reputation is evaluated; B, buyer evaluating S_t's reputation;
Output : A set of honest witnesses regarding S_t;
1 Collect local information regarding S_t as $L^B_{S_t}$;
2 $C_1, C_2, ..., C_Z = \text{DBSCAN}(L^B_{S_t})$;
3 $\exists b, R^B_{S_t} \in C_b$ ($1 \leq b \leq Z$);
4 Return $W_T = \{B_i | R^{B_i}_{s_t} \in C_b \wedge B_i \neq B\}$;

Algorithm 1: Making Use of Local Information

In Algorithm 1, the Local component first collects the local information regarding S_t (Line 1). DBSCAN, a density-based clustering routine [1], is then applied on the collected testimonies $L^B_{S_t}$ to generate a set of clusters (Line 2). After that, the Local component returns as honest witnesses the set of witnesses whose rating vectors are included in the same cluster as the buying agent's rating vector (Lines 3-4).

In Algorithm 2, the Global component first finds the honest witnesses for each seller with which the buyer has transactions, using the Local() procedure (Lines 1-3). Then, a set of common honest witnesses W_F are formed as the intersection of the set of the honest witnesses for each seller except

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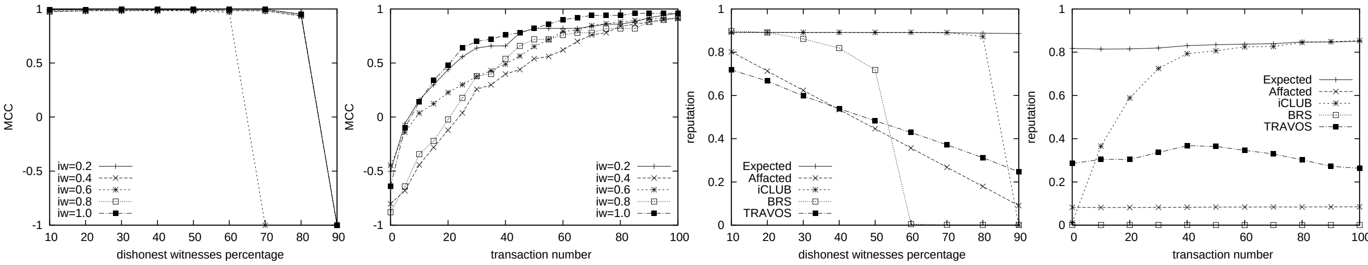

(a) **(b)** **(c)** **(d)**

Figure 1: (a, b) Filtering Accuracy of the iCLUB Approach; (c, d) Comparison with other Approaches

S_t (Line 4). The Global component obtains the clustering result for S_t (Line 5). It then calculates the intersection of W_F with the witnesses whose rating vectors are in each cluster achieved in Line 5 if W_F is not an empty set (Lines 6-11). Finally, it returns as honest witnesses the ones whose rating vectors are in the cluster which has the largest intersection result with W_F (Lines 12-13). Our iCLUB approach further integrates the Local and Global components using a threshold ε. If the number of transactions between B and S_t is greater than ε, Global() procedure will be triggered, otherwise Local() procedure will be called.

Procedure: Global(S_t, B)
Input : S_t, seller whose reputation is evaluated;
B, buyer evaluating S_t's reputation;
Output : A set of honest witnesses regarding S_t;

1 **foreach** *selling agent* S_i $(1 \leq i \leq M, i \neq t)$ **do**
2   **if** B *has transactions with* S_i, $R^B_{S_i} \neq 0$ **then**
3         $W_i = \text{Local}(S_i,B)$;
4 $W_F = \bigcap_{i=1}^{M} W_i$, where $R^B_{S_i} \neq 0$ and $i \neq t$;
5 $C_1, C_2, ..., C_L = \text{DBSCAN}(L^B_{S_t})$;
6 **foreach** *cluster* C_j $(1 \leq j \leq L)$ **do**
7     $W_{C_j} = \{B_i | R^{B_i}_{S_t} \in C_j\}$;
8   **if** $W_F \neq \emptyset$ **then**
9         $W_{F_j} = W_F \bigcap W_{C_j}$;
10   **else**
11         $W_{F_j} = W_{C_j}$;
12 $q = \arg\{\max_j(|W_{F_j}|)\}, j = 1, 2, \cdots, L$;
13 Return $W_T = \{B_i | R^{B_i}_{S_t} \in C_q\}$ as honest witnesses;

Algorithm 2: Making Use of Global Information

3. EXPERIMENTAL RESULTS

We simulate a trading community that involves 10 selling agents, 100 witnesses and 1 buying agent B. Each selling agent is attached with a profile, describing its initial willingness (iw) value, the percentage of badmouthing witnesses (P_l) and the percentage of ballot-stuffing witnesses (P_h) [3]. The ratings for the transactions between each witness or B and S are generated through the normal distribution whose mean is $iw - 0.1$, and standard deviation is 0.2. We set $\varepsilon = 1$ and the DBSCAN radius is 0.4. When iw=0.2 or iw=0.4, P_l=0 and P_h increases from 10% to 90%. When iw=0.8 or iw=1.0, P_h=0 and P_l increases from 10% to 90%. When $iw = 0.6$, we fix P_h to 20% and make P_l increase from 10% to 70%. The first 100 transactions of each witness or B are for the presetting stage. In this stage, the witnesses will randomly select one seller among the 10 sellers as the partner for each transaction, and B will randomly select one seller among the first 9 as the partner for each transaction.

Figures 1(a) and 1(b) show the changes of the accuracy of filtering unfair testimonies (measured by MCC value [2]) for S_{10} with the percentage of dishonest witnesses and the number of transactions after the presetting stage in different scenarios, respectively. Note that some lines overlap in Figure 1(a). According to the results, the iCLUB approach can work well when the percentage of the dishonest witnesses is smaller than 80% when B does not have any experience with S_{10}. When 90% of witnesses are dishonest, our approach can still achieve high performance (MCC ≥ 0.9) after B has more than 8 transactions with S_{10}. Figures 1(c) and 1(d) show the comparison results of reputation estimation for S_{10} when the percentage of dishonest witnesses or the number of transactions increases respectively, by using BRS, TRAVOS [3] and iCLUB. The reputation estimated using iCLUB is very close to the expected value. But the reputation value estimated using BRS or TRAVOS continuously deviates from the expected value, indicating that iCLUB achieves more accurate filtering than BRS and TRAVOS.

4. CONCLUSIONS

Reputation systems have contributed much to the success of online trading communities. However, the reliability of reputation systems can easily deteriorate due to the existence of unfair testimonies. Therefore, we propose the iCLUB approach to filter unfair testimonies to improve the robustness of reputation systems. Our approach supports reputation systems with multi-nominal rating levels. Experimental results confirm that our approach is effective in filtering unfair testimonies and outperforms the competing approaches (BRS and TRAVOS) even in the scenario where only binary ratings are supported.

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