A Biclustering-Based Approach to Filter Dishonest Advisors in Multi-Criteria E-Marketplaces

(Extended Abstract)

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ABSTRACT

In this paper, we propose a biclustering-based approach to identify dishonest advisors (who provide misleading opinions about sellers), while evaluating seller trustworthiness on multiple criteria. It considers correlation between advisors' ratings to various criteria and trust transitivity to accurately filter the dishonest advisors. Evaluation results demonstrate the robustness of our approach against various types of unfair rating attacks.

Categories and Subject Descriptors

I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence - Intelligent Agents, Multiagent Systems

General Terms

Algorithm

Keywords

Reputation System; Unfair Rating Attack; Biclustering; Multiple Criteria; Electronic Marketplaces

1. INTRODUCTION

Existing approaches [1–3] dealing with the unfair rating problem are only designed to operate in a single-criterion environment and cannot effectively cope with sophisticated attacks in a multi-criteria scenario (seller is evaluated on multiple criteria). In this paper, we propose a novel approach to filter dishonest advisors in a multi-criteria environment using a biclustering technique [4], which can cluster advisors behaving honestly to a subset of criteria.

2. BICLUSTERING-BASED APPROACH

Consider an e-marketplace consisting of a set of buyers $\mathbb{B}$ and sellers $\mathbb{S}$, who are rated based on a set of criteria $\mathbb{C}$. Let b denote the active buyer, evaluating the trustworthiness of the current seller s. All other buyers are considered as advisors to buyer b. A bicluster for buyer b is defined as a trusted group $G_b = (B, C)$, where $B = \{b, A_b\} \subseteq \mathbb{B}$ contains buyer b and her trusted advisors regarding several criteria $C \subseteq \mathbb{C}$. The trusted group G_b indicates that advisors in A_b share similar rating behavior with buyer b on the criteria set C. There could be several such biclusters (denoted as $\mathbb{G}_b$) for buyer b based on the trusted groups formed for different combinations of criteria. The rating set in each bicluster $G_b = \{B, C\}$ is denoted using $R_B^S = \{r_b^s | s \in S,\ b \in B\}$, where $r_b^s = \langle r_{b,c}^s \rangle, c \in C$ is a rating vector consisting of ratings on all criteria from buyer b to seller s. S denotes the set of sellers rated by buyers in B.

Algorithm 1: Biclustering(b, s)

Input : tolerance ε; forgetting λ; importance ω; weight ν;

1 step = 0; $\mathbb{G}_b = \emptyset$;
2 **foreach** combination of criteria $C \subseteq \mathbb{C}$ **do**
3 $\quad B = \{b\}$; initial bicluster $G_b = (B, C)$; $G'_b = \emptyset$;
4 $\quad$ **repeat**
5 $\quad\quad G'_b = G_b$; step++;
6 $\quad\quad \tilde{b}$ = central buyer of G_b;
7 $\quad\quad$ **if** step is odd **then**
8 $\quad\quad\quad$ select an advisor $a \in \mathbb{B} - B$ where $N_s(\tilde{b}, a) > 0$;
9 $\quad\quad\quad$ **if** $\triangle(\tilde{b}, a, C) \leq \varepsilon$ **and** $\nabla(b, a, C) \leq \varepsilon$ **then**
10 $\quad\quad\quad\quad$ include advisor a to B; update $\tilde{b}$;
11 $\quad\quad\quad$ **foreach** advisor $a \in B - \{b\}$ **do**
12 $\quad\quad\quad\quad$ **if** $\triangle(\tilde{b}, a, C) > \varepsilon$ **or** $\nabla(b, a, C) > \varepsilon$ **then**
13 $\quad\quad\quad\quad\quad$ delete advisor a from B; update $\tilde{b}$;
14 $\quad\quad$ **if** step is even **then**
15 $\quad\quad\quad$ select any criterion $c \in \mathbb{C} - C$;
16 $\quad\quad\quad$ **if** $\triangle(\tilde{b}, a, C{+}c) \leq \triangle(\tilde{b}, a, C)$ **and** $\nabla(b, a, C{+}c) \leq \varepsilon$ **then**
17 $\quad\quad\quad\quad\quad$ //for all advisors $a \in B$
18 $\quad\quad\quad\quad$ include criterion c to C; update $\tilde{b}$;
19 $\quad\quad\quad$ **foreach** criterion $c \in C$ **do**
20 $\quad\quad\quad\quad$ **if** $\triangle(\tilde{b}, a, c) > \varepsilon$ **or** $\nabla(b, a, c) > \varepsilon$ **then**
21 $\quad\quad\quad\quad\quad\quad$ //for any advisor $a \in B$
22 $\quad\quad\quad\quad\quad$ delete criterion c from C; update $\tilde{b}$;
23 $\quad$ **until** $G'_b = G_b$ **and** B has all advisors satisfying 2 constraints;
24 $\quad \mathbb{G}_b = \mathbb{G}_b \bigcup G_b$;
25 **return** $\mathbb{G}_b$;

The **Biclustering** algorithm (Alg. 1) identifies a set of biclusters $\mathbb{G}_b$ for buyer b. It begins with an initial bicluster G_b, containing buyer b and several randomly chosen criteria (Lines 2-3). On every odd iteration (Lines 7-13), advisors in the bicluster are updated (added or deleted). A new advisor a is added to $G_b = \{B, C\}$ (Lines 9-10) if: 1) her distance (Eqn. 2) from the central buyer $\tilde{b}$ is not larger than a tolerance value ε. The central buyer $\tilde{b}$ contains the average ratings of buyers in the bicluster, with more weights (ω) to the ratings from buyer b; 2) she has a similar criteria correlation as that of buyer b, where the criteria correlation difference between a and b is given by Eqn. 3. Lines 11-13 signify that an advisor will be removed from G_b, if she violates any of the above two constraints.

On the even iteration, a new criterion c is added to G_b, if the dis-

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tance from the central buyer $\tilde{b}$, for any advisor a in the bicluster is not further increased and if the advisors in the bicluster have a similar criteria correlation as b, even after adding criterion c (Lines 16-18). Lines 19-22 check for consistency among criteria and delete them if necessary. We iterate until convergence (Line 23) to obtain the final bicluster. Each possible combination of criteria C (Line 2) is used to obtain a complete set of biclusters for buyer b.

Distance from the Central Buyer. The distance (rating difference) between advisor a and central buyer $\tilde{b}$ on the criteria set C for current seller s is defined using normalized Euclidean distance as:

$$\triangle(\tilde{b}, a, C, s) = \frac{\sqrt{\sum_{c \in C} (r^s_{\tilde{b},c} - r^s_{a,c})^2}}{\sqrt{\sum_{c \in C} (r^s_{\tilde{b},c})^2} \sqrt{\sum_{c \in C} (r^s_{a,c})^2}} \quad (1)$$

The total distance is calculated for all rated sellers, giving more weights (ν) to the current seller s and the mean distance is obtained. If $\triangle_j(\tilde{b}, a, C)$ is the distance in time window t_j and λ ($\in [0, 1]$) is the forgetting factor, then the time weighted distance is given by:

$$\triangle(\tilde{b}, a, C) = [\sum_{j=1}^{n} \lambda^{j-1} \times \triangle_j(\tilde{b}, a, C)] \,/\, (\sum_{j=1}^{n} \lambda^{j-1}) \quad (2)$$

Correlation between Criteria. Correlation information is especially useful to distinguish dishonest advisors, when buyer b has no direct experience with some sellers and rating distance in Eqn. 2 becomes less reliable. The correlation difference between buyer b and advisor a under a set of criteria C is given by:

$$\nabla(b, a, C) = \frac{1}{2 \times |C|^2} \sum_{i=1, j=1}^{|C|} |\rho_b(c_i, c_j) - \rho_a(c_i, c_j)| \quad (3)$$

where $c_i, c_j \in C$, and $\rho_b(c_i, c_j)$ represents the Spearman's rank correlation between c_i and c_j for buyer b.

Transitivity of Trust. While selecting advisors to be added to the bicluster (Line 8 of Alg. 1), those having commonly rated sellers with central buyer $\tilde{b}$ are considered at first (number of commonly rated sellers $N_s(\tilde{b}, a) > 0$) to ensure transitive propagation of trust, in order to deal with sparse scenarios.

Once the bicluster G_b is formed (using Alg. 1), it is again scanned for possible malicious advisors by employing the majority rule. Such filtering is especially helpful to identify dishonest advisors, when the active buyer b is a newcomer and its bicluster contains all possible advisors, who have rated the current seller s.

Confidence in Trusting Advisors. The confidence in trusting an advisor a in buyer b's biclusters $\mathbb{G}_b$ for criterion c is given by:

$$\mathcal{T}_{b,c}(a) = \frac{N_c(a)}{MAX[N_c(a_j)]} \quad (4)$$

where $c \in C$, $N_c(a)$ is the number of criteria for which advisor a is honest, and $MAX[N_c(a_j)]$ is the maximum number of criteria for which any advisor a_j in $G_b \in \mathbb{G}_b$ with criterion c included is honest.

3. EVALUATION

We simulate an e-marketplace involving 30 buyers, evaluating 15 sellers on 3 criteria. Seller honesty is uniformly distributed in $[0, 1]$. The simulation is run for 10 days, resulting in a total of 300 transactions with an average of 30 ratings per buyer. The proportion of dishonest advisors is in the range $[0.3 - 0.7]$. Six typical unfair rating attacks [5] from dishonest advisors are designed: Constant, Camouflage, Whitewashing, Sybil, SybilCamouflage and SybilWhitewashing. Also, half the number of dishonest advisors give unfair ratings to sellers only on the first two criteria while the rest behave dishonestly towards the third criteria. We compare the MCC [1] of our approach ($\varepsilon = 0.1$, $\lambda = 0.6$, $\omega = 0.8$, $\nu = 0.7$) in predicting advisor trustworthiness with two extended versions of BRS [2, 3] and iCLUB [1]: 1) BRS and iCLUB applied to each criterion separately, denoted by BRS-S and iCLUB-S, respectively and 2) BRS and iCLUB applied on the average rating of all criteria, denoted by BRS-A and iCLUB-A, respectively.

Table 1: MCC of trust models vs. attacks

Model	Constant	Camouflage	Whitewashing	Sybil	SybilCam	SybilWW
BRS-S	-0.03±0.70	-0.07±0.06	-0.11±0.02	-0.10±0.03	-0.12±0.01	-0.22±0.08
BRS-A	-0.04±0.10	-0.09±0.08	-0.12±0.20	-0.11±0.02	-0.17±0.08	-0.22±0.08
iCLUB-S	0.88±0.10	0.78±0.13	0.62±0.12	0.76±0.03	0.81±0.03	0.46±0.14
iCLUB-A	0.82±0.07	0.76±0.10	0.60±0.16	0.73±0.05	0.75±0.09	0.45±0.06
Ours	**0.99±0.01**	**0.89±0.02**	**0.99±0.01**	**0.95±0.02**	**0.87 ±0.03**	**0.94±0.02**

* SybilCam: Sybil Camouflage; SybilWW: Sybil Whitewashing

Table 1 presents the mean and standard deviation (over 10 runs) for MCC of advisor trustworthiness at the end of simulation. We find that under Constant attack, our approach performs better than other trust models with MCC = 0.99 at the end of simulation, and iCLUB outperforms BRS as expected [1]. iCLUB-S performs better than iCLUB-A, and BRS-S outperforms BRS-A because considering each criterion separately will not be affected by dishonest advisors that provide unfair ratings only on some criteria. For Camouflage attack, our approach obtains an MCC of 0.89 as it is able to cope with the changing behavior using the forgetting factor (λ).

Our approach obtains a MCC of 0.99 under Whitewashing attack, where a dishonest advisor whitewashes its trustworthiness by leaving the market and entering again with default trustworthiness value. Though the attacker has insufficient transactions after reentering, our approach can still filter them even in such sparse scenarios using the transitive property. Also, our approach obtains a better MCC under Sybil, SybilCamouflage and SybilWhitewashing attacks, as it can easily identify the dishonest advisors who form the majority using the transitive property.

4. CONCLUSION AND FUTURE WORK

We propose a biclustering-based approach to filter dishonest advisors in multi-criteria e-marketplaces. Correlation and trust transitivity features of the approach are used to accurately identify dishonest advisors even in sparse scenarios. Experimental results confirm that our approach outperforms BRS and iCLUB in accurately detecting dishonest advisors. Our future work will be to consider approximation strategies (like randomization of initial bicluster members) to reduce the computational complexity of the approach.

5. ACKNOWLEDGMENTS

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