RepRev: Mitigating the Negative Effects of Misreported Ratings

Yuan Liu[†] **Siyuan Liu** **Hui Fang** **Jie Zhang** **Han Yu** **Chunyan Miao**
School of Computer Engineering
Nanyang Technological University, Singapore
{yliu3, syliu, zhangj, hfang1, han.yu, ascymiao}@ntu.edu.sg
[†]http://trust.sce.ntu.edu.sg/ liuyuan/

Abstract

Reputation models depend on the ratings provided by buyers to gauge the reliability of sellers in multi-agent based e-commerce environment. However, there is no prevention for the cases in which a buyer misjudges a seller, and provides a negative rating to an original satisfactory transaction. In this case, how should the seller get his reputation repaired and utility loss recovered? In this work, we propose a mechanism to mitigate the negative effect of the misreported ratings. It temporarily inflates the reputation of the victim seller with a certain value for a period of time. This allows the seller to recover his utility loss due to lost opportunities caused by the misreported ratings. Experiments demonstrate the necessity and effectiveness of the proposed mechanism.

Introduction

Reputation systems are proposed to assist a buyer agent in selecting his interaction partners (seller agents) in multi-agent based e-commerce environment. Impacting the future expected utility gain of a seller, reputation systems can be viewed as a sanctioning mechanism for a community to self-police. Thus, the accuracy of reputation is important for the well-being of the e-commerce environment. One of the challenges faced by today's reputation systems is that of unfair ratings (Zhang and Cohen 2008). Computational models have been proposed for handling intentionally unfair ratings. However, there is no prevention for the case in which a buyer misjudges a seller by providing a negative/positive rating to an original satisfactory/unsatisfctory transaction. This situation is referred to as *misreporting* in our work, which is usually caused by unintentional factors such as communication delay, as explained in an example: *In an e-marketplace, Alice provided a negative rating to a seller, Bob, because it appeared to her that she did not receive the ordered product on time. Bob's reputation dropped accordingly, and other buyers adapted their decisions in view of this change in Bob's reputation. Several days later, Alice found out that her mother actually signed for the item (which actually arrived on time) on her behalf, but forgot to pass it to her.*

Although no specific data is available on how widespread this type of situations are, it is apparently significant enough to prompt major e-commerce operators to implement mechanisms that recover the sellers' reputation and recall their utility loss. However, the current approaches tend to be based on intuition drawn from the trusting behaviors in human societies. For example, in the popular Chinese e-commerce website – Taobao.com, buyers are allowed to provide additional comments to transactions they have already rated. Other more sophisticated approaches include either attempting to filter out (Liu et al. 2011) or assigning smaller weights (Zhang and Cohen 2008) to potentially unfair ratings. However, existing approaches suffer from two major limitations when facing the challenge of misreporting: 1) the dissemination of the additional remedial comments is not efficient (i.e., buyers who have viewed the misreport might not return to read the additional comments); 2) filtering/weakening ratings cannot effectively help the seller recover his utility loss due to the lost opportunities. In this work, we propose a reputation revision mechanism, named *RepRev*, to address these limitations.

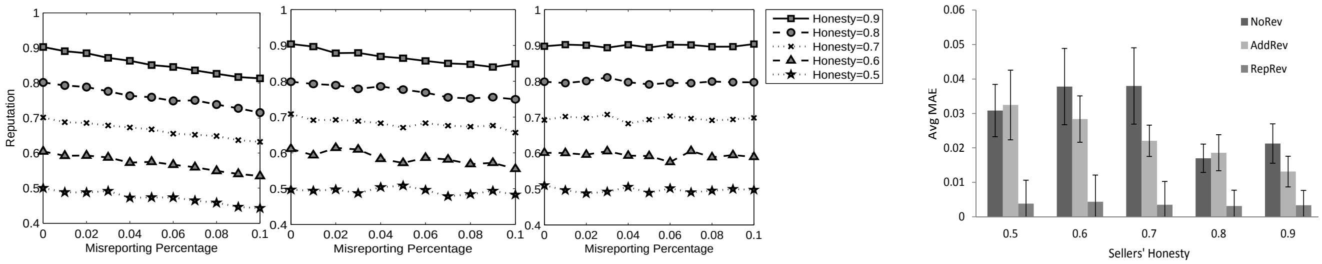
The RepRev Mechanism

Reputation is widely known to be difficult to build up but easy to lose. This is because people tend to pay more attention to negative ratings to avoid possible risk of losing their own interests. For this reason, in our current work, we focus on mitigating the impact of misreports that negatively rate sellers who actually deserve positive ratings.

In essence, *RepRev* repairs the damage caused by a misreport by artificially inflating the reputation of the victim seller for a period of time. Suppose a seller j receives γ misreported ratings provided by buyers at time t_0. j's reputation may consequently drop by as much as δ. Let $R_j(t_0)$ denote j's reputation at time t_0 if the misreports did not occur, and $R_j^{'}(t_0)$ denote j's reputation at time t_0 with these misreports. The exact value of δ depends on the reputation evaluation model used by a given reputation system. For example, under the Beta Reputation System (Jøsang and Ismail 2002), δ can be calculated as:

$$\delta = R_j(t_0) - R_j'(t_0) = \frac{(\alpha+\gamma)+1}{\alpha+\beta+2} - \frac{\alpha+1}{\alpha+\beta+2} = \frac{\gamma}{\alpha+\beta+2}, \quad (1)$$

where α and β denote the total number of positive and negative ratings (including γ misreported ratings) for seller j, respectively. Suppose the buyers become aware of the mis-



(a) Reputation (*NoRev*) (b) Reputation (*AddRev*) (c) Reputation (*RepRev*) (d) Sellers' Utility

Figure 1: Experiment Results

reported ratings at time t_1 and notify the system. With the help of *RepRev*, the system activates a repairing process:

1. *RepRev* computes the value of δ based on the reputation evaluation model, and replaces j's reputation by $R_j(t_1)$ without the misreports and inflates $R_j(t_1)$ as $R_j(t_1)+\delta$.
2. *RepRev* calculates the length of the time period $t_2 - t_1$ during which j's reputation is inflated by δ in order to help j recover utility loss caused by the misreports. To fully recover j's utility loss, the reputation inflation period needs to satisfy:

$$\int_{t_0}^{t_1} U(R_j(t))dt - \int_{t_0}^{t_1} U(R_j^{'}(t))dt = \int_{t_1}^{t_2} (U(R_j(t)+\delta) - U(R_j(t)))dt \quad (2)$$

When approximating $U(R_j(t))$ with $U(R_j(t_1))$ as $t \in [t_1, t_2]$ and assuming $U(R_j(t))$ to be a monotonically increasing function of $R_j(t)$, t_2 can be determined as:

$$t_2 = \frac{\int_{t_0}^{t_1} U(R_j(t))dt - \int_{t_0}^{t_1} U(R_j^{'}(t))dt}{U(R_j(t_1)+\delta) - U(R_j^{'}(t_1))} + t_1, \quad (3)$$

where $U(R_j(t))$ is a function mapping the reputation value of j to his expected utility gain per time step. In reality, this mapping can be determined through statistical analysis as the past transaction information in many large scale e-commerce systems is recorded.

3. After t_2, j 's reputation is allowed to fluctuate with its behavior again according to the reputation evaluation model used by the system.

Experiments

To evaluate the performance of *RepRev*, we construct a simulated multi-agent environment with 1,000 seller agents and 10,000 buyer agents. The sellers are equally divided into 5 groups. In each group, the sellers have the same probability of conducting transactions honestly (i.e., the probability values are 0.9, 0.8, 0.7, 0.6, and 0.5, respectively). When a buyer requests an item, she will select a seller with probability proportional to each seller's reputation standing among all sellers. In a transaction where the seller behaves honestly, he will gain a utility of 2. Otherwise, he will gain a utility of 3. This is to ensure that behaving dishonestly is profitable in the immediate term for a seller agent. We vary the probability of a buyer providing misreports for a seller at a value from the set $\{0, 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1\}$. *RepRev* is compared against two other approaches: 1) *NoRev*, in which no action is taken to correct the misreports; and 2) *AddRev*, in which the same number of additional corrective ratings as the misreported ratings are inserted by the system after the buyer becomes aware of the misreports.

The average reputation of each group of the sellers calculated using the three approaches is shown in Figures 1(a), 1(b) and 1(c), respectively. It can be observed that, under *NoRev* and *AddRev*, the reputation values of the sellers decrease as the probability of misreporting increases. Moreover, with the same probability of misreporting, the utility of more reputable sellers drops more saliently. Under *RepRev*, the revised reputation is close to the one without misreports.

Figure 1(d) shows the mean absolute error (MAE) between the average seller utility using various approaches and the case in which the misreports did not occur. It can be observed that, under *RepRev*, the MAE of sellers' utility is remarkably reduced. The results suggest that *RepRev* significantly outperforms the other two approaches in terms of mitigating the negative effect of misreports on sellers' utility.

Conclusions

In this work, we proposed a novel reputation revision mechanism - *RepRev* - to mitigate the effect of negative ratings which are provided by buyers due to their misjudgement of transaction outcomes. It enriches the computational trust literature by providing a new type of action for reputation systems to maintain the well-being of a trust-based community. In subsequent work, we will analyze the existing real-world datasets to study the utility function mapping the reputation of a seller to his expected utility gain per time step, which will improve the effectiveness of the proposed mechanism.

References

Jøsang, A., and Ismail, R. 2002. The beta reputation system. In *Proc. of the 15th Bled Electronic Commerce Conference*.

Liu, S.; Zhang, J.; Miao, C.; Theng, Y.-L.; and Kot, A. C. 2011. iCLUB: An integrated clustering-based approach to improve the robustness of reputation systems. In *AAMAS*.

Zhang, J., and Cohen, R. 2008. Evaluating the trustworthiness of advice about selling agents in e-marketplaces: A personalized approach. *Electronic Commerce Research and Applications* (ECRA), 7(3):330–340.