# An Incentive Mechanism for Eliciting Fair Ratings of Sellers in E-Marketplaces

Jie Zhang
David R. Cheriton School of Computer Science
University of Waterloo
Waterloo, ON, Canada N2L 3G1
j44zhang@uwaterloo.ca

Robin Cohen
David R. Cheriton School of Computer Science
University of Waterloo
Waterloo, ON, Canada N2L 3G1
rcohen@uwaterloo.ca

## ABSTRACT

In this paper, we propose a novel incentive mechanism for eliciting fair ratings of selling agents from buying agents. In our mechanism, buyers model other buyers and select the most trustworthy ones as their neighbors from whom they can ask advice about sellers. In addition, however, sellers model the reputation of buyers. Reputable buyers always provide fair ratings of sellers, and are likely to be neighbors of many other buyers. In marketplaces operating with our mechanism, sellers will increase quality and decrease prices of products to satisfy reputable buyers. In consequence, our mechanism creates incentives for buyers to provide fair ratings of sellers.

## 1. INTRODUCTION

In electronic marketplaces buyers may provide unfairly high ratings to promote the seller. This is referred to as "ballot stuffing" [1]. Buyers may also provide unfairly low ratings, in order to cooperate with other sellers to drive a seller out of the marketplace. This is referred to as "bad-mouthing". Besides, rating submission is voluntary in most trust management systems. Buyers do not have direct incentives to provide ratings because, for example, providing reputation ratings requires some effort [3]. Providing fair ratings for a trustworthy seller may also decrease the chance of doing business with the seller because of competition from other buyers. Two mechanisms developed to address these problems include side-payment mechanisms (e.g. [4], offering side payment to buyers that fairly rate results of business with sellers) and credibility mechanisms (e.g. [5], decreasing the credibility of a buyer and seller with different ratings about their business result). In this paper, we propose a novel incentive mechanism to elicit fair ratings of sellers in electronic marketplaces. Buyers are encouraged to be truthful in order to gain more profitable transactions. This idea is supported by Gintis et al. [2]. They argue that altruism in one context signals "quality" that is rewarded by increased opportunities in other contexts.


*AAMAS'07* May 14–18 2007, Honolulu, Hawai'i, USA.


## 2. INCENTIVE MECHANISM

To formalize the proposed incentive mechanism, we consider the scenario that in an electronic marketplace a buyer $B$ wants to buy a product $p$. It sends the request to a central server. The request contains information about a set of non-price features $\{f_1, f_2, ..., f_m\}$ of the product, as well as a set of weights $\{w_1, w_2, ..., w_m\}$ that correspond to how important each non-price feature is. The buyer also provides a function $D()$ to convert descriptive non-price feature values to numeric values. We use a quasi-linear function to represent the buyer's valuation for the product as follows:

$$V(p) = \sum_{i=1}^{m} w_i D(f_i) - P(p) \tag{1}$$

where $P(p)$ is the price of the product $p$.

The central server forwards the request to sellers in the marketplace. A set of sellers $\overline{S}$ that are interested in selling the product to the buyer can submit their bids containing their prices for the product, as well as values for non-price features. We formalize how a seller should bid for the buyer's request in the next section.

### 2.1 Seller Bidding for Buyer's Request

A seller $S \in \overline{S}$ sets the price and values for the non-price features of $p$, depending on how much instant profit it can earn from selling $p$ to $B$. The instant profit is the profit earned by the seller from the current transaction if it wins the auction. We define the instant profit as follows:

$$U(p) = P(p) - C(p) \tag{2}$$

where $C(p)$ is the cost for the seller to produce $p$.

To gain profit from each possible transaction, the seller may not include in its bid the true cost of producing $p$ with certain non-price features. The best potential gain the seller can offer the buyer from the transaction is as follows:

$$V'(p) = \sum_{i=1}^{m} w_i D(f_i) - C(p) \tag{3}$$

We define the distribution function for $V'(p)$ as $F(V')$. A symmetric Bayes-Nash equilibrium can be derived. The equilibrium bidding function can be derived as follows:

$$P^*(p) = C(p) + \frac{\int_{V_L - C_H}^{V'(p)} F(x)dx}{F(V')} \tag{4}$$

where $V_L$ is the lower bound of the value for the non-price features of $p$ and $C_H$ ($V_L \geq C_H$) is the higher bound of the cost for the seller to produce $p$.



978-81-904262-7-5 (RPS) ©2007 IFAAMAS

By taking into account the reputation of the buyer, the seller has the expected future profit from winning the current auction. Cooperating with reputable buyers will allow the seller to build its reputation and to be known as a trustworthy seller by many buyers in the marketplace. It will then be able to obtain more opportunities of doing business with buyers. The seller will reduce the instant profit and gain more chance to win the auction if the minimum expected future profit is no less than the loss of the instant profit. The bidding function of the seller in Equation 4 then should be changed to be:

$$P^*(p) = C(p) + \frac{\int_{V_L - C_H}^{V'(p)} F(x)dx}{F(V')} - V_D(R) \tag{5}$$

where $V_D(R)$ is the valuation of the discount for the buyer $B$ with reputation $R(B)$.

The seller models the reputation of a buyer based on the number of the buyer's neighborhoods. Our mechanism allows the central server to maintain for each buyer a list of neighbors that are the most trustworthy to this buyer. A buyer models trustworthiness of another buyer (an advisor) through a personalized approach [6]. The buyer first models private reputation of the advisor based on their ratings for commonly rated sellers. When the buyer has limited private knowledge of the advisor, the public reputation of the advisor will also be considered. The public reputation is estimated based on all ratings for the sellers ever rated by the advisor. Finally, the trustworthiness of the advisor will be modeled by combining the weighted private and public reputation values. Our mechanism also allows sellers to see how they have been rated by buyers, allowing sellers to reward those buyers deemed to be honest.

## 2.2 Buyer Choosing Winning Seller

After receiving sellers' bids, the buyer $B$ will then determine the winner of the auction. The winner is the seller whose bid includes the highest valuation of the product $p$ that it is willing to offer. The buyer chooses the winner of the auction among only sellers that are considered to be trustworthy. The buyer models trustworthiness of a seller by also using a personalized approach. Suppose that $B$ has provided some ratings[2] for the seller $S$. The ratings are ordered from the most recent to the oldest according to the time when they are submitted. The ratings are then partitioned into different elemental time windows $\{T_1, T_2, ..., T_n\}$. We then count the number of positive ratings $N_{pos,i}^B$ and negative ratings $N_{neg,i}^B$ in each time window $T_i$. The private reputation of $S$ can be estimated through the beta family of probability density functions [3] as follows:

$$R_{pri}(S) = \frac{\sum_{i=1}^{n} N_{pos,i}^B \lambda^{i-1} + 1}{\sum_{i=1}^{n} (N_{pos,i}^B + N_{neg,i}^B)\lambda^{i-1} + 2} \tag{6}$$

where $\lambda$ ($0 \leq \lambda \leq 1$) is a forgetting rate.

If the buyer $B$ does not have enough personal experience with the seller $S$, it will send a request to the central server to ask for all the ratings provided by its neighbors $\{A_1, A_2, ..., A_k\}$ for $S$. Suppose that the neighbor $A_j$ provided $N_{pos,i}^{A_j}$ positive ratings and $N_{neg,i}^{A_j}$ negative ratings within the time window $T_i$. The public reputation of $S$ can be calculated as follows:

$$R_{pub}(S) = \frac{[\sum_{j=1}^{k}\sum_{i=1}^{n} N_{pos,i}^{A_j} \lambda^{i-1} Tr(A_j)] + 1}{[\sum_{j=1}^{k}\sum_{i=1}^{n} (N_{pos,i}^{A_j} + N_{neg,i}^{A_j})\lambda^{i-1} Tr(A_j)] + 2} \tag{7}$$

where $Tr(A_j)$ is the trustworthiness of the neighbor $A_j$.

The trustworthiness of $S$ is estimated by combining the weighted private and public reputation values as follows:

$$Tr(S) = wR_{pri}(S) + (1-w)R_{pub}(S) \tag{8}$$

The weight $w$ is determined by the reliability of the estimated private reputation value as follows:

$$w = \begin{cases} \frac{N_{all}^B}{N_{min}} & \text{if } N_{all}^B < N_{min}; \\ 1 & \text{otherwise.} \end{cases} \tag{9}$$

where $N_{min}$ represents the minimum number of ratings needed for the buyer $B$ to be confident about the private reputation value it has of $S$. $N_{all}^B$ is the total number of ratings provided by $B$ for the seller. The seller will be considered to be trustworthy only if $Tr(S)$ is no less than a threshold $\delta$, and will be considered to be untrustworthy if its trust value is below a threshold $\gamma$ ($0 < \gamma < \delta < 1$).

If there are no trustworthy sellers submitting bids, the winner of the auction will be selected among the sellers with trust values that are between $\delta$ and $\gamma$.

# 3. EXPERIMENTAL RESULTS

We simulate a marketplace operating with our mechanism in the period of 20 days. The marketplace involves 100 buyers and 10 sellers. Every 10 buyers has a different number (from 2 to 20) of requests. Each buyer will submit a rating for each of its transaction with a seller. Therefore, buyers having a larger number of requests will provide a larger number of ratings. 50 buyers provide unfair ratings. Every 10 of them provides different percentages (from 10% to 50%) of unfair ratings. We assume that there is only one product in each request and each buyer has a maximum of one request each day. We also assume that the products requested by buyers have the same features. Initially, we randomly assign 5 other buyers to each buyer as its neighbors. Each 2 sellers acts dishonestly in different percentages (0%, 25%, 50%, 75% and 100%) of their business with buyers. Half of them model reputation of buyers and adjust prices of products according to buyers' reputation. Another 5 sellers do not model reputation of buyers. They offer the same price for products. We assume that all sellers have the same cost for producing the products.

After each day, we measure total profit gained by buyers that provide different numbers of unfair ratings. The profit gained by a buyer from buying a product is the valuation of the product received from its business partner. From Figure 1, we can see that buyers providing fewer unfair ratings will gain more total profit. Note that the profit difference of different types of buyers is fairly small. This is because buyers do not have many requests (at most 20).

[2]We assume that a rating is binary. For example, "1" (a positive rating) means that the valuation of the delivered product is not less than that described in the seller's bid, and "0" (a negative rating) otherwise.

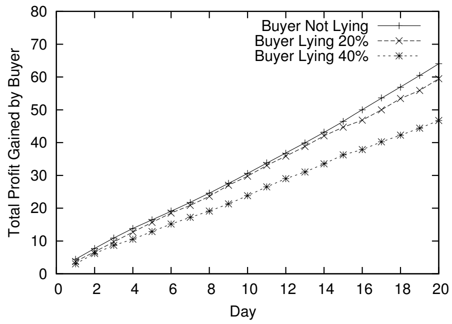


**Figure 1: Profit Gained by Different Buyers**

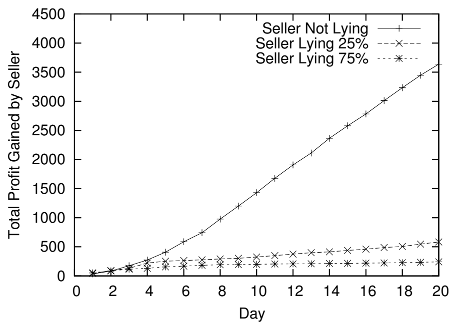


**Figure 2: Total Profit Gained by Different Sellers**

We also compare total profit gained by different sellers. Results are shown in Figures 2 and 3. From Figure 2, we can see that sellers being honest more often will gain more profit. Therefore, it is better off for sellers to be honest. Results in Figure 3 indicate that sellers are better off to model reputation of buyers and adjust prices of products according to buyers' reputation, in order to gain more profit.

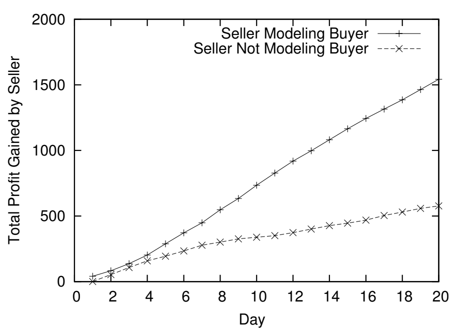


**Figure 3: Total Profit Gained by Different Sellers**

## 4. DISCUSSION AND CONCLUSION

In this paper, we propose a novel incentive mechanism to elicit fair ratings of sellers in electronic marketplaces. In our mechanism, a buyer maintains a neighbor list of other buyers that always provide fair ratings. Honesty is promoted in our marketplace because we allow sellers to see how they have been rated by buyers and to model the reputation of buyers based on the social network. Reputable buyers are likely to be neighbors of many other buyers. Sellers then increase quality and/or decrease prices of products to buyers who are determined to be reputable. Hence, buyers are better off providing truthful feedback and becoming neighbors of as many other buyers as possible. Sellers are also kept honest, because buyers are modeling the sellers' trustworthiness, based on ratings provided by neighbors. Sellers are motivated to provide quality service to reputable buyers, in order to progressively build their reputation in the social network. In summary, our mechanism is generally applicable to marketplaces where sellers may offer goods of different values to different buyers, and will promote honesty in such environments. The above expectations are upheld in our model and shown by our experiments.

We contrast favourably with side-payment and credibility mechanisms, as follows. Side payment mechanisms assume that buyers act independently, and therefore have difficulty with the situation where buyers collude in giving unfair ratings. In contrast, in our mechanism, sellers can view the ratings provided by buyers and can in this way detect dishonesty. Since sellers also only reward reputable buyers, buyers who collude in providing dishonest ratings will not profit. In addition, honest buyers will not be adversely affected by collusion in the marketplace; with our personalized approach for modeling the trustworthiness of advisors, each buyer can rely on private knowledge to detect dishonest buyers and will will have their neighborhood of advisors limited to those which are determined to be trustworthy. Credibility mechanisms cannot deal with the situation where buyers and sellers collude to increase each other's credibility. Because our mechanism allows buyers to maintain a list of trustworthy other buyers as their neighbors, a buyer can make an informed decision about which sellers to do business with.

## 5. REFERENCES


[1] C. Dellarocas. Immunizing online reputation reporting systems against unfair ratings and discriminatory behavior. In *Proceedings of the 2nd ACM Conference on Electronic Commerce*, Minneapolis, MN, October 2000.

[2] H. Gintis, E. A. Smith, and S. Bowles. Costly signaling and cooperation. *Journal of Theoretical Biology*, 213:103–19, 2001.

[3] A. Jøsang, R. Ismail, and C. Boyd. A survey of trust and reputation systems for online service provision. *(to appear). Decision Support Systems*, 2005.

[4] R. Jurca and B. Faltings. An incentive compatible reputation mechanism. In *Proceedings of the IEEE Conference on E-Commerce, Newport Beach, CA, USA*, 2003.

[5] R. Jurca and B. Faltings. Confess: An incentive compatible reputation mechanism for the online hotel booking industry. In *Proceedings of the IEEE Conference on E-Commerce, San Diego, CA, USA*, 2004.

[6] J. Zhang and R. Cohen. A personalized approach to address unfair ratings in multiagent reputation systems. In *Proceedings of the Fifth International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS'06) Workshop on Trust in Agent Societies*, 2006.