Towards the Design of a Robust Incentive Mechanism for E-Marketplaces with Limited Inventory

(Doctoral Consortium)

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ABSTRACT

In e-marketplaces, reputation systems are prevalently applied to assist buyers to model seller trustworthiness based on ratings shared by other buyers. However, dishonest buyers may share untruthful ratings. Many incentive mechanisms have been proposed to elicit truthful ratings from buyers. These mechanisms have a common implicit assumption that sellers can provide a large number of products. In reality, e-markets with limited inventory exist in many scenarios. For example, dentist booking in US, as a marketplace, has been observed the phenomenon that the service demand is much larger than the service supply, and the second-hand markets where some used and workable goods (e.g., second-hand textbooks) are often in short supply due to lower prices. We call a marketplace in which the demand outweighs the supply *a marketplace with limited inventory.* In such marketplaces, buyers may lose profit if they provide truthful ratings due to competition from other buyers for the limited products provided by trustworthy sellers. In other words, providing truthful ratings is costly. The existing incentive mechanisms seldom consider such cost imposed on providing truthful ratings, which motivates us to design a new incentive mechanism for e-marketplaces with limited inventory. Moreover, a general assumption for incentive mechanisms is that every agent is rational and has the belief that others are also rational. However, in a realistic scenario, some agents may be irrational (bounded rationality or adversary), which may impede the efficiency of the mechanisms. In all, the aim of our research is to design an incentive mechanism for e-marketplaces with limited inventory that is robust against irrational agents.

Categories and Subject Descriptors

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

Keywords

Robust Incentive Mechanism; Limited Inventory Markets

1. PROGRESS TO DATE

Up to date, we have proposed an incentive mechanism for e-marketplaces with limited inventory in [3] and a simulation framework to evaluate the robustness of incentive mechanisms against various types of irrational agents in [2].

1.1 An Incentive Mechanism

Our incentive mechanism is composed of a *normalized proper scoring rule*, a *reputation model*, a *pricing algorithm*, and an *allocation algorithm*. More specifically, in the mechanism, we measure buyer honesty by a *score* and seller honesty by the *reputation*, which are updated after each transaction period. Buyer score will be updated after the buyer submits a rating, according to the normalized proper scoring rule making sure that truthful ratings provided by buyers are awarded maximum expected scores (see Proposition 1 in [3]). Seller reputation is calculated by the reputation model which aggregates ratings of the seller provided by buyers. The pricing algorithm sets higher prices for the products provided by sellers with higher reputation. The allocation algorithm ranks buyers according to their scores, and allocates products of honest sellers to buyers with highest scores.

In the pricing algorithm, the price of a product provided by a seller is determined by a quadratic function of the seller reputation (see Algorithm 1 in [3]). It has two nice properties. The first property is that buyers' utility is positive when the system parameters are set properly ensuring that the buyers allocated with products of sellers will be willing to carry out the transactions with the sellers (see Proposition 2 in [3]). The second property is that buyers allocated products from sellers with higher reputation will be able to gain larger utility even though the prices of these products are higher because the quality of received products will be higher (see Proposition 4 in [3]). Therefore, sellers are individually rational to join our marketplace and are able to sell their products at a high price for which buyers are willing to pay. In other words, sellers have incentive to be honest in delivering promised products to achieve high reputation. (see Proposition 5 in [3]).

Following the two properties of the pricing algorithm, we design the allocation algorithm (see Algorithm 2 in [3]). It randomly divides all available products into two sets. The first set is allocated to the most honest buyers (i.e. the buyers with the largest scores). To be specific, these products are sorted according to their sellers' reputation in a descending order, and the buyers are also sorted according to their scores. The products are then allocated to the buyers one by one according to the descending order. For the products in the second set, they are randomly allocated to buyers who have not gained a product. According to the second property of the pricing algorithm, buyers with a high score are better off to successfully receive products from honest sell-

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ers. Thus, buyers have incentive to provide truthful ratings in order to gain high scores (see Proposition 3 in [3]).

In [3], we theoretically analyze the properties of the proposed incentive mechanism, namely individual rationality, and incentive compatibility. We also carry out a set of experiments to evaluate our incentive mechanism in both static and dynamic settings.

Moreover, to make the mechanism robust against the whitewashing attack, we discuss how to set initial reputation values and scores for new sellers and buyers. The whitewashing attack is caused by buyers or sellers with lower scores or reputation values than their initial values, who leave the marketplace and re-register as new buyers and sellers, respectively. In our mechanism, for new sellers, the initial reputation is set as a positive value. By designing a properly determined membership fee, sellers do not have the incentive to re-enter the market. For new buyers, the initial scores are set as zero (minimum value) to avoid buyer reentering. Our quantitative analysis and experimental results have shown that our mechanism can effectively discourage both buyers and sellers from performing the whitewashing attack.

Even though we have proven through both theoretical analysis and experimentation that both rational buyers and sellers have incentive to be honest and not to conduct the whitewashing attack, it is still insufficient, due to the following two reasons. First, the robustness of the proposed mechanism against other attacks is still difficult to qualitatively analyze, such as collusive attack. For collusive attack, if a small number of buyers or sellers collusively conduct malicious behavior, our mechanism may still work well as long as the seller and buyer honesty is accurately modeled such that the pricing and allocation algorithms can promote honesty from rational buyers and sellers. However, if many buyers or sellers conduct collusive attack, our mechanism may fail to work. Second, we only consider rational agents in our analysis, but in a realistic system irrational agents may exist. Therefore, one natural question comes into our mind is: to what extent our mechanism is robust against various attacks, including sophisticated ones, where attackers irrationally deviate from the desired strategy of the mechanism. Thus we propose a robustness evaluation framework in [2] to fully evaluate the robustness of our incentive mechanism and compare with other mechanisms in the literature, towards the design of a more robust incentive mechanism.

1.2 Robustness Evaluation Framework

Inspired by the studies of evolutionary game theory, the robustness of incentive mechanisms is defined as follows.

Definition (**Robustness**) The robustness of an incentive mechanism is the maximum proportion of irrational agents which mutate their strategy in a certain way (referred to as a type of irrational agents) such that all rational agents still sustain the strategy desired by the incentive mechanism.

Due to the complex settings of incentive mechanisms and complicated attacks, we propose a simulation framework to evaluate the robustness. Our simulation framework is based on the evolutionary process [4] to study the strategy dynamics of a specific population and effectively model the evolution of strategy propagation.

In the framework, we first implement the evaluated incentive mechanism for a population composed of rational agents. we then gradually involve irrational agents and observe the strategy evolution of the population (excluding the irrational agents), until all rational agents abandon the desired strategy of the incentive mechanism. In each generation, the evolutionary process includes three steps: fitness calculation, reproduction and mutation. The fitness of a strategy is reflected by the expected payoff that agents can obtain by performing the strategy. The mapping between payoff and fitness is captured by the intensity of selection. Given the fitness of strategies, the probability of a strategy being selected for reproduction is proportional to the fitness of the strategy and the number of agents performing the strategy. The mutation rate of an agent from one strategy to another is determined by the Fermi function [4]. After a large number of generations, the strategies chosen by the rational agents will converge (sustaining or abandoning the desired strategy).

We verify the simulation framework on a symmetric coordinate game. It has been shown that the robustness measured by our simulation framework can always converge to the theoretical results, which validates the effectiveness of the simulation framework. Finally, we demonstrate the usage of our simulation framework in measuring and comparing the robustness of some incentive mechanisms where irrational agents adopt different irrational strategies.

2. FUTURE RESEARCH

For future research, we plan to improve the robustness of the incentive mechanism for e-marketplaces with limited inventory, based on the robustness evaluation and comparison of different incentive mechanisms. We have observed that the existing incentive mechanisms show high robustness against some attacks but not every attack. For example, the side-payment mechanism [1] is highly robust against collusive attack; the trust based mechanism [5] is highly robust against constant attack. Therefore, we will continue to identify the significant factors which impact the robustness of incentive mechanisms, for the design of a more robust incentive mechanism.

Furthermore, we plan to extend the robustness evaluation framework. Inspired by the k-t robust Nash equilibrium, we will generalize our robustness evaluation approach to find out k value for incentive mechanisms being k-robust. Our simulation framework can be easily extended by checking the strategies of all possible coalitions with k agents when increasing k from 1. However, the computational complexity of exploring each possible coalition is a challenge to address.

3. REFERENCES

[1] R. Jurca. *Truthful Reputation Mechanisms for Online Systems*. PhD thesis, EPFL, 2007.

[2] Y. Liu and J. Zhang. Robustness evaluation of incentive mechanisms. In *Proccedings of AAMAS*, 2013.

[3] Y. Liu, J. Zhang, and Q. Li. Design of an incentive mechanism to promote honesty in e-marketplaces with limited inventory. In *Proceedings of the International Conference on Electronic Commerce (ICEC)*, 2012.

[4] M. A. Raghunandan and C. A. Subramanian. Sustaining cooperation on networks: An analytical study based on evolutionary game theory. In *Proceedings of the AAMAS*, pages 913–920, 2012.

[5] J. Zhang, R. Cohen, and K. Larson. Combinding trust modeling and mechansim design for promoting honesty in e-marketplaces. *Computational Intelligence*, 28(4):549–578, 2012.