Truth and Learning in Multi-Agent Markets

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Abstract

In this paper, we propose an algorithm for improving the ability of decision making of buying and selling agents in an agent-based electronic marketplace. In proposed model, Selling agents use k-nn learning to adjust the first bid for new buying agents based on their similarity with the past buyers. Each selling agent learns to evaluate the reputation of buying agents based on their profits for that seller and uses this reputation to dedicate discount for reputable buying agents. Also they alter their bids in order to satisfy the buying agent's preferences. In contrast, buying agents learn to model the truth of selling agents to specify that how much they can rely on selling agents' bids. Also buying agents evaluate the reputation of selling agents based on three different factors: reputation on quality, price and delivery-time and avoid interacting with disreputable ones. The proposed model has been implemented with Aglet and tested in a large-sized marketplace. The results show that selling/buying agents that use the proposed algorithms in this paper obtain more satisfaction rather than the other selling/buying agents.

Key words: Truth, K-nn Learning, Reinforcement Learning, Electronic Commerce Agents

1. Introduction

Agent-based electronic marketplace is one of the most important results of applying mobile and intelligent agent technology over electronic commerce [1,2 ,5 ,7 ,10 ,11 ,15]. The most important agents which participate in electronic marketplace are buying and selling agents Reinforcement learning [13] has been studied for various multi-agent problems [3], [12], [17], [18]. Also, k-nn learning has been used in different applications. However, these efforts are not directly modeled as economic agents and market environments. On the other hand, there are some research on reputation and trust modeling for electronic marketplace agents which do not use reinforcement learning [2], [6], [8], [14], [24].Number of agent models for electronic market environments have been proposed. Jango [7] is a shopping agent that

assists customers in getting product information. But, Jango is not equipped with any learning capability to help customers choose more and more appropriate merchants.
Another interesting agent model is Kasbah [4], designed by the MIT Media Lab. Kasbah is a multi-agent electronic marketplace where selling and buying agents can negotiate with one another to find the .best possible deal for their users. Kasbah's agents are not very smart as they do not make use of any AI learning techniques. Vidal and Durfee [21] address the problem of how buying and selling agents should behave in an information economy such as the University of Michigan Digital Library. The main problem addressed in this model is that reinforcement learning has been applied in market environments for buying and selling agents, but reputation has not been used as a means to protect buyers from purchasing low quality goods. Moreover, selling agents do not consider altering the quality of their products while learning to maximize their profits. Tran and Cohen in [19] exploit reinforcement learning for buying agents to model the reputation of selling agents to protect buyers from communicating with non-reputable sellers. Nevertheless, buyers in this model should have fixed priorities on quality and price of their desired goods. In this way, they can not change their preferences to buy a good in a sequence of purchases. That is, a buying agent can not purchase a good in an auction with priority on quality and willing to buy the same good in another auction with on price. In addition, selling agents do not model the reputation of buyers to consider discount and just only focuses on two factors of quality and price.

2. Buyer Algorithm

Let S be the set of sellers, G be the set of goods, B be the set of buyers, Q be the set of qualities, P be the set of prices and D be the set of deliveries, and S, G, B, Q, P and D are finite sets. The process of choosing the best bid by buyer b is done as follows:

Buyer b uses functions $G_q^{\,b}:(q_s,trurh^s{}_q)\longrightarrow(0,q_{\max})$ and $G_d^b:(d_s,truth_d^s)\longrightarrow(0,d_{\max})$ to guess the probable real value of quality and delivery of the sellers ' bids by using the truth of sellers. q_s is the quality which seller s has offered. $truth_q^s$ is the truth of seller s computed by buyer b and $G_q^{\,b}:(q_s,trurh^s{}_q)$ shows the quality that buyer b guessed for sellers bid based on truth on quality of that seller. Truth of sellers is used to specify that how much buyer b can rely on sellers' bids. Buyer b evaluates the truth of sellers on two factors of quality and delivery, separately. To evaluate the truth of each seller, buyer b uses functions $truth_q^b:S\rightarrow(-1,1)$ و $truth_d^b:S\rightarrow(-1,1)$ which are called truth functions of b based on quality (q) and delivery (d), respectively. For example, $truth_q^b(s)$ shows the truth of seller s on quality evaluated by buyer b. Initially, buyer b sets the truth ratings $truth_q^b(s)=0$ and $truth_d^b(s)=0$ for every seller . Assume that each seller send its bid in triple $bid(q_s,p_s,d_s)$ to buyer b. Then, buyer b guesses the real value of quality of good based on truth of that seller as follows:

$$G_q^b(q_s,truth_q^b(s))=q_s+(truth_q^b(s)*q_s) \tag{1}$$

Where q_s is the quality offered by seller s, and $truth_q^b(s)$ is the truth of seller s on quality computed by buyer b. Also ,buyer b guesses the real delivery of the good which offered by seller s ,i.e.,

$$G_d^b(d_s,truth_d^b(s))=d_s-(truth_d^b(s)*d_s) \tag{2}$$

Where d_s is the delivery offered by seller s, and $truth_d^b(s)$ is the truth of seller s on delivery computed by buyer b.
In subsection 5 , we describe that how buying agents can evaluate and update the truth of each seller on factors quality and delivery. Buyer b should estimate the value of sellers' bids by function $Est(q_s, p_s, d_s, s)$, which uses the guessed values of quality and delivery and also price. $Est(q_s, p_s, d_s, s)$ presents the real value of bid of seller s which include triple(q_s, p_s, d_s). Let w_q, w_p, w_d be the weight of values quality, price and delivery for buyer b so that $w_q + w_p + w_d = 1$. These parameters show the importance of each factor for buyer b. Each buyer can has its own preferences. Buyer b estimates the real value of sellers' Bids as follows:

$$Est(q_s, p_s, d_s, s) = w_q * \frac{G_q^b(q_s, truth_q^b(s))}{q_{\max}} - w_p * \frac{p_s}{p_{\max}} - w_d * \frac{G_d^b(d_s, truth_d^b(s))}{d_{\max}} \quad (3)$$

Where $q_{\max}, p_{\max}, d_{\max}$ are the maximum value of quality, price and delivery, respectively.
In previous section we define the $Est(q_s, p_s, d_s, s)$ for estimating the real value of sellers bids. Buyer b estimates the real value of all bids and selects the seller $\hat{s}$ who belongs to the set of reputable sellers for buyer b whose bid value for buyer b is more than the other sellers', i.e.,

$\hat{s}$ =arg max $Est(q_s, p_s, d_s, s)$

Where, arg is an operator such that arg Est(s) which returns.
Updating Truth on Quality:

If $\hat{q} \geq q_s$ then the truth of seller $\hat{s}$ on quality is updated using reinforcement learning as follows:

$$truth_q^b(s) = \begin{cases} truth_q^b(s) + \mu_{qt}(1 - truth_q^b(s)) & if \quad truth_q^b(s) \geq 0 \\ truth_q^b(s) + \mu_{qt}(1 + truth_q^b(s)) & if \quad truth_q^b(s) < 0 \end{cases} \quad (4)$$

Where, μ_{qt} is a positive factor called the cooperation factor for quality in evaluating truth. μ_{qt} is computed as follows:

$$\mu_{qt} = \begin{cases} \frac{\hat{q} - q_s}{q_{\max}} \; if \; \frac{\hat{q} - q_s}{q_{\max}} > \mu_{\min\_qt} \\ \mu_{\min\_qt} otherwise \end{cases} \quad (5)$$

That is, seller $\hat{s}$ delivers good g with a quality greater than or equal to the value that has offered for quality of good g and therefore the truth of seller $\hat{s}$ on quality is increased by equation (5) accordingly. $\mu_{\min\_qt}$ is a positive factor called minimum cooperation factor in evaluating of truth for quality.
If $\hat{q} < q_s$ then the truth of seller $\hat{s}$ on quality is updated using reinforcement learning as follows:

$$truth_q^b(s) = \begin{cases} truth_q^b(s) + v_{qt}(1 - truth_q^b(s)) & if \quad truth_q^b(s) \geq 0 \\ truth_q^b(s) + v_{qt}(1 + truth_q^b(s)) & if \quad truth_q^b(s) < 0 \end{cases} \quad (6)$$

Where, v_{qt} is a negative factor called the non-cooperation factor for quality in evaluating the truth. v_{qt} is calculated as follows:

$$v_{qt} = \lambda_{qt} * \frac{\widehat{q} - q_s}{q_{\max}} \tag{7}$$

In which, λ_{qt}(λ_{qt}>1) is called the penalty factor so that $|v_{qt}| > |\mu_{qt}|$ to implement the traditional assumption that trust be difficult to build up, but easy to tear down.

Updating Truth on Delivery:

If $d_s \geq \widehat{d}$ then the truth of seller $\widehat{s}$ on delivery is updated using reinforcement learning as follows:

$$truth_d^b(s) = \begin{cases} truth_d^b(s) + \mu_{dt}(1 - truth_d^b(s)) & if \quad truth_d^b(s) \geq 0 \\ truth_d^b(s) + \mu_{dt}(1 + truth_d^b(s)) & if \quad truth_d^b(s) < 0 \end{cases} \tag{8}$$

Where, μ_{dt} is a positive factor called the cooperation factor. μ_{dt} is calculated as follows:

$$\mu_{dt} = \begin{cases} \dfrac{d_s - \widehat{d}}{d_{\max}} \; if \; \dfrac{d_s - \widehat{d}}{d_{\max}} > \mu_{\min\_dt} \\ \mu_{\min\_dt} otherwise \end{cases} \tag{9}$$

That is, seller $\widehat{s}$ delivers good g with a delivery lower than or equal to the value that has offered for delivery of good g and therefore the truth of seller $\widehat{s}$ on delivery is increased by equation (8) accordingly. $\mu_{\min\_dt}$ is a positive factor called minimum cooperation factor in evaluating the truth on delivery.

If $d_s < \widehat{d}$ then the reputation of seller $\widehat{s}$ on delivery is updated as follows:

$$truth_d^b(s) = \begin{cases} truth_d^b(s) + v_{dt}(1 - truth_d^b(s)) & if \quad truth_d^b(s) \geq 0 \\ truth_d^b(s) + v_{dt}(1 + truth_d^b(s)) & if \quad truth_d^b(s) < 0 \end{cases} \tag{10}$$

Where, v_{dt} is a negative factor called the non-cooperation factor. v_{dt} is calculated as follows:

$$v_{dt} = \lambda_{dt} * \frac{d_s - \widehat{d}}{d_{\max}} \tag{11}$$

In which, λ_{dt}(λ_{dt}>1)is called the penalty factor so that $|v_{dt}| > |\mu_{dt}|$.

4. EXPERIMENTAL RESULTS

We have implemented the proposed model with Aglet which is a java based environment for building mobile and stationary agents. Our results show that when buyer agents model the truth and reputation of selling agents, obtain greater satisfaction rather than buyer agents who just model the reputation of sellers. Seller agents, who apply k-nn learning for adjusting the first bid for new buyer agents are more successful in their trades and attracting new buyers to their market compare to sellers who just alter their bids based on buyer preferences. Also, seller agents who model the reputation of buyers and dedicate discount for them obtain more profits than the others. In addition, there are parameters are considered for sellers:

Quality is chosen equal to cost to support the common assumption that it costs more to produce high quality goods.That is, a good in quality of 38 costs just 38 . A seller can produce goods at the maximum quality of 50.Maximum price and delivery of goods are 60 and 20 respectively.

A seller can produce goods at the maximum quality of 50 . Expected values for buyer b on quality, price and delivery are 40,45 and 3 respectively while weights w_q, w_p, w_d are 0.7,0.2,0.1 respectively.

there are 30 seller and 20 buyer agents in our simulated marketplace. Assume that buyers arrange totally 2000auctions. That is, each buyer makes 100purchases. Let triplet g (quality, price, delivery) be the structure of a good's specification. All buyer agents use the proposed algorithm in this paper for buyer. Seller agents are divided into six groups:

Group A consists of five sellers $s_1, s_2, ..., s_5$. These are dishonest sellers on quality who try to attract buyers with high quality goods and then cheat them with really low quality ones. They offer g (48.50 and 2) and then deliver its good as g (38.5 and 2).

Group B consists of five sellers $s_6, s_7, ..., s_{10}$. These are dishonest sellers on delivery who try to attract buyers by offering the best delivery along with suitable quality but then cheat them by delivering goods so late. They offer g(48.5 and 2) but deliver their good as g(48.5 and13).

Group C consists of five sellers $s_{11}, s_{12}, ..., s_{15}$ that do not cheat buyers and use fixed bid for any buyer. They offer and deliver goods as g (40.44 and 7).

Group D consists of five sellers $s_{16}, s_{17}, ..., s_{20}$which alter quality, price and delivery of their goods but do not model the reputation of buyers. Moreover, they do not consider discount for buyers. They start their bids as g (38.45.6 and 1) and then alter their offers based on buyers' requirements.

Group E consists of five sellers $s_{21}, s_{22}, ..., s_{25}$ that in addition to altering the quality, price and delivery of their goods, model the reputation of buyers and also consider discount for them based on their reputation. They start their bids as g(38 , 45.6and 1) and then use the proposed algorithms to alter their bids.

Group F consists of five sellers $s_{26}, s_{27}, ..., s_{30}$ that not only apply the algorithms used by sellers in group E, but also use k-nn learning to adjust first bid for new buyers as described in buyer algorithms.

At first we send 10 buyers$b_1, b_2, b_3, ..., b_{10}$ into the market. Seller agents of group F are trained during some of buyers' interactions. They should know the buyers. preferences and use this knowledge to adjust the first bid for newcomers' buyers by applying k-nn learning. Afterward, we send the 10remainder buyers $b_{11}, b_{12}, b_{13}, ..., b_{20}$ into the market.

The results of this experiment confirm that sellers who exploit the proposed algorithms (i.e., group F), achieve better satisfaction than the other sellers, especially in interacting with new buyers. In addition, buyers learn to focus their business on sellers who make the better bids for them. Average and total number of sales made by each of these five groups of sellers in interacting with two groups of sellers(Training Buyers $b_1, b_2, b_3, ..., b_{10}$ and newcomers 'buyers $b_{11}, b_{12}, b_{13}, ..., b_{20}$) is shown in Table 2and 3 respectively.

Group of seller	**A**	**B**	**C**	**D**	**E**	**F**
Total of seles	50	50	67	185	330	318
Average of sales	10	10	13.4	37	66	63.6

Table 1. Total and average number of sales made by six groups of seller agent with first 10 buyers.

Group of seller	A	B	C	D	E	F
Total of seles	50	50	42	138	241	479
Average of sales	10	10	8.4	27.6	48.2	95.8

Table 2. Total and average number of sales made by six groups of seller agent with newcomers' buyers .

Sellers of groups A and B are dishonest sellers which lie on quality and delivery, respectively. In real markets, it is expected that when buyers purchase from a seller who tries to cheat them, they will not deal with him for their future purchases. Table 1 and 2 confirms this matter so that each buyer purchases from dishonest sellers no more than once. There are buyers in the market and each of them was cheated by a dishonest seller once. Therefore each dishonest seller can cheat each buyer one time and totally wins in auctions (table shows sales for each group of A and B and table shows). Actually buyers learn to stay away from disreputable sellers. Sellers of group C, offer goods in fixed quality, price and delivery. Although they may sell some of their goods in their first deals, but because of the existence of sellers of the other groups who alter their bids to offer goods in high quality, buyers will no longer purchase from sellers of this group, since they can not visit the buyers' requirements. Sellers of group D alter their bids based on buyer requirements and they achieve further sales in comparison to sellers of groups A, B and C. In table we see that groups E and F made most sales. They almost made the same sales because both of them model the reputation of buyers and consider discount for them.

CONCLUSION AND FUTURE WORK

In this paper we proposed a marketplace based on trust, reputation and k-nn and reinforcement learning algorithms for buying and selling agents. Selling agents apply k-nn learning to adjust the first bid for newcomers. buyers in order to attract them to the market forever. Also they use reinforcement learning to model the truth and reputation of sellers and learn to interact with them wisely. Buyers also learn to purchase from sellers who tribute them by dedicating discounts. We have investigated this fact that marketing and consumer relationship management are two important factors in business, so that sellers who obey this fact construct better reputation for themselves among buyers and get greater profit in comparison to the others. This model is very flexible to develop marketing purposes and modeling a real market completely. However, the proposed model and algorithms can be improved so that both sellers and buyers who exploit the improved model can obtain best results as fast as possible. For example, the most important factors in marketing are personality and culture of the people. That is, the behavior of sellers should be based on customers. personality and culture in order to success in business. These factors are very important to attract consumers to the market. The other problem is that buyers have not co-operation with each other to avoid interacting with disreputable sellers. It means that buyers should share their knowledge with new buyers to help them doing their best in the market. Also, reputation and truth in a real world are fuzzy variables. In a real world no body says that the reputation of a seller is, for example. They say that reputation of that seller is high or very low and so on. They say that seller s is really truthful or he may say a little lie in his offers. Therefore, fuzzy modeling of this approach can be so valuable. Our future researches aims to provide co-operation algorithms for buyers in order to know honest and dishonest sellers as quickly as possible. Also, we are going to use some effective features of personality and culture in our marketing strategy. Finally, for making the effective economic agents and desirable market environments it is attractive to model the reputation of buyers and sellers based on fuzzy logic.

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