How Vickrey can turn into Chicken:
an instructive example of mechanism design application

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Abstract

Existing methods of mechanism design offer us the mechanisms that are based on the assumption of exogenously defined agents' preferences. These mechanisms however could fail in the situations when agents have either imperfect preferences or no preferences at all. This could lead to the inefficient and undesirable distribution of resources. In this paper the illustration of such a mechanism failure is made. The data was taken from the Trading Agent Competition that was held in the Internet in June-July 2000. A special two-step strategy was developed by the agents in the Vickrey multiunit auction because of their difficulties with calculation of their own private valuations. In particular, during the auction all the agents conducted collective determination of the common value. Moreover, the presence of fixed deadline in the auction gave birth to last minute bidding, which has finally turned the Vickrey auction into the game strategically equivalent to N-dimensional game of Chicken. Pareto-optimality of the auction was violated and the goods were distributed almost randomly. In the paper the model of real agents' behaviour is drawn. Afterwards, the importance of two-stage mechanisms is stated and several examples of such mechanisms from different fields are provided. The conclusion is made that without studying of phenomena alike it will be hardly possible to design the mechanisms for agents to behave optimally. Thorough further research of preferences refinement mechanisms is needed to obtain such results.

Keywords: Vickrey auction, last minute bidding, evolution of preferences, artificial agents.

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Introduction

The basic idea of mechanism design is to construct mechanisms (or rules of the game), which would lead to some desired outcome given that economic agents behave in some particular way. Existing methods offer us the mechanisms that are based on the assumption of exogenously defined agents' preferences (Bowles, 1998) (the term "preferences" usually means any type of knowledge or information that *determines* agent's behaviour). But in practice, when mechanism designer wants to construct a mechanism for the practical use he or she often faces the problem of the absence of predefined agents' preferences. This means that agent's preferences and thus behaviour strongly depend on the preferences of other agents. In this situation, standard mechanisms, which are based on the assumption of exogenous preferences, fail to provide either Pareto efficient outcome or any other desired resource distribution.

Such kind of a failure can become a serious problem especially in the light of recent appearance of a number of applications of mechanism design. It is primarily new markets like electricity auctions, spectrum auctions (Klemperer, 2000), and e-commerce applications. Also one of the most rapidly growing domains of applying mechanism design today is markets for artificial (automated) agents. Artificial agents are expected to become major players in the future Internet economy. That is why it is of the utmost importance to design new markets in the way that would allow artificial agents to find efficient outcomes (of course, this idea is also applicable to the real markets).

The auction market involving artificial agents under consideration is an illustration of what can happen when a mechanism failure coming from badly defined preferences is present. This example is good for several reasons. At first, due to the peculiarities of situation, agents (or in this case bidders) had almost *no private values* of the good they were proposed to buy. At second, the mechanism that was used gave agents the possibility to behave in a wide range of different ways and this let them adapt themselves to the established rules. And at third, the situation was simple enough to make straightforward conclusions.

The paper is structured in the following way. After presenting the example I offer the model of agents' behaviour in this example. And in the end the results of the analysis are discussed along with the directions of further research.

Trading Agent Competition

Trading Agent Competition (TAC) held within the framework of The Fourth International Conference on Multiagent Systems[1] (ICMAS-00) in June-July 2000 (for more information see Eisenberg, 2000). It provides us with an example of the auction markets for artificial agents. The crux of the competition was that trading agents, programmed by the groups of developers from all over the world, played in a series of auctions of different types to provide their clients, participants of the *imaginary* scientific conference, with air tickets, rooms in the hotel, and tickets for some entertainments. Agents were functioning in the online Internet environment of a multi-purpose Internet auction server developed at the University of Michigan[2]. This interface called AuctionBot (Wurman et al., 1998) is a configurable auction server that implements a diverse set of auction rules and thus enables a wide variety of market games.

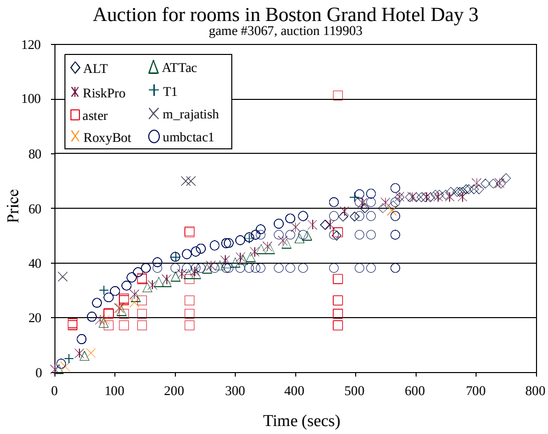
In all, there were three types of auctions in which agents took part. But we will consider only one type, namely *Vickrey multiunit continuous-time fixed-deadline auction*. This type of auction was used for selling rooms in the hotel that were the most important resource for the agents. During the auction players could make any bids (there was no reservation price) and change them if necessary. In addition, at any time each agent could enquire the *"quote"* — $(k + 1)$-highest price at that moment (there were k rooms for sale). After auction closure, k agents with highest bids got the rooms at the highest rejected price. Auction could end in the two cases: 1) if during some randomly chosen from some known probability distribution period of time there were no any new bids or 2) after 15 minutes from the beginning of the auction. These cases were the common knowledge for all agents.

The basic theory of Vickrey auctions tells us that the dominant strategy in Vickrey auction is to bid one's *private valuation*. So, apparently, agents were supposed to

[1] http://tac.eecs.umich.edu/
[2] http://auction.eecs.umich.edu/

make one bid each. And these bids were expected to be agents' private valuations of the room.

In reality, agents behaved in a very different way. As there were a lot of auctions for the rooms agents had time to adapt specific *two-stage strategy*. The first stage was to make many bids, which are a little bit higher than the current quote. So during the auction the price slightly increased. As a result, such a price arose that was acceptable by all agents. After the price was determined all agents knew their (now common) valuation (or it was, say, some price level that is known by everybody). Nevertheless, k winners of the auction were to be finally chosen. This fact stimulated emerging of the second stage — "sniping" or last minute bidding (Roth and Ockenfels, 2000) that is characterized by submitting the bids in the last few seconds before the ultimate auction closure. If the auction didn't close at a random time because of the absence of new bids, it lasted for 15 minutes (the time known by all agents). In this case some agents made last minute bids that were 5-7 times higher than current quote. In the $(k + 1)$-highest price auction such strategy gave them a great advantage over other agents, which did not make high last minute bids. So "snipers" could easily win the auction and, moreover, pay the real price, which was collectively worked out during the game (see Figures 1 and 2).



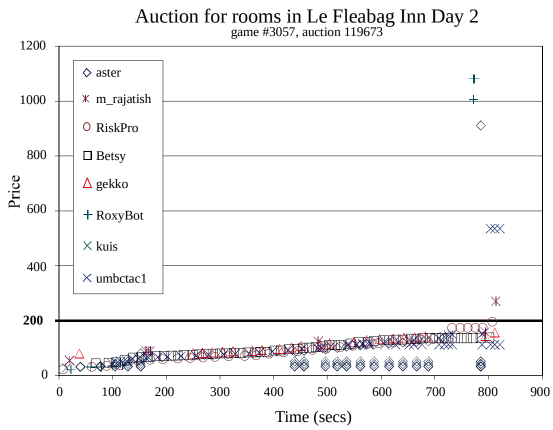


Fig. 1 and 2. Auctions for hotel rooms. Two cases: 1) randomly determined deadline auction; 2) fixed-deadline auction.

What was the reason for agents to behave in such a strange way? To understand, it is worthwhile to look at how the competition was carried out. In the beginning agents were endowed with the equal sums of money. Then they were proposed to participate in a lot of different auctions buying the goods. No additional information about the prices was provided. Thus, participating in the Vickrey auction agents found themselves in a situation when they had no idea neither about their own private valuations nor the valuations of others. This total myopia left the agents with nothing but bidding a little higher than current quote. This strategy theoretically guaranteed them winning in case of auction closure at any time. As for the last minute bidding, it was also the only way to win the auction.

The model

Let us concentrate on the "sniping" strategy more closely. In fact, last minute bidding replaced the rules of Vickrey auction (proposed by the auctioneer) with another game, which is strategically equivalent to the game of Chicken (or Hawk-Dove game). In this game agents have two alternatives: to bid “high” ("snipe") or to make a “real” bid. Bidding high agent increases the probability of winning but at the same time, if more than k players use “high” strategy, it risks buying the room at too high a price. If agent makes real bid it risks to buy nothing and lose the competition.

Let us consider the game, which models the behaviour of N agents. Each agent has two pure strategies: 1) to make “real” bid (R); or 2) to make “high” bid (H). Lets suppose that agent gets utility $-a$ ($a > 0$) in case of buying the room at “high” price, utility b ($b > 0$) in case of buying the room at “real” price, and utility c if it did not get the room (the simplest case is $c = 0$). Let n_H denote the number of high bids and n_R denote the number of real bids. Then:

$$n_H + n_R = N,$$

where N is the total number of bidders (we assume one bidder to make one bid).

Then agent’s payoffs are the following, assuming that agents are risk neutral and that $N > M$, where M is the quantity of objects being sold:

1. Under condition $n_H > M$:

   expected payoff of each agent, which bids “high”, is

$$\frac{M}{n_H}(-a) + (1 - \frac{M}{n_H})c,$$

expected payoff of each agent, which bids “real”, is *c*.

2. Under condition $n_H = M$:

   expected payoff of each agent, which bids “high”, is *b*,

   expected payoff of each agent, which bids “real”, is *c*.

3. Under condition $n_H < M$:

   expected payoff of each agent, which bids “high”, is *b* and

   expected payoff of each agent, which bids “real”, is

$$\frac{M-n_H}{n_R}b+(1-\frac{M-n_H}{n_R})c.$$

This game has one symmetric mixed-strategy equilibrium (Rasmusen, 2001). To find the probability γ that the agent will choose “high” strategy let us use the payoff-equating method. The agent i 's pure-strategy payoffs are:

$$\pi_i(\text{Real}) = c\sum_{m=M}^{N-1} C_{N-1}^m \gamma^m (1-\gamma)^{N-m-1} + \sum_{m=0}^{M-1}(\frac{M-m}{N-m}b+\frac{N-M}{N-m}c)C_{N-1}^m \gamma^m (1-\gamma)^{N-m-1} \quad (1)$$

$$\pi_i(\text{High}) = \sum_{m=M+1}^{N}(-a\frac{M}{m}+(1-\frac{M}{m})c)C_{N-1}^{m-1}\gamma^{m-1}(1-\gamma)^{N-m} + b\sum_{m=1}^{M} C_{N-1}^{m-1}\gamma^{m-1}(1-\gamma)^{N-m} \quad (2)$$

where binomial coefficient $C_n^r = \dfrac{n!}{r!(n-r)!}$.

Equating these payoffs gives the following equation for γ:

$$(a+c)M\sum_{m=M}^{N-1}\frac{C_{N-1}^m \gamma^m (1-\gamma)^{N-m-1}}{m+1} + (N-M)(c-b)\sum_{m=0}^{M-1}\frac{C_{N-1}^m \gamma^m (1-\gamma)^{N-m-1}}{N-m} = 0. \quad (3)$$

To somehow illustrate this game let us consider the example where *N=2, M=1, a=b=1, c=0*. This means that there are two players, one good for sale, player’s payoff in the case of buying the good at “high” price is –1, at “real” price is 1 and its payoff in the case of not buying is 0. The matrix of this game is shown in Figure 3.

Player 1 \ Player 2	High	Real
High	-0.5; -0.5	1; 0
Real	0; 1	0.5; 0.5

Fig. 3. Generalized game of Chicken. Two-dimensional case N=2, M=1, a=b=1, c=0.
Payoffs: (Player 1; Player 2)

For this case equation (3) becomes:

$$\frac{1}{2}\gamma - \frac{1}{2}(1-\gamma) = 0 \qquad (4)$$

Solving (4) we get $\gamma = \frac{1}{2}$.

Thus, the model predicts that in average one agent will make high bid and another one the real bid. The “High” bidder will buy the good at the price of the “real” bidder who will get nothing.

TAC Results

The main result of the Trading Agent Competition is, without any doubts, the failure of the auction mechanism. It has come into being because of the agents' incapability to satisfy the assumptions of the Vickrey auction, which implies having predefined private values. If to analyse real agents' behaviour we can make a conclusion that the game of Chicken played by the agents in the end of the auction made the final distribution of the goods Pareto inefficient. Any agent regardless of his willingness to buy the room could use “sniping” strategy. As a result, winners were determined almost randomly.

Conclusion

The situation with this auction is far from perfect and auctioneer or mechanism designer cannot be satisfied with such an outcome. If one would desire to create a real market alike, it does not seem that this design could make anyone better off. But there is an interesting result that is worth mentioning. The two-stage strategy that was actually "invented" by the agents is a good example of a widely spread phenomenon. It seems that the mechanisms of this type, which include two steps, are popular because of their important features. On the first stage agents *form* and/or *refine* their imperfect preferences while on the second stage they actually *play* the game.

Some well-known examples of such mechanisms are the following. Klemperer (2000) proposed to use two-stage auction (Anglo-Dutch auction) for selling 3G licenses in the UK. Though he did not explain the need of using this mechanism in the terms of preferences' refining, it implied the idea of two-stage games. Another example is two-stage voting system when only two candidates pass to the second round (Moulin, 1988). This system is used in many countries all over the world. This type of voting evolved throughout the history "competing" with other voting systems. It seems that this system is suitable for many nations because it makes people aware of others' political preferences by means of two-stage voting.

Despite its popularity two-stage mechanisms are still not well investigated. The situation around the first stage, where agents are to form or refine their preferences, is not clear. It seems that it would be extremely helpful to make a research on finding possible rules that could govern the process of refinement. It is possible that such kind of results could be obtained in the theory of learning and social evolution (Young, 1998; Samuelson, 1997; Fudenberg and Levine, 1998) which provide us with wide range of methods of agents' collective finding of the equilibrium.

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