Automated Bidding in Overlapping Auctions with Unit-Demand Buyers: A Laboratory Experiment

Robert W. Day, The University of Connecticut School of Business
Sarah Rice, The University of Connecticut School of Business
Corresponding author: srice@business.uconn.edu

WISE 2010

Summary

This paper outlines a bidding mechanism for a setting where multiple unit-demand bidders participate in multiple heterogeneous auctions. Specifically, we develop a surplus-maximizing bidding agent that coordinates bids across all market participants, resulting in greater profits for all buyers. Next, we test this bidding agent in a laboratory experiment using economic incentives. We structure three different bidding agents to simulate various strategies observed in practice, and after playing with each of these agents in turn, we allow bidders to choose which one of the three agents they would prefer to use. The value of this experiment is two-fold. First we show that our mechanism outperforms other bidding strategies such as sniping and proxy bidding. Second, we test whether individuals can learn to choose an optimal bidding mechanism, in this case our automated agent, when economic decisions are salient.

Introduction

In a simultaneous auction setting unit demand bidders are presented with a number of decisions that include choosing which auction to bid in, how much to bid in that auction, and when to place a particular bid. We assume the bidder to be economically rational such that her goal is to maximize surplus, thus prompting her to engage in surplus-seeking strategies. However, effectively maximizing surplus among multiple bidders with multiple auctions becomes problematic, as coordination can be difficult. In this type of setting we show that coordination is aided by a bidding agent that enables bidders to tacitly collude without explicitly communicating their private information, all while maintaining the primary goal of maximizing surplus. In other words, by avoiding costly competition a group of surplus-seeking agents can coordinate mutually beneficial outcomes among all buyers.

We define a surplus-seeking agent as one that always bids the minimum winning amount in an auction that generates the most profit, or surplus, except when the bidder is currently winning some other auction. We then implement a “protection” bid at the end of the auction, referring
to this combined strategy as “seek-and-protect” bidding. A protection bid is placed by the bidding agent in the final seconds of bidding, and is placed for the full proxy amount initially specified by the bidder. For example, suppose Suzy is willing to pay $5 for a widget and specifies this information to the bidding agent. As the auction draws to a close, she is the current winner of the widget at a price of $3. In the final seconds of the auction our seek-and-protect strategy is for the agent to raise Suzy’s bid to $5, the proxy amount she initially entered, in order protect her bid from other snipers. If anyone snipes over Suzy’s $3 bid, but under her $5 proxy bid, she will still win that auction. The difference between our technique and other sniping agents such as esnipe and cniper.com, is that our agent coordinates bids across several auctions, determining a surplus maximizing outcome among all bidders who adopt the agent.

Because one of the difficult tasks bidders face in simultaneous auctions is deciding where to bid, particularly when there is unit demand, our technique provides value by choosing the “best” auction to bid in at any moment based on surplus calculations. So, if Suzy wants to win a widget and there are four auctions for widgets running simultaneously, she can place bids with our agent for each of the four auctions, even though she only wants to win one item. Our agent will then consider those bids, along with all other bids entered, and proceed with the surplus maximizing bidding strategy, while ensuring that only a single unit is won.

Related Literature

Much of the earlier work on bidding agents focuses on “sniping agents”, which automatically submit high bids in the final seconds of the auction, on behalf of the bidder. A sniping strategy occurs when auctions have a “hard” end time, meaning the point at which the auction ends is fixed. Rather than submit true values to the eBay proxy function at the start of the auction, sniping requires that bidders withhold their bids until the final seconds of the auction. Roth and Ockenfels (2002) and Ockenfels and Roth (2006) develop the theory as to how and why sniping benefits bidders, showing that waiting to place last second bids is in fact a rational strategy, as it can lead to greater bidder surplus. Bapna et al. (2005) also studies sniping in online auctions by using data from a sniping website to measure bidder surplus. Examples of existing sniping agents that automatically place last second bids include esnipe and cniper .com.

Because our agent is equipped to manage bids across multiple auctions, we turn our attention to literature relating to multi-auction bidding agents. Our design differs from the perennial Trading Agent Competition, in that our bidders have demand for only one unit, while Trading Agent Competition specifies bidders that have multi-unit demand. Ito et al. (2000) describe the structure of a generalized bidding agent, and outlines the necessary structures and protocols for the design of a multi-auction bidding agent. Anthony et al. (2001) focus on a scenario where auction formats are heterogeneous, and use simulation to investigate various ways to select
bids and auctions in a multi-auction setting. Yuen et al. (2003) evaluate several heuristic strategies and address the effects of heterogeneity among the auction items, noting that a bidder may have different valuations for different items. They assume bidders to be surplus maximizing, such that their goal is to maximize the difference between their value for the good and the final price paid. Judas and Parkes (2006) also study a multi-auction unit demand setting, which they term the “sequential auction problem”. They show that if bidders can buy the option to purchase a good from a certain seller at a specified time and price, market outcomes improve. An equilibrium bidding strategy for unit demand bidders in simultaneous auctions is formalized by Peters and Severinov (2006), who show that the optimal strategy is for bidders to place single bids in auctions where the price is currently the lowest. Their model does not account for sniping, or late bidding, which presents a coordination problem as the auctions draw to a close. When sniping is possible, the bidder’s problem is how to decide which auction to place their snipe bid. When there are other bidders in the market place it is possible, even likely, that multiple bidders will place last minute bids in the same auction. The result of bidders clustering on a single auction while leave others untended, is a loss of allocative efficiency as well as reduced bidder surplus. Our agent is designed to prevent such inefficiencies, however, its effectiveness depends on the number of bidders who choose to use it. While our bidding mechanism has some theoretical appeal, the more interesting question is how it will fare in live auctions. To address this question we conduct a rigorous laboratory experiment to compare our mechanism with several other bidding strategies. We then test whether subjects can learn the benefits of our bidding agent, such that they choose to use it when all options are presented.

**Experimental Design**

Our experimental market is structured to run four heterogeneous auctions at the same time, each for a single good. There are six bidders and each has four different valuations, one for each of the auctions. Bidder valuations range from $6 to $10, and are drawn from a discrete uniform distribution. Rounds run for approximately 90 seconds. Before the timed portion of the round each bidder sees the list of her four valuations, and treats these draws as her personal value for the items. These individual values will be used in determining individual payoffs, explained below. Our incentive structure is based on induced value theory (Smith 1976), which is intended to instill a homogenous value structure across all participants.

In accordance with other auction experiments (Kagel et. al.), profits for each round are calculated as:

$$(\text{price paid for the winning good})-(\text{private value for that good}).$$
Because bidders have unit demand, winning two items is not beneficial, though it is possible given our design specifications. If subjects win more than one item, profits are calculated as:

(Value of the highest valued good won) – (payments made for all items won)

Our design is within subjects, so each participant plays in all treatments. We specify four different bidding regimes:

1. Active bidding: each bidder enters in an amount they want to bid up to and can increase this amount if he/she is outbid.

2. Snipe bid: each bidder can enter one bid for each auction and the sniping agent waits until the end of the round to submit this bid. The time limit for these rounds can be shorter (when all bidders are forced to use the snipping agent) say 1 minute.

3. Seek-and-Protect: Bidders enter a vector of maximum bids and the bidding agent bids actively in the different auctions based on which one gives the highest surplus.

4. Bidder chooses: The bidder can choose whether he/she wants to use the Seek-and-Protect agent, the sniper agent, or to simply bid actively.

Our experiment runs from an html platform specifically designed and programmed for this study. Each subject is seated at a computer terminal where they will remain for the entire experiment. Subjects will play a total of 20 rounds, and will experience five instances of each of the four regimes outlined above. Of particular interest is whether our bidders will learn the benefits of the seek-and-protect agent over time, such that they will choose it when given the option to do so.

One of the most important design considerations in an experiment such as ours is what information to reveal to subjects during the session, and at the close of the auction. During each round of bidding all bidders will see the current price for all four items, as well as whether they are winning any of the auctions where they chose to place bids. Also, bidders will see the amount of time remaining in the round. At the end of each auction we will tell bidders the bid history of all auctions in which they participated, the winning price of the auctions, and if a bidder won the auction we will show his or her surplus. Our analysis will include comparing surplus and revenue outcomes between the four treatments, and our primary interest is the choice variable indicating whether subjects choose to use our agent.
Experiments are scheduled to run during the fall of 2010 and we welcome the opportunity to present our findings to the WISE community in December 2010.

Conclusion

The Internet has enabled the growth of on-line auctions by providing access to a large number of buyers and sellers. The result is an increase in the volume of on-line auctions, leading to a much more complex market setting. No longer is the bidder’s only task to decide how much to bid, instead there are now multiple decisions required in on-line bidding activities. Our seek-and-protect bidding agent is designed to act in the bidders’ best interest by coordinating multiple bids across multiple auctions, with the goal of maximizing bidder surplus. While the theory behind this mechanism is of some interest, its importance lies in how it is used by actual bidders in live auctions. Our economic experiment tests the effectiveness of this bidding agent in a controlled laboratory setting. We then test whether subjects will understand the coordination benefits of our mechanism, and whether they will choose to use it when given the option to do so.

References


