An Agent-based Platform for Online Auctions

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Abstract ***This paper proposes a web-based agent platform for E-commerce which allows humans and software agents to perform automatic auctions over the Internet. Internet-based auction is a profitable, exciting and dynamic part of E-commerce. However, the lack of standard on negotiation protocol between agents and an auctioneer makes full automation of E-commerce infeasible. Hence, we design a complete architecture and a set of negotiation protocols based on advanced agent technologies. Moreover, we evaluated the negotiation protocol using a Markov chain model. Our experimental results show that (1) the Markov chain can model independently simulated bidder's behaviour accurately, (2) a wider range of bidder's behaviour can be simulated with agents having partial knowledge of other bidders' willingness to bid and the closing time. In summary, our agent-based platform can incorporate realistic scenarios for simulation in online auction and other E-commerce applications.***

Keywords: software agent, E-commerce, negotiation protocol, Markov chain

1 Introduction

With the advent and proliferation of the Internet, E-commerce has recently been a very hot topic in the academic as well as in the commercial arena. In recent years, companies of all sizes ranging from international corporations to small companies are migrating towards an E-commerce marketplace. Recent statistics show that the electronic market will continue to grow in the near future because the number of potential customers will grow to 90 million by the end of year 2001 [1].

For non-electronic business transactions, customers and sellers often want to negotiate the price, particularly if the order is large. Traditionally, negotiations are conducted with human interactions. However, it is desirable to carry out this negotiation process either automatically or at least semi-automatically with human interventions only when necessary. Consequently, researchers and practitioners are attracted to develop automated negotiation systems [2, 3, 4]. However, the lack of standard on negotiation protocol makes it difficult to develop fully automated negotiation systems.

We have designed and implemented a web-based agent platform for conducting negotiations automatically [5, 6, 7]. There are several forms of negotiation such as bidding, auction and bargaining. Our platform employs a set of negotiation protocols in the auction process for the following reasons: (1) an auction is useful when selling an item of undetermined quality, (2) an auction is more flexible than setting a fixed price, (3) an auction can be programmed using software agents with a negotiation strategy and the agents negotiate a solution with the seller automatically, and (4) an auction is an excellent method of distributing goods to those who value them most highly. Our work focuses on (1) the development of the set of negotiation protocols, (2) the evaluation of negotiation rules using a Markov chain model,

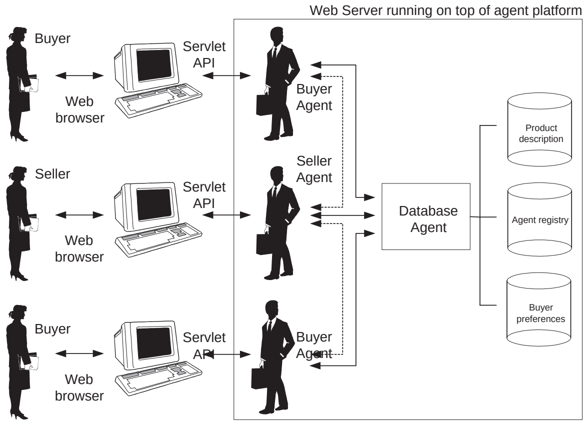

Figure 1: The system architecture.

and (3) the implementation of software agents which can analyze information and respond to changing market conditions quickly.

This paper is organized as follows. Section 2 will introduce the multi-agent platform. Section 3 will describe using Markov chain as a baseline approach to model the negotiation phase. Section 4 will present our experimental investigation and results. Conclusion of the paper is provided in Section 5.

2 The Multi-Agent Platform for Online Auction

2.1 System Architecture

Our platform is a multi-agent system in which three semi-autonomous agents interact or work together to perform a user's goal. They are the *Buyer Agent(BA)*, *Seller Agent(SA)* and *Database Agent(DA)*. Figure 1 shows the complete system architecture and the relationships between the platform and client computers.

In the proposed web-based platform, sellers and buyers should register in our registry before using our automated negotiation service. An SA will be created for the seller, and a BA will be created for the buyer. Both will be registered in the agent registry database. After that, potential sellers can advertise information about their goods and services on our web site. The product information is stored in one of the databases until the completion of the auction process. Buyers can browse advertisements and identify potential sellers through their web browser.

2.2 Roles of the Agents

A buyer initiates the negotiation phase by issuing an initial negotiation request to the BA. The BA requests for product or services specifications from the buyer. The BA queries the product description database and the agent registry for the list of SAs that may satisfy the buyer's interest. The buyer chooses one of the potential SAs from the list and specifies the maximum and minimum bid. The BA stores the buyer's preferences into the database and sends a start-negotiation request to the SA. After that, the BA will negotiate with the SA with the English ascending-bid auction which will be described in Section 2.3. During the negotiation phase, the BA is responsible for confirming the placement of a bid to the buyer and notifying the buyer when he is no longer the current winner.

The SA receives seller's request for the product or service he wants to sell and advertises the request to the product description database. After that, it will wait for the initial negotiation request from any BAs. The SA plays as an auctioneer and negotiates with the BA until the completion of the auction or the auction is terminated by the buyer. During the auction process, the SA assumes (1) the seller sells a single item, (2) the seller does not advertise future auctions or items, and (3) the auction process closes at a preset time which does not depend on the auction activity. The SA is also responsible for notifying the buyer after the auction has closed.

The DA manages the databases including the Product Description, the Agent Registry, and the Buyer Preferences. The Product Description database stores the specification of the seller's product or services with the following attributes: seller name, product name, reserve price, minimum price minimum bid increment, closing time and comments.

The Agent Registry is a yellow page for the DA. The content of Agent Registry is agent's name, agent's type, and agent's data. The agent name composes of the IP address of the buyer or seller and the creation time of that agent. The agent type specifies the agent's role and the agent data stores temporary values.

The Buyer Preference database is designed for the BA. It stores the negotiation strategy of the buyer such as the minimum bid, the minimum bid increment, and the maximum bid. The BA will follow these negotiation constraints until an agreement is reached or the auction process is terminated by the seller or the buyer.

2.3 Negotiation Protocol

An automated negotiation takes place when the negotiation phase is performed by an intelligent software agent programmed with a negotiation strategy. Our platform uses auction as the negotiation protocol and applies the English ascending-bid auction as the auction format. This type of auction is the most common format used by Internet auctioneers because it is relatively easy for bidders to participate. According to a survey conducted in 1999 [1], 121 out of 142 sites used English ascending-bid auction and their revenue was higher than that from other sites using Dutch, sealed-bid or double auctions.

3 The Markov Chain Model

The negotiation phase is a complex decision making process and it is dominated by the SA and BA. Therefore, we need a systematic and justifiable mathematical model to evaluate the behaviour of the SA and BA. Carrie and Segev [8] proposed a mathematical model to simulate the negotiation phase of English auction. It models the auction in terms of a Markov chain on a state space defined by the current price of the item and the number of bidders. The model was developed using a combination of stochastic modeling techniques

Table 1: Transition probabilities of different states.

State Transition	Probability
$A_t(p, L) \rightarrow A_{t+1}(p, L)$	$\frac{\lambda}{\lambda+\mu L} F(p)$
$A_t(p, L) \rightarrow A_{t+1}(p+c, L+1)$	$\frac{\lambda}{\lambda+\mu L} \overline{F}(p)$
$A_t(p, L) \rightarrow A_{t+1}(p, L-1)$	$\frac{\mu L}{\lambda+\mu L} G(p)$
$A_t(p, L) \rightarrow A_{t+1}(p+c, L)$	$\frac{\mu L}{\lambda+\mu L} \overline{G}(p)$

and actual Internet auction data from Onsale, Inc. It can be used to predict the price trajectory and the final selling price of an online auction under some assumptions.

The sequence of auction events in the model is as follows: (1) New bidders arrive at the auction site; (2) New bidders view the current price of $\$p$. They should offer the going price of $\$p + \$c$ to become the next winner or drop out of the auction; (3) If the bidder is unwilling to pay the going price, he drops out of the auction; (4) If the bidder is willing to pay the going price, he places a bid for $\$p + \$c$; (5) If the new bidder bids successfully, the auctioneer registers the new winner and updates the current price with the going price, $\$p + \$c$; (6) The previous winner is now bumped to the orbit queue to join any others there; (7) The orbit queue contains all previous winners who have been bumped; and (8) A previous winner from the orbit queue awakens and visits the auction site, viewing the new current price.

The state of the negotiation phase can be described by $A_t(p, L)$ where t is the event index, p is the current price and L is the number of bidders in the orbit queue. It can be calculated from the equations in Table 1.

In Table 1, $F(p)$ is the cumulative distribution function (CDF) of bidder valuations for an item, λ is the arrival rate of the new bidders, μ is the departure rate of a bidder who awakens from the orbit queue and revisits the auction, $G(p)$ is the conditional CDF approximating the bidder's willingness to pay a price $\leq p$ for an item, $\overline{F}(p) = 1 - F(p)$, and $\overline{G}(p) = 1 - G(p)$.

With the use of the transition probabilities in Table 1, we can compute the expected revenue of the auction process over a fixed time interval and use the results to demonstrate the behaviour of the software agents, and compare the outcome obtained from the agent-based simulations against that provided by the Markov chain model.

4 Experimental Results

The following experimental results focus on comparing the expected revenue calculated by the Markov chain model and the one simulated by the software agents. We want to (1) know whether the behaviour of the SA and the BA are modeled properly, (2) measure the performance of the negotiation protocol, and (3) find out the limitations of the Markov chain model.

4.1 Simulation Environment

The Markov chain model is a good tool to model simple bidder's behaviour. On the other hand, simulation presents a particularly attractive computional alternative for investigating online auction because it averts the need for overly restrictive assumptions and because it can model a wider range of bidder's behaviour than Markov chain model can cope with. Therefore, we developed a platform to provide a simulation environment for the BAs and SAs to run the negotiation phase automatically. The expected revenue simulated by the software agents will be discussed later.

The simulation environment runs on a PC with a 300MHz PII Intel CPU, 128Mb memory and a 12Gb harddisk. The experimental results are generated with the following assumptions: (1) BAs are independent to each other, meaning that they will not have any interactions, (2) The negotiation phase runs a single-item auction, (3) The SA will not advertise future items and does not contain any purchasing history. Input parameters are the arrival rate of BAs, the minimum bid increment, the reserved price of the item, the maximum bid of each BA, the probability of the BA's willingness to pay the bid, and the closing time of the auction process.

Table 2: Parameter value of Experiment One (Markov Chain Model).

Parameter	Value
λ	1
μ	1/3
c	1
r	1
time	20 rounds

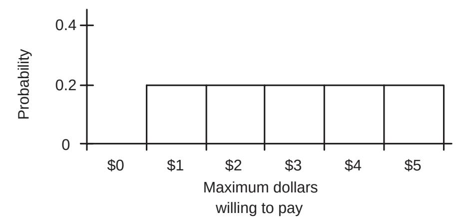

Figure 2: CDF of bidder valuations for an item.

4.2 Experiment One: A small auction

First, we use the Markov chain model to calculate the expected revenue with the parameter settings described in Table 2 and the CDF of bidder valuations for an item shown in Figure 2.

Based on the previous assumptions, we then try to compare the expected revenue with the one simulated by our software agents with the same parameter settings as shown in Table 3. Figure 3 shows the expected revenue calculated by the Markov chain model and the expected revenue simulated by the software agents from an initial revenue of \$0 to the final revenue of \$5.

4.3 Experiment Two: A large auction

In this experiment we test the scalability of the maximum bid. A single-item auction with a maximum bid of \$5 is considered small. Therefore, we try to apply the Markov chain model

Table 3: Parameter value of experiment one (Simulation Environment).

Parameter	Description	Value
λ	arrival rate of Possion process	1
c	minimum bid increment	1
r	reserved price of the item	1
max_bid	maximum bid of each BA	5
$prob$	probability of the BA's willingness to pay the bid	According to Figure 2
t	closing time of the auction process	20 rounds
n	number of BAs	10

and the software agents to a similar auction process but with a larger maximum bid of \$10 and a longer auction time. Figure 4 shows the simulation result.

We find that the curves of the expected revenue are close to each other. They grow exponentially and tend to the asymptote of the maximum expected revenue. Therefore, we believe that the behaviour of the SA and the BA is well modeled by the Markov chain and does not affect by the size of the maximum bid and

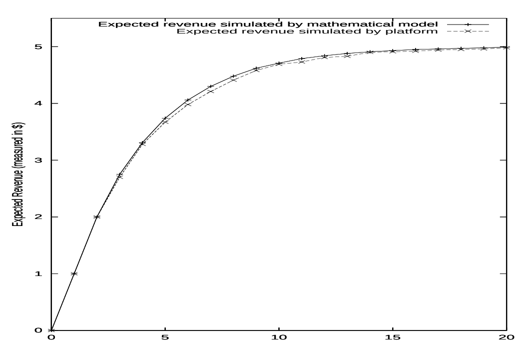

Figure 3: Expected revenue over time for a small auction.

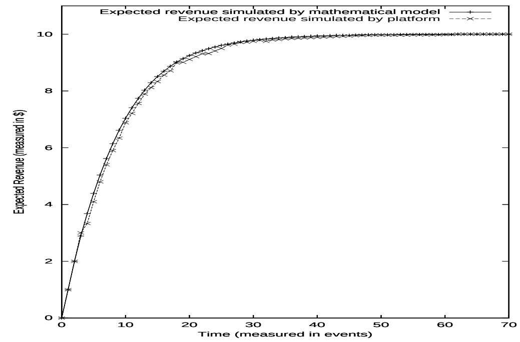

Figure 4: Expected revenue over time for a large auction.

the auction duration.

4.4 Experiment Three: Partial knowledge on other bidders

Next, we try to model a wider range of bidder's behaviour. In the previous experiments, we assume BAs are independent to each other with no interactions between them. Now, we want to give them partial knowledge: (1) each of them knows the bid paid by the others, and (2) each of them knows the probability of other's willingness to bid. In the auction process, the following strategy is used: When a BA is interested in bidding for an item, and it knows that no other BAs are willing to bid, the BA will raise the current bid only by the minimum bid increment. However, if there are other competitors, the BA wll compare their bids and find out the maximum bid. Then, if it is still willing to bid, it will offer a new bid which is the maximum bid among other BAs plus the minimum bid increment. This complex strategy cannot be modeled by the Markov chain approach, but it can be simulated by our agents-based platform. Figure 5 shows the simulation result.

If we compare the result with the expected revenue calculated by the Markov chain model in Experiment One, we find that the curve simulated by our platform grows and approaches to the asymptote faster than the one predicted by the Markov chain model. This indicates

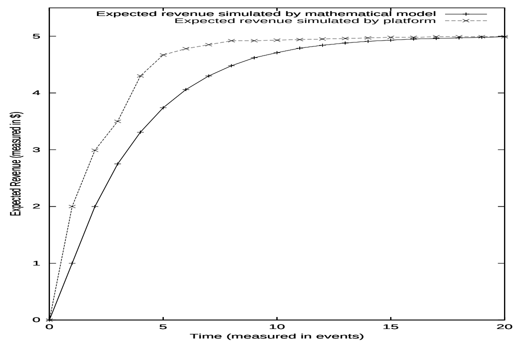

Figure 5: Revenue vectors under partial knowledge of other bidders.

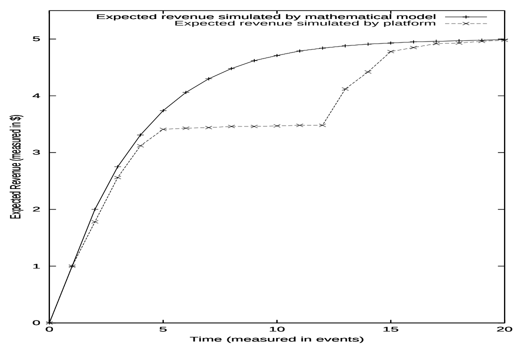

Figure 6: Revenue vectors under partial knowledge of closing time.

that the auction process will speed up due to the partial knowledge about other bidders in the new bidding strategy.

4.5 Experiment Four: Partial knowledge on closing time

In this experiment, we want to show that the expected revenue is affected by the closing time of the auction process. We try to increase the probability of willingness to bid towards the end of the auction process. Again, the Markov chain model will become extremely complicated to model this behaviour, but our agent-based platform can simulate the results rather easily and faithfully. Figure 6 shows the simulation result.

The experimental result shows that our agent-based platform can model a common phenomenon as in the real auction, i.e., bidders are unwilling to make new bids in the middle of the auction process, but they will submit bids at the very last moment. Figure 6 indicates that the growth of the expected revenue is divided into two phases. In the first phase, the expected revenue grows as usual, but it stops growing in the middle of the auction process. The second phase is triggered by the approaching closing time of the auction process when bidders are actively taking bids, and the revenue grows at a fast speed toward the expected maximum bid.

4.6 Comparisons and Discussions

From the above experimental results, we find that the analytical approach based on the Markov chain model has some limitations:

- It does not allow bidders to interact with one another.
- It does not consider the case where the market value of the item may decline over time. In this case, a depreciation term should be included.
- It cannot model whether the auctions run on a weekend or a weekday, if the results can be distinguished.

On the other hand, the advantages of our agent-based simulation environment are:

- It does well in approximating the expected revenue in a single-item auction.
- It allows the analyst to easily scale up the auction complexity in the agent-based simulation with a higher maximum bid value and more bidders, while the result still matches well with that obtained from a mathematical analysis.
- It can model simple as well as complex bidder's behaviour and the assumptions used in the simulation are realistic.
- It can be applied to other complex scenarios in an auction process. For example,

multi-item auctions, multi-seller auctions, different CDF distributions for bidder valuations, different arrival rates for bidders, and different negotiation constraints.

In summary, we find that our platform can provide a more sophisticated simulation environment. We can model a wider range of human's behaviour than what the Markov chain model can cope with. Furthermore, the assumptions used in the simulation approach can be made as realistic as possible.

5 Conclusion

In this paper, we have presented the architecture for an agent-based platform which can perform online auctions. We discussed the negotiation protocol between agents. Moreover, we used software agents to simulate the expected revenue on the platform and compared it with the value calculated by a mathematical model. Experimental results show that simple bidder's behaviour can be well analyzed using a Markov chain model as well as our agent-based simulation approach. However, it is difficult to extend the Markov chain model to cover a wide range of bidder's behaviour. Nonetheless, our platform can deal with this problem easily. Furthermore, the agent-based approach can be extended and refined with more realistic scenarios for automatic agent-based simulations, allowing us to construct a dynamic and diverse environment for a variety of E-commerce applications.

Acknowledgments

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