ABSTRACT

SHAH, HARSHIT SHARADBHAI. Identifying Bidding Strategies on eBay: A Feasibility Study (Under the direction of Dr. Peter Wurman)

Millions of people participate in online auctions on websites such as eBay. The data available in these public markets offer interesting opportunities to study internet auctions. The main purpose of this research is to identify common bidding patterns that appear on eBay. We examine data from eBay videogame console auctions. A new way of interpreting bidding behaviors is proposed. The analysis reveals that there are certain bidding behaviors that appear frequently in the data. We identify the behaviors and infer bidder's strategy that might lead to such behaviors.

Identifying Bidding Strategies on eBay: A Feasibility Study

by

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Biography

Harshit Shah was born in Ahmedabad, India in 1979. He received Bachelor of Engineering degree in Electronics and Communication from Gujarat University in 2000. In the fall of 2000, he joined the Computer Science Graduate program at North Carolina State University.

Acknowledgements

I would like to take this unique opportunity to express my deep gratitude towards my advisor, Dr Peter Wurman. His vision and continuous guidance have made this thesis possible. I cannot thank him enough for helping me in making this work coherent and presentable.

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Chapter 1 Introduction

In the past few years, there has been a widespread rise in the popularity of online auctions, especially in the consumer-to-consumer electronic commerce. Once considered esoteric by common man, millions are engaging in auctions today via online auction sites at eBay, Yahoo, uBid etc. At any given time, there are millions of auction listings across thousands of categories.

These websites rank high in average time spent per visitor and the average number of auctions participated in is increasing. Simple software agents have been developed that assist a bidder in placing bids on these sites, particular on eBay. These come in two forms: downloadable programs that run on the bidder's own computer, and web-based services like eSnipe, AuctionStealer etc. In addition to placing bids for the bidder, these agents offer other features too. The bidder can specify the time of the bid (usually in terms of minutes or seconds before the end of the auction). They may allow the bidder to group several auction items together so that the first winning auction cancels the rest of the auctions in the group automatically. There is motivation and scope for enhancing such agents with flexible bidding strategies that can respond to other agents' bidding strategies.

In this work, we examine people's bidding behavior in auctions on eBay. We try to answer the following questions: 1) Is it feasible to model the bidding strategies and classify the bidders based on it? 2) Can we identify enough bidders to make it worthwhile? 3) What strategies are common on eBay? 4) Can we detect shill (cases where sellers use aliases to hike up the auction price)?

Ebay keeps information of completed auctions on their server for 30 days after the end of the auction. We collected data of nearly 12,000 completed auctions for a period of about 3 months. The category of the auctions is video game-consoles, particularly Sony Playstation II (PS2) and Nintendo GameBoy Advance (GBA).

In Chapter 2, I describe eBay's mechanism and it's important features. Chapter 3 discusses how the data was collected and the approach that was adopted to analyze the data. I present the results of the analysis in Chapter 4. Chapter 5 discusses related work. The last chapter includes conclusion and future work.

Chapter 2 eBay – Model and Mechanism

eBay offers various features to it's user. In this chapter, I describe eBay's auction mechanism. I discuss the important features in detail.

2.1 Sample Listing

The following figure shows a sample listing taken from eBay's website. It displays information about the item on sale, status of the auction, and other important features for prospective bidders.

Figure 2.1: Sample Listing

2.2 Listing Items

To list an item for sale, the seller enters an auction category, the description & location of the item, the shipping terms & payment methods, the starting price, the (secret) *reserve price* if any, and the duration of the auction (3,5,7 or 10 days).

The reserve price is the lowest price at which the seller is obligated to sell the item. Ebay does not disclose the seller's reserve price to bidders. A notice is displayed on the item listing, indicating whether the reserve is met or not. (When a bidder's maximum bid is equal to or greater than the reserve price, the item's current price is raised to the reserve price.)

The seller pays eBay an "Insertion Fee" which depends on the listing options. The seller is also charged a "Final Value Fee" which is based on the final sale price of the item.

2.3 Bidding on eBay

Any registered user at eBay can bid in an auction of his choice. Generally, the user searches for the item of his interest. Once he finds the auction that matches his requirements, along with acceptable payment, shipping and insurance terms, he may decide to participate in that auction. The buyer may also consider the seller's reputation (available in the form of feedback rating and comments from other buyers). Bids on eBay are considered binding, although bid retraction is possible in certain circumstances.

2.4 Auction Mechanism

All eBay auctions use an ascending-bid (English) format with the important distinction that there is a fixed end time set by the seller. [1] Ebay provides four variations of this standard auction:

2.4.1 Types of listing

- Standard Listing: This is the most prominent type of listing. Here only one item (or group of items sold together) is being offered to the highest bidder.
- Dutch Auction: The seller offers more than one of the exact same items. The bidders enter the quantity of the items desired along with the price he is willing to pay per item. All winners pay the lowest winning bid price.
- Reserve Price Auction: The seller has a hidden reserve price that the bidding must exceed before the seller is required to sell. When a bidder's maximum bid is equal to or greater than the reserve price, the item's current price is raised to the reserve price amount.
- Buy It Now Price: A bidder can immediately win the item by choosing the Buy It Now option. If selected by the seller, this option is available until the first bid (or the first high bid that meets or beats the reserve price). A single item auction ends prematurely once a bidder exercises this option.

[1] Other online sites may differ from this approach by providing a flexible end time for the auctions, which will greatly impact the bidders' strategies. [4]

2.5 Reputation Mechanism

Each eBay user has a feedback profile consisting of comments left by other users. Each comment is classified by the poster as positive, neutral or negative with scores of

+1, 0, and –1, respectively. These scores are added to give an overall feedback score. Only comments from unique users are used in computing overall feedback scores.[2]

2.6 Proxy Bidding

Ebay uses a proxy mechanism for all submitted bids. Each bid on eBay is interpreted as the bidder’s *maximum bid* (i.e., maximum willingness to pay). The proxy system would bid for the bidder as the auction proceeds, bidding only enough to outbid other bidders. We refer to the bid placed by the proxy system as bidder’s *proxy bid*. If someone outbids the bid, the system automatically ups his bid. This continues until someone exceeds this maximum bid, or the auction ends and this bidder wins the auction. In a reserve price auction, the seller’s reserve price is treated like any other bid. If the buyer’s offer meets or exceeds the reserve (secret) set by the seller, the buyer’s bid would be raised to that price immediately.

[2] Ebay describes it’s feedback mechanism in the help section of it’s website: http://pages.ebay.com/help/myinfo/feedback.html

Table 2.1 : Bid Increments

Current Ask Price	Bid Increment
$0.01 - 0.99	$0.05
$1.00 - 4.99	$0.25
$5.00 - 24.99	$0.50
$25.00 - 99.99	$1.00
$100.00 - 249.99	$2.50
$250.00 - 499.99	$5.00
$500.00 - 999.99	$10.00
$1000.00 - 2499.99	$25.00
$2500.00 - 4999.99	$50.00
$5000.00 and up	$100.00

2.7 Minimum Bid and Bid Increments

The *minimum bid* at any time is *bid increment* over the current ask price of the auction. However, bid increments get bigger as the current ask price increases. Table 2.1 shows how eBay determine the bid increments.

Chapter 3 Our Approach

We take an empirical approach in this work. This chapter describes how we collected the data and a description of the data. We also discuss in detail how to interpret the data and how we compute the ask prices and *excess increment* parameters.

3.1 Data Collection

We chose to collect data for the auctions of Sony Playstation 2 console (PS2) and Nintendo Gameboy Advanced consoles (GBA). One reason for choosing these categories is that both products can be assumed to have private values significantly greater than their retail value at the time when the data was collected. A second reason is that a normal consumer is most likely to need only one of such consoles.

The data was collected from eBay using spider software written in JAVA. Ebay keeps information about completed auctions publicly available for one month. Each item on eBay is categorized with a unique category number. The categories for PS2 and GBA on eBay are 11328 and 18809, respectively.[3] The spider generates the URL (Universal Resource Locator) to request links to completed auctions in each category. A URL for links to GBA auctions completed on the first day of current month would be:

http://cayman.ebay.com/aw/listings/completed/category18809/day1page1.html

Each day may have more than one page each comprising of around 50 auction links. The software grabs all the pages for each day. From the HTML retrieved, the spider extracts links to the *auction_details* pages. Each auction_details page has details pertaining to the

[3] The category of the item is chosen by the seller. Ebay does not enforce the category of the item. However, we believe that it is safe to assume that sellers would be rational enough to choose the closest category for self-interest.

current auction along with a link to the *bid_history* page for the auction. The bid_history page of a completed auction contains details of bids submitted to the auction. The software follows these links and grabs both the auction_details and bid_history pages for each auction. The requests are staggered so as not to put too much load on eBay's server. The cached HTML pages are parsed locally, to extract the relevant information that is stored in a database for further processing.[4]

3.2 Description of the data

The data for PS2 was collected over a two-day period in October 2000(PS2 launch in US) and for 3 weeks during Jan 2001. The data for GBA was collected from May 31 to July 29, 2001 (GBA launch in US – June 11, 2001). In total, details of 11,537 auctions were collected. We refer to this dataset as *D*.

For each auction the following variables were collected:

- Auction ID (eBay refers it as "Item#")
- Auction Category
- Number of Bids
- Start Time
- End Time
- Seller ID [5]
- Seller Rating
- Reserve Information: No Reserve, Reserve Not Met, Reserve Met
- Highest Bid

[4] The earlier version of the software used a different technique to get the links of completed auctions.

[5] In our analysis, we gave each user (who appeared in our dataset) a unique ID by which that user is identified in our analysis.

- Bid History (For all the bids placed in the auction)
    - Bid Time
    - Bidder ID
    - Bid Amount

3.3 Data Interpretation

There are several ways to analyze the bidding behavior on eBay. In this work, we chose one approach that we feel worthwhile to analyze. We restrict our analysis to auctions with standard listing. The standard listing is the most common type of listing on eBay. Other listing types demand different approaches. For example, without knowing the seller's reserve price, it is not possible to interpret reserve-price auctions in the same way as we interpret standard auctions. Moreover, the behavior of bidders might be different for other listings.

We refer to the restricted dataset as D_r. It includes data regarding all the submitted bids i.e. time of bid, bid amount and bidder. However, it does not capture the proxy bids that were placed by eBay's system on behalf of the bidders. The ask-price (i.e. the price that eBay announced on its web page) of the auction that the bidder saw, while submitting the bid is also not known.

We believe that price of the auction at the time of bid submission might help us understand the bidding behavior. For all the submitted bids, we compute the then ask-price of the auction. The next section defines the model of the auction that would allow us to analyze bidding behaviors. Then I describe the way in which we calculate the ask price.

3.3.1 Formal Definition

Consider an auction, k, on eBay. Let $j \in J_k \subseteq J$, where J is the set of all bidders that appear in the restricted dataset D_r and J_k represents the subset of bidders who participate in auction k. The i^{th} bid of bidder j in the auction is represented as b_{ij}. We define the time range of the auction as $t_s - t_{end}$, where t_s and t_{end} represent the start and end time of the auction, respectively. At any time t, such that $t_s \leq t \leq t_{end}$, the ask price is denoted by π_t. From the definition on eBay's site, the minimum bid at time t, denoted b_t is:

$$b_t = \pi_t + \theta(\pi_t)$$

where $\theta(\pi_t)$ is the value of bid increment from Table 2.1

3.3.2 Excess Increment of a bid

We introduce a new parameter in the model, the *excess increment* of a bid. The excess increment of a bid is defined as the excess amount over the minimum bid and represents the bidder's use of the proxy system. We denote excess increment of bid b_{ij} as δ_{ij} and calculated it by:

$$\delta_{ij} = b_{ij} - b_t = b_{ij} - \pi_t - \theta(\pi_t)$$

After we have ask-price (π_t) of the auction at the time b_{ij} was placed, it is trivial to calculate the excess increment of the bid.

3.3.3 Calculating the Ask-Price

It is non-trivial to recover π_t from the data available on eBay. We have the bid history of the auction that gives the details of each submitted bids (bid amount, time of the bid and the bidder), except the winning bid. From this information, we can reverse engineer the ask prices and then the excess increment of almost all bids submitted to the auction. For the winning bid, we can compute only a lower bound on the offer.

To calculate the ask price and excess increment of the bids for an auction, we replay the auction by:

- Sorting the bids according to bid-time.

- Process each bid one by one, calculating the excess increment of the bid, the new ask price, and the high bidder.

To process the bids, we require knowledge of how eBay handles the incoming bids. There is no official publication given by eBay in this regard. We discovered the process partly from ‘eBay’s Help System’ and partly by trial-and-error.

We list the procedure here:

i. The starting price set by the seller is the ask price and minimum bid, when the auction starts.

ii. The first bid does not affect the current ask price, but the bidder becomes the high bidder at the starting price.

iii. Any bid has to at least match the minimum bid at that time.[6]

iv. When another bid comes, the new ask price and high bidder are determined as follows:

   a. Compare current high bidder's maximum bid and the new bid. The higher bid decides the new high bidder. A proxy bid is placed on behalf of the new high bidder which becomes the new ask price.

   b. The high bidder's proxy bid is always more than the second highest bidder's maximum bid by one bid increment. (The exception is when the high bidder's maximum bid is less than one bid increment over the second highest bidder's maximum bid. In this case, the high bidder's proxy bid is his maximum bid)

v. When two bids are for the same amount, the earlier one takes precedence.

vi. A bidder cannot lower his previous maximum bid.

[6] However, we found an exception in our dataset. If the bid is within a second of the previous bid, eBay may accept the later bid before processing the prior bid. Thus, we occasionally see bids that are lower than the new minimum.

Table 3.1 : Example - Calculating Ask Prices

Bid Number	Bid Time	Bidder ID	Bid Amount	Excess Increment	New High Bidder	New Ask Price	New Minimum Bid
1	Jun-17-01 15:06:20	63246	89.99	0	63246	89.99	90.99
2	Jun-17-01 15:53:20	59729	95	4.01	59729	90.99	91.99
3	Jun-17-01 17:51:12	59207	95	3.01	59729	95	96
4	Jun-17-01 17:53:06	59207	96	0	59207	96	97
5	Jun-17-01 17:56:57	45020	100	3	45020	97	98
6	Jun-17-01 17:58:32	59207	98	0	45020	99	100
7	Jun-17-01 17:58:45	59207	100	0	45020	100	101
8	Jun-17-01 18:01:08	45020	102.5	*2.5*	45020	102.5	105

vii. A bidder can outbid himself, but it will not change his proxy bid. Except in the following cases:

a. The bidder is tied with another bidder, but he is the high bidder because he placed the high bid first. If he places another bid to raise his maximum bid, he looses the favored ‘early bird’ status. Ebay would increase his bid by one bid increment so that he will remain the high bidder.

b. The current price is less than one increment above the second highest submitted maximum bid, which can occur if the high bidder’s maximum bid was less than the minimum increment above the second highest. In this case, if the high bidder submits a new bid, eBay would raise the current price to the minimum increment above the second highest maximum bid.

Table 3.1 shows how ask price and excess increment of bids are calculated for a sample auction. The auction discussed here is for a Game Boy Advanced console having auction ID – 1246919732. The auction is a 3-day auction that started on June 14, 2001 with a scheduled end on June 17 at 18hr 3min and 14sec PST. The starting price (i.e. ask price at the start) of the auction, set by the seller is $89.99.

63246(Bidder ID) places the first bid of $89.99. Minimum bid and ask price are equal at the start of the auction (by i). Hence, the excess increment for this bid is zero. After this bid is processed, the high bidder is 63246. The first bid does not change the ask price (by ii). However, the new minimum bid becomes $90.99. ($1 increment from Table 2.1). The second bid of $95 is placed by 59729. The excess increment, by definition, is the difference between the minimum bid ($90.99) and bid amount ($95) i.e. $4.01. After processing the bid, the new high bidder is 59729 (by iv-a). The new ask price is one bid increment over the second highest bid (by iv-b) i.e. $89.99 + $1.00. 59207 places the third bid of $95. As 59729 had placed the bid earlier, he remains the high bidder even though there is a tie in bid amounts (v). 59207 bids again to become the high bidder. 45020 places the fifth bid to become the new high bidder. 59207 bids again, but the bid amount is less than 45020's maximum bid. His next bid, too, does not make him the high bidder, as 45020 had bid the same amount earlier. Though 45020 was the current high bidder, he places the eighth bid of the auction. Generally, this would not change the ask price. However, in this case the there was a tie between the maximum bid's of 45020 and 59207. Therefore, eBay raises the current price to one increment over $100 i.e. $102.5 (by vii-a). The auction ends with bidder 45020 winning the item at $102.50. The excess increment value for the winning bid (eighth bid) is a lower bound on the actual excess increment.

Chapter 4 Analysis and Results

This chapter describes the analysis of the data and the results. We take a high level look at the data in section 4.1. The next section explains how we identified bidding behavior. Sections 4.3 and 4.4 describe the analysis we performed to find occurrences of the identified behaviors and results of the analysis.

4.1 Descriptive Statistics

In this section, we provide a statistical summary of the dataset *D*. This provides a quick look at the data.

Table 4.1 gives descriptive statistics of selected variables for both categories of auctions i.e. PS2 and GBA. However, the data is skewed, so statistics such as standard deviation, mean do not describe the data very well.

Table 4.1 : Summary Statistics (PS2|GBA)

<table>
<tr><th>Variable</th><th colspan="2">Mean</th><th colspan="2">Std. Dev.</th><th colspan="2">Min</th><th colspan="2">Max</th></tr>
<tr><td>Highest Bid</td><td>422.59</td><td>122.42</td><td>82.92</td><td>35.68</td><td>250.00</td><td>90.01</td><td>2500.00</td><td>1299.00</td></tr>
<tr><td>First Bid</td><td>238.02</td><td>81.37</td><td>198.00</td><td>63.16</td><td>0.01</td><td>0.01</td><td>2500.00</td><td>1299.00</td></tr>
<tr><td>Bids</td><td colspan="2">10.85</td><td colspan="2">11.10</td><td colspan="2">0</td><td colspan="2">64</td></tr>
<tr><td>Bidders</td><td colspan="2">6.43</td><td colspan="2">6.03</td><td colspan="2">0</td><td colspan="2">29</td></tr>
<tr><td>Seller Rating</td><td colspan="2">249.54</td><td colspan="2">619.22</td><td colspan="2">-7</td><td colspan="2">10,800</td></tr>
<tr><td>High Bidder Rating</td><td colspan="2">36.21</td><td colspan="2">180.19</td><td colspan="2">-6</td><td colspan="2">9,894</td></tr>
</table>

Table 4.2 : Auction Summary

	PS2		GBA		Total	
No. Of Observations	6526		5011		11537	
Dutch Auctions	2		28		30	
Reserve Price Auctions (Reserve Met | Not Met)	1880		716		2596	
	1132	748	457	259	1589	1007
Buy It Now	1151		1168		2319	
Standard Listing	3714		3259		6973	

Table 4.2 shows the distribution of different auction listings in the data. We observe that the standard listing is the most common of all types, accounting for over half of all listings. However, other listings are gaining popularity on eBay. Although they are slightly more complex, it would be worthwhile to analyze other listings too.

Figures 4.1 and 4.2 display the average final price of auctions for GBA and PS2 over the time the data was collected. It is interesting to note that the retail prices of GBA and PS2 consoles during that time were around $100 and $300 respectively. Overall, we can observe that the average prices are significantly higher than the retail prices and they tend to decrease with time. This might be due to the initial shortage of consoles on the market in both cases. With increase in the availability of the consoles, the prices on average decreased.

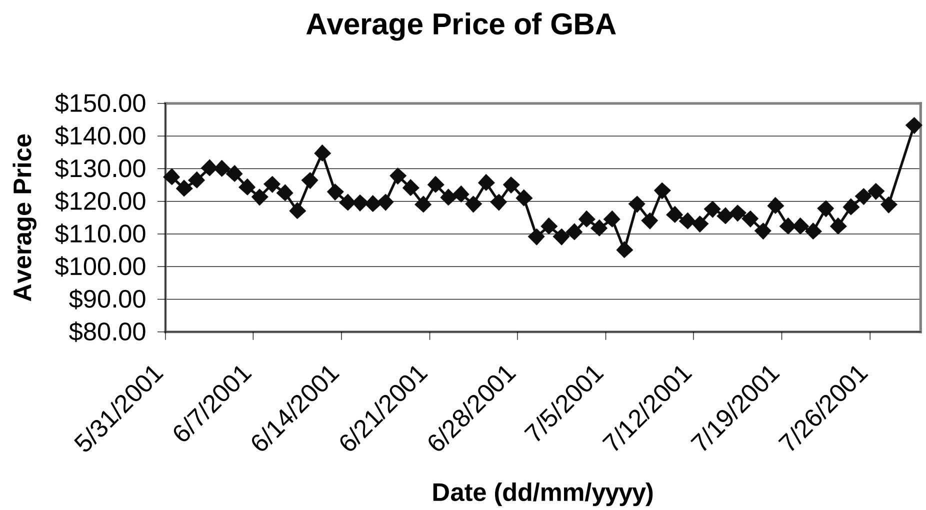

Figure 4.1: Average Price of GBA over time

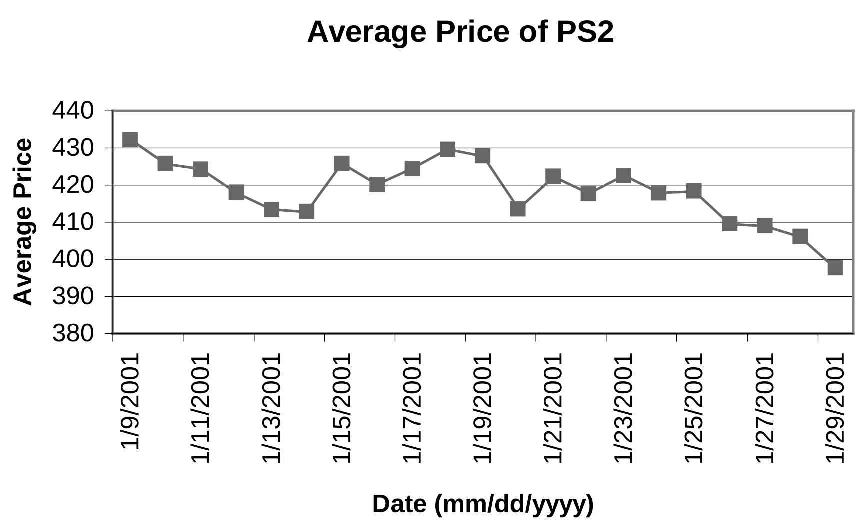

Figure 4.2: Average Price of PS2 over time[7]

Table 4.3 shows the distribution of users in the dataset when classified by whether they bought and/or sold each type of item (GBA, PS2). The total number of users that appeared in dataset *D* are 33,445. A user is considered to have been a buyer if he has bid

[7] The average prices for PS2 during 14 and 15 of October 2000 were $511 and $476 respectively.

Table 4.3 : User Role

	GBA Seller	GBA Buyer	Both	Neither
PS2 Seller	53	17	1	3740
PS2 Buyer	12	97	2	16973
Both	2	1	1	146
Neither	1534	10712	154	--

in at least one auction in that category. The table indicates that 97 of the eBay users appeared in the data as both GBA and PS2 buyers. Similarly, 154 users appeared as both GBA buyer and seller, and neither of PS2 roles.

Figures 4.3 and 4.4 show the distribution of buyers in terms of number of auctions participated in the dataset. The data is divided into 1-5 auctions (Fig 4.3) and more than 5 auctions (Fig 4.4) to allow for the difference in scale. For example, 19352 buyers in the dataset appeared in only one auction. The most auctions participated in by a single bidder in our dataset was 242. The figures reveal that there are bidders on eBay who appear in several auctions. We might be able to derive value by modeling bidding strategies of such users.

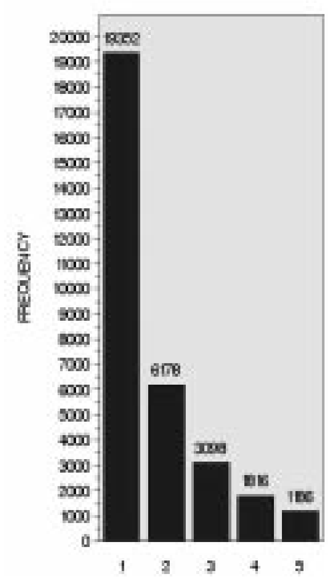

Figure 4.3 : User Participation

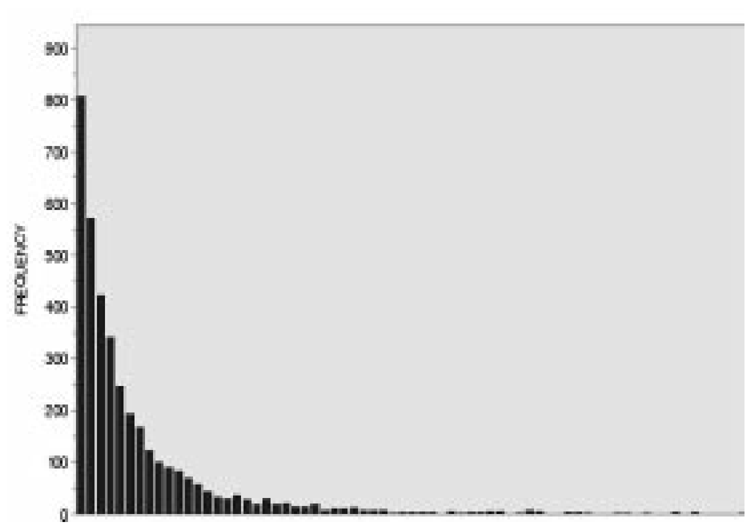

Figure 4.4 : User Participation (6 - 242)

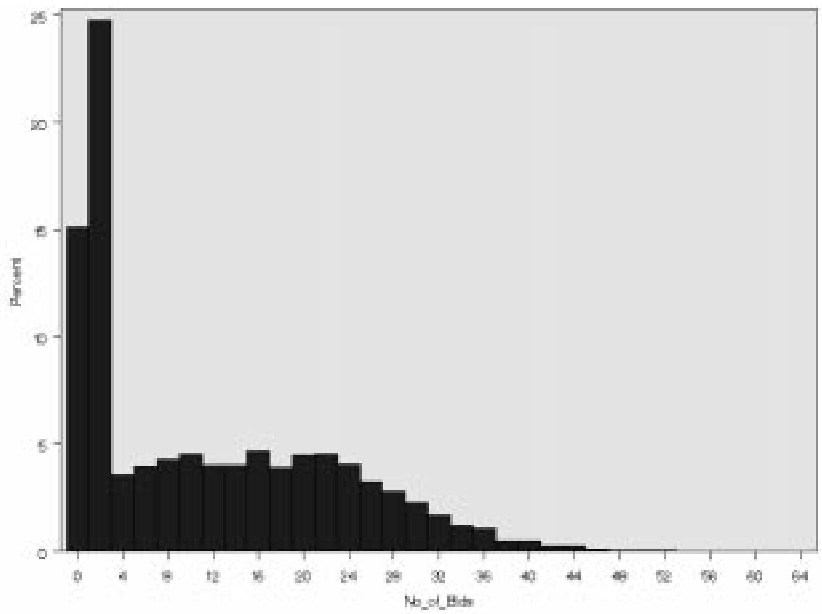

Figure 4.5: Bids per auction

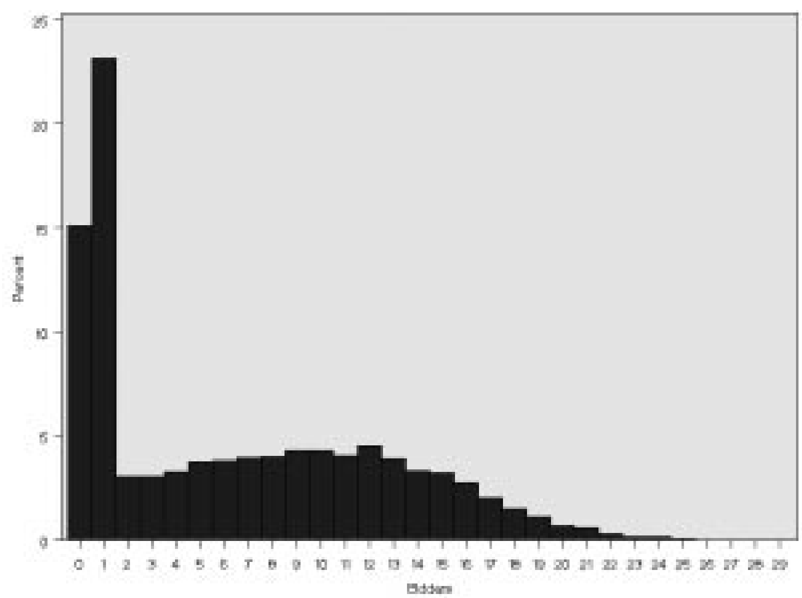

Figure 4.6: Bidders per auction

Figures 4.5 and 4.6 display histograms of ‘bids per auction’ and ‘bidders per auction’ respectively. 15% of auctions in the dataset did not receive any bids. However, there are auctions with significant activity in terms of the bidder participation and submitted bids.

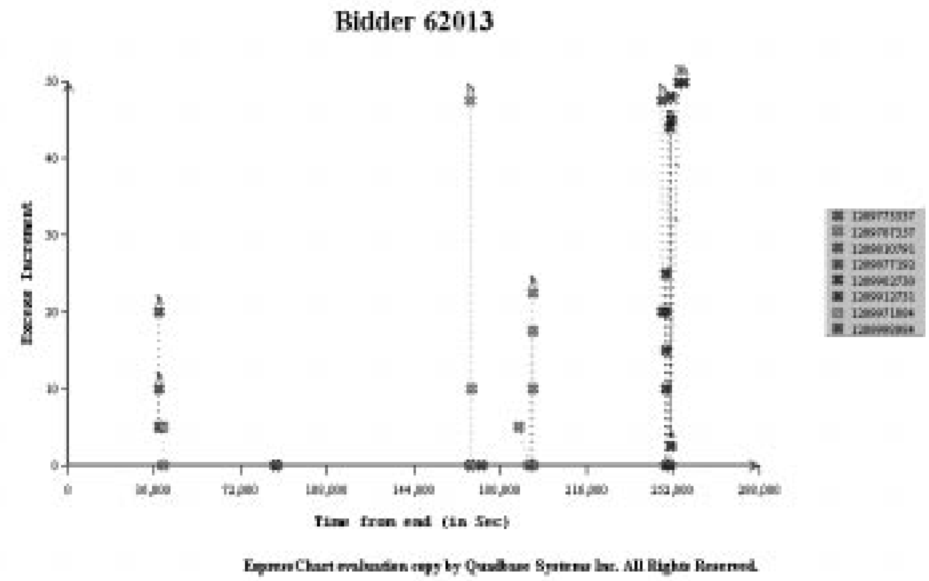

Figure 4.7: Sample Chart

4.2 Identifying strategy

There are many attributes of a bidder's activity that could be clues as to the bidder's strategy. We suggest that the excess increment of the bids is one such manifestation of the bidder's strategy. To test the hypothesis, we examine the excess increments of a bidder across all the auctions he participated.

Figure 4.7 represents a graph of excess increment values of all bids submitted by bidder-62013 across all 3-day auctions he participated. The horizontal axis denotes the time of the bid from auction end (in seconds). The vertical axis denotes the excess increment value of the bids (in $). All bids for a specific auction are connected by a line. Each

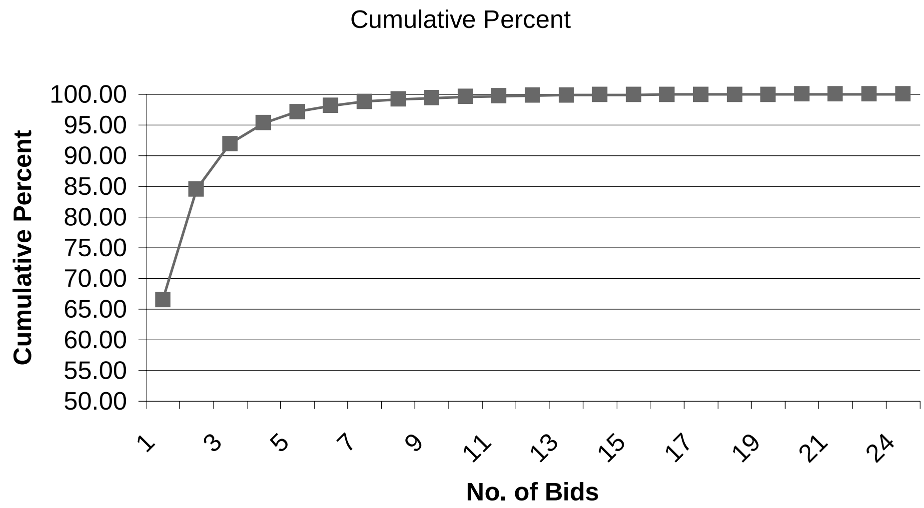

Figure 4.8: Number of bids in Engagements

auction is represented with a different color of marker and line. A character 'h' on top of a marker denotes that the bidder became the high bidder after this bid was processed.

We observe that in several auctions the bidder bids multiple times in a short span of time with increasing excess increment values, until he becomes the high bidder. We find that this kind of behavior is very common on eBay and discuss it further in section 4.4.

On visual inspection of such charts, we identified certain patterns that appear several times across bidders. We performed an analysis to find how frequently they occurred in the restricted dataset (D_r). For the purpose of the analysis, we introduce the notion of an *engagement*. An engagement refers to a bidder's participation in single auction (i.e., a bidder-auction pair). Intuitively, the count of engagements would be the total of all bidders' participation in auctions appearing in D_r. There are 49,523 engagements in D_r.

Let E denote the set of all engagements in the restricted dataset (D_r). We define $E_1 \subseteq E$, where E_1 is the subset of engagements in which the bidder has placed only one bid in the auction. Similarly, E_2 denotes the engagements with two bids, and so on.

Figure 4.8 shows the distribution of bids in engagements. About 66% of engagements belong to subset E_1. The rest of the engagements exhibit multiple-bidding, with nearly 15% having three or more bids.

This work concentrates on classifying engagements according to bidder's bidding behavior in them. Future work can use data-mining tools to classify bidders based on the labeled engagements.

4.3 Single Bid Engagements (E_1)

We find that a large number of these single bid engagements have bids placed near the end of the auction, irrespective of the auction duration. Nearly 58% of the bids were placed on the last day of the auction. We refer to this behavior as *late bidding*. Ockenfels and Roth [8] investigates strategic and non-strategic reasons for late bidding.

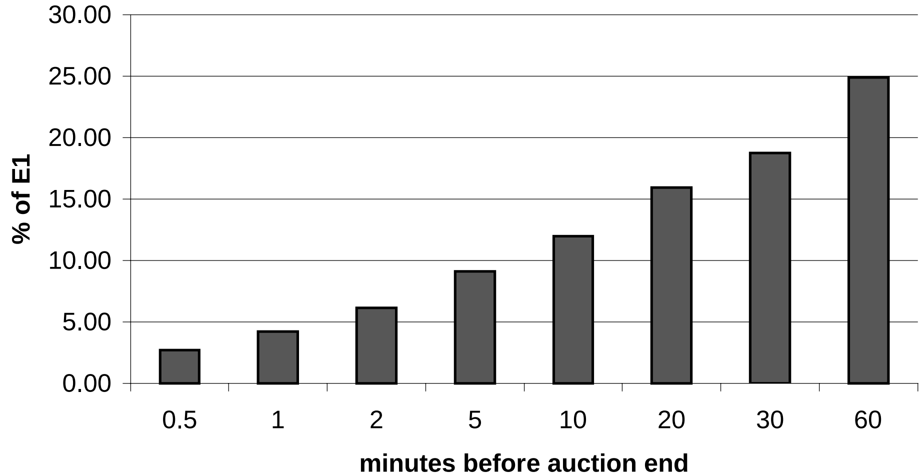

Figure 4.9: Distribution of bids during the last hour

Figure 4.9 shows the bid distribution during the last hour. A significant fraction of bids are submitted in the closing seconds of the auction, a practice called *sniping.* This behavior arises despite advice from both eBay and sellers that bidders should simply submit their maximum willingness to pay, once, early in the auction. Hence, it is easy to attribute sniping behavior as being primarily due to naïve, inexperienced or plain irrational behavior. However, [Roth, Ockenfels 2000] show that the sniping need not result from either common value properties of the objects being sold or irrational behavior. They mention:

"[Sniping] can occur at equilibrium even in private value auctions. The reason is that very late bids have a positive probability of not being successfully submitted, and this opens a way for bidders to implicitly collude, and avoid bidding wars, in auctions such as those run by eBay, which have a fixed end time"

[Roth,Ockenfels 2000]

We also investigate the rest of the engagements in E_1, where the single bid was placed at least one day before the end of the auction (E_1^*). We refer to the bidder classification by [Gupta, Bapna 2001] in which they identify a bidder type called *Evaluators*. Evaluators have the following characteristics:

- Early one time high bidders who have a clear idea of their valuation
- Bids are, usually, significantly greater than the minimum required bid at that time
- Rare in traditional auction settings - high fixed cost of making a single bid

[Gupta, Bapna 2001]

We try to identify the engagements in E_1^* having the evaluator characteristics. However there are several reasons that make this task non-trivial. 1) It is not uncommon that the game consoles that are auctioned on eBay are accompanied by other things like games, extra joystick etc. that affect buyer's willingness to pay. 2) The bidder's valuation might have changed with the descending market price.

To identify evaluator behavior, we group engagements in E_1^* according to bidder and the type of item i.e. PS2 and GBA. The standard deviation (σ) of the bid amounts is calculated. If it falls within a specified lower value (σ_{lower}), we may classify the corresponding engagements as an evaluator's behavior.

Figure 4.10 depicts bids and the ask prices for Bidder-45122 that appear in E_1^*. The bidder participated in six auctions. The standard deviation of the bids in these auctions is 0.52. We observe that the bids are significantly greater than the ask price at that time. Hence, we may classify this behavior as an evaluator behavior.

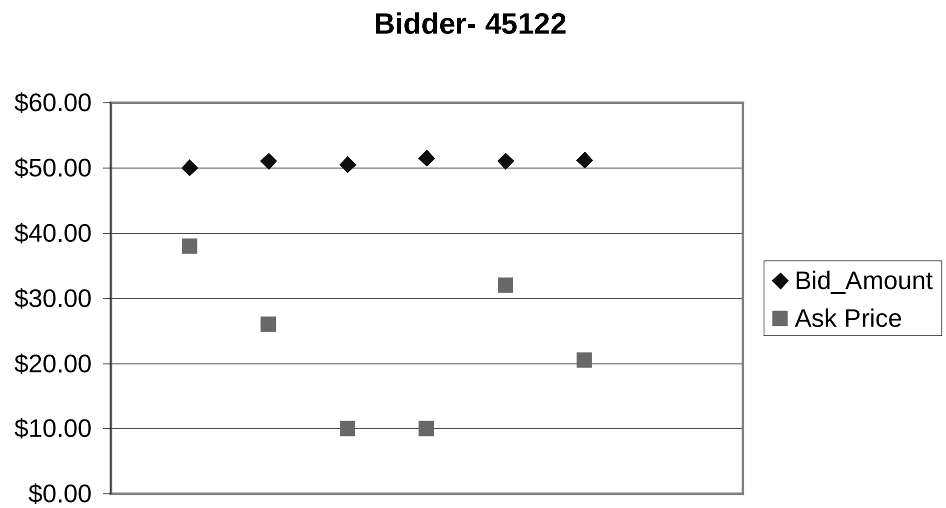

Figure 4.10: Example of evaluator behavior

For cases where the standard deviation is higher than $\boldsymbol{\sigma}_{lower}$ but less than an upper value ($\boldsymbol{\sigma}_{upper}$), we examine the correlation of the bid amounts with final price of the corresponding auctions ($\boldsymbol{r}_{final\_Price}$) and with the ask prices of the auction at bid time ($\boldsymbol{r}_{ask\_Price}$). If there is a strong correlation between bid amounts and final prices, we can assume that the high standard deviation in bid amounts might be due to different options in the sellers' offerings. Further, a weak correlation between bid amounts and ask prices support classifying the behavior as evaluator behavior because it suggests that the bidder's valuation does not depend on the ask price. Figure 4.11 shows an example having such characteristics. In this case, $\boldsymbol{r}_{final\_Price}$ = 0.30 (Strong-Weak association) and $\boldsymbol{r}_{ask\_Price}$ = 0.08 (Little, if any association). Thus, we also classify this case as depicting evaluator behavior.

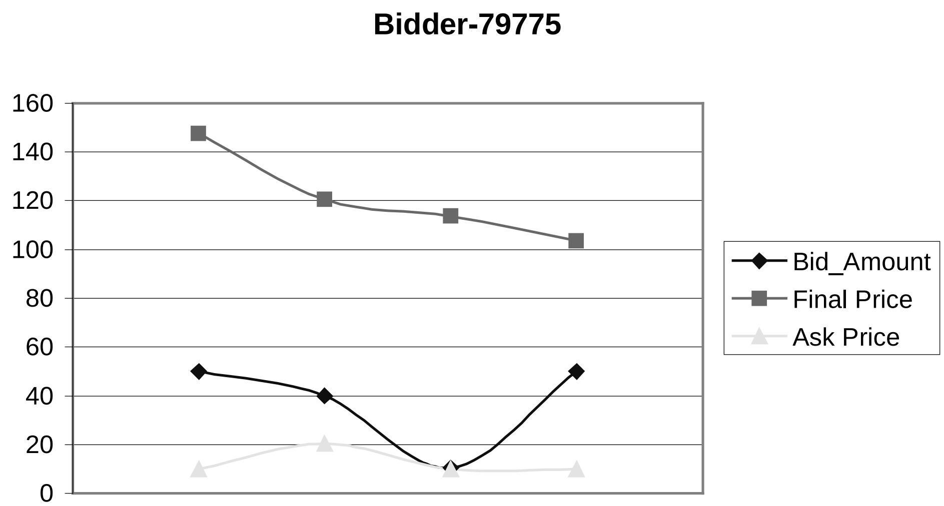

Figure 4.11: Another example of evaluator behavior

Keeping σ_{lower} = 10.00, σ_{upper} = 20.00, $r_{final\_Price} > 0.2$ and $r_{ask\_Price} < 0.2$, we have 13% of E_1 (comprising of 1074 bidders i.e. PS2 - 501 and GBA – 573), exhibiting the evaluator behavior. There is a scope for improving this analysis by using better statistical analysis. It would also be interesting to explore other explanations for such behavior.

4.4 Multiple Bid Engagements

Multiple-bid engagements ($E_{>1}$) are engagements having two or more bids. More than 30% of E are multiple-bid engagements.

One commonly occurring behavior in $E_{>1}$ is the *skeptic* behavior. The skeptic behavior is one in which the bidder submits multiple bids, all of which have zero excess increment; the bidder always bids the minimum increment over the current ask price. One

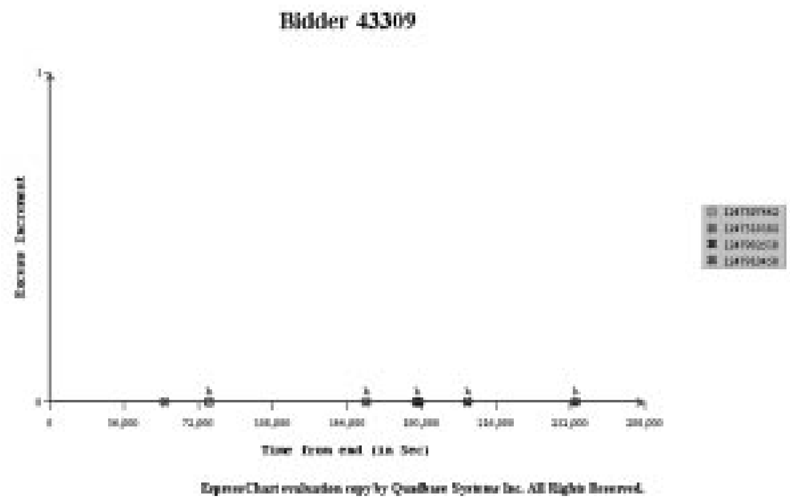

Figure 4.12: Example of skeptic behavior

possible reason for this behavior is that the bidder might be skeptical of eBay's proxy system and hence would always bid the minimum acceptable bid.

Figure 4.12 shows a bidder exhibiting skeptic behavior. He participated in four auctions, submitting multiple bids all of which had zero excess increment.

In around 18% of E_2 (1658 out of 8936), bidders exhibit skeptic behavior. In the remaining group i.e. $E_{>2}$, nearly 10% (738 out of 7649) have skeptic behavior.

We have identified another behavior very common in $E_{>2}$ that we call *unmasking* behavior. An example of such behavior was shown in Figure 4.7. In such engagements, the bidder tries to find the maximum bid of the current high bidder by successively increasing his bid in a short span of time.

If a bidder in an auction is outbid by another bidder, eBay notifies the losing bidder via e-mail. If a bid is in-between the ask price and the current high bidder's maximum bid, the notification is issued by eBay almost immediately. The bidder may also look at the web page of the auction to see the effect of his bid. In unmasking behavior, the bidder reacts to the outbid situation immediately by raising his bid. He continues to do so until he becomes the high bidder or until he reaches his maximum willingness to pay. [8]

We identify this behavior by the following characteristics:

- The bidder places multiple bids in a short span of time. (We vary the time span from 2 min to 10 min)
- There are no bids by other bidders in-between these bids.
- At least two non-winning bids are submitted before becoming the high bidder.

Figure 4.7 shows a bidder exhibiting unmask behavior. We find the unmasking behavior in 40%-43% of the $E_{>2}$, when we vary the time of successive bids from 2 minutes to 10 minutes. It suggest that generally this behavior is executed rapidly.

[8] Though it is not possible to know the bidder's true valuation, it is logical to conclude that if he stopped unmasking without being a high bidder at the end, he might have reached his true valuation or switched to a different auction.

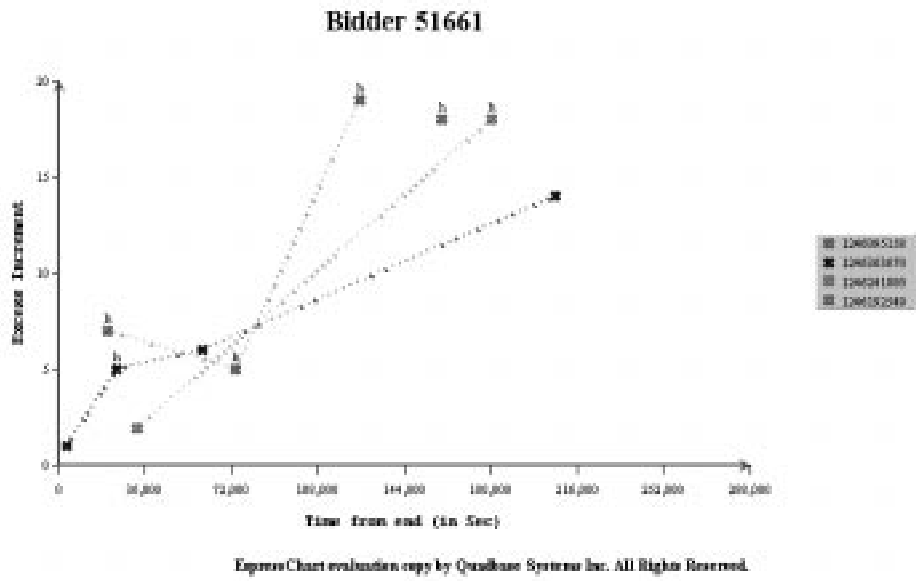

Figure 4.13: Engagements of Bidder 51661

Around 5% of $E_{>2}$ engagements have behavior in which the excess increment of successive bids decreases. Figure 4.13 is representative of engagements in this class, showing a typical behavior that appears as slanted lines. This behavior is probably attributable to a bidder who periodically attends to the auction to check whether he is outbid. The excess increment decreases as the end of the auction approaches because the price is increasing. Although this type of behavior was easy to identify by visual inspection, we have not yet identified the key attributes that form a coherent cluster for automatic detection.

Chapter 5 Related Work

A great deal of recent work has concentrated on online auctions. Ebay, being the most popular site, is the first choice of many such studies. David Lucking-Reiley et al. [2,3] analyze the effect of various eBay features on the final price of auctions. They find that seller's feedback rating have a measurable effect on his auction prices, with negative comments having a much greater effect than positive comments. Houser and Wooders [5] work finds a similar effect of the feedback ratings on the auction price. Roth and Ockenfels [6,8] observe late bidding in online auctions and suggest that multiple causes contribute to late bidding, with strategic issues being related to the rules about auction ending. Ünver [7] analyze the evolution of strategic multiple and last minute bidding using artificial agents. The work found support for multiple bidding in both private-value and common-value models. Bapna et al [1] reveal that the traditional theoretical assumptions regarding the homogeneity of bidders are violated in online auctions.

Chapter 6 Conclusion and Future Work

The thesis described the collection of auction data from eBay. After an exploratory analysis of the data, I introduce a way to interpret and identify bidding strategies from the data. The results reveal that we cannot assume bidders on eBay to be homogeneous. They exhibit different bidding behaviors. We are able to identify the following behaviors:

- Sniping
- Late bidding
- Skeptic
- Evaluator
- Unmasking

We could explain a significant portion of engagements, based on the identified behaviors.

We used an empirical approach to identify bidding strategies. Data mining techniques may be used to enhance the approach. Shill detection in online auctions is an interesting, and important extension to this work. Another extension of this work is modeling of bidders based on their bidding strategies and simulate auctions where the participants use such models. The simulation might help us to determine whether we can benefit from modeling the bidders.

Chapter 7 References

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[8] A. Ockenfels and A.E. Roth. Last-Minute bidding and the rules for ending second-price auctions: evidence from eBay and amazon auctions on the internet, *American Economic Review*, forthcoming.