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Rong-An Shang
Soochow University, rashang@scu.edu.tw

Yu-Chen Chen
Soochow University, cyc@scu.edu.tw

Mei-Ching Cheng
Soochow University, marc_cmj@yahoo.com.tw

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Rong-An Shang	Yu-Chen Chen	Mei-Ching Cheng
Soochow University	Soochow University	Kao (Taiwan) Corporation
rashang@scu.edu.tw	cyc@scu.edu.tw	marc_cmj@yahoo.com.tw

Abstract

Auctions have been a popular way of transaction on the Internet. Most of the studies of auction assume participants attending the auction are homogeneous. However, this assumption is open to question. In fact, every participant has his own personality, risk attitude, behavior, and cost when attending online auctions. This study takes an empirical approach and uses four variables, time of entry, time of exit, number of bids, and number of jump bids, to find the heterogeneity among bidders. We first used k-means clustering method to identify the types of bidders of online auctions, and then used C5.0 decision tree learning algorithm to find the rules to differentiate bidders. A taxonomy of four types of bidders is proposed in the study, which include observers, adventurers, opportunists, and early players. The results also suggest pacing of the auctions is an important factor that will affect bidder's behavior in online auctions.

Key Words: Online auction, bidding behavior, K-means clustering method, C5.0 decision tree algorithm

1. Introduction

For the Internet has lowered the cost of a bidder to participate in an auction, auction has been a usual way of transaction on the Internet. Online auctions possess some unique properties compared with traditional auctions, which cause their growing popularity. First, the bidder can stay anywhere to participate in the auction instead of having to come to the auction house. Second, online auctions can last for several days, which gives sellers and bidders more flexibility. Third, search engines and clickable hierarchies of categories for browsing make bidders find what they want more easily. Therefore, online auctions are more efficient, less expensive, and easily accessible to buyers.

Most of the previous researches on auction are based on an assumption that all of the participants attending online auctions are homogenous, they are rational and will bid strategically to achieve their best benefits. However, this assumption is open to question for online auction. Because of the low cost of attending an online auction, more variety of participants will be attracted. For testing the homogeneity between bidders, Bapna et al. (2004) conducted an inductive study to develop a bidder taxonomy challenges the notion that one can build a theory by assuming a single bidder type. They found that bidders pursue different bidding strategies resulting in different winning likelihoods and consumer surplus.

Based on Bapna's taxonomy model, this study used k-means clustering methods to find the heterogeneity among bidders. A new variable, number of jump bidding, was added in the model to the completely consider the special strategies in online auction. After that, we used a decision tree learning method to build the rules that can discriminate between types of bidders. This taxonomy not only assists us in finding out different kinds of bidding behaviors, but also helps us explain the divergence among these bidding behaviors. Finally, because the length of an auction is a major distinctive feature of online auction and may affect behaviors of online bidding, we also compared types of bidders in auctions with different length to explore the impacts of time on bidders' behavior.

2. Theoretical Background

An auction is "a market institution with an explicit set of rules determining resource allocation and prices on the basis of bids from the market participants" (McAfee et al. 1987). Such mechanism sets out rules for bidding and allocates the goods to a certain bidder based on the predefined rule set (Klein 1997). There are various mechanisms for auctions, such as ascending or descending bidding, valuation revealed of not, bids updated once or more. However, English auction is the dominant mechanism on the Internet (Pinker et al. 2003). In English auction, once the bidder finds the item she's interested in, he/she can view the current high bid, and decide whether to raise it by filling out her own bid amount in a text box in her Web browser (Lucking-Reiley 2000). English online auction allows bidder interaction and competition, and suits particularly well periods longer than a few minutes, which means bidders can bid asynchronously. The designs of online English auction also lead to some special online bidding behaviors:

Late bidding Late bidding means bidders will not bid until the last few minutes or even seconds to avoid revealing their preference early. We also call this sniping. Late bidding can be found in the online auction frequently (Bajari et al. 2004). Roth and Ockenfels (2002) found in a sample of 240 antique auctions on eBay, 89 had bids in the last minute and 29 in the last 10 seconds. Bidders bid late for several reasons. First, Ockenfels and Roth (2006) argued that late bidding may be a form of "tacit collusion" by the bidders against the seller. Second, by bidding early, a bidder may signal information to other bidders and cause them to update their beliefs about the common value of the item in a common value auction. This may increase the price that a bidder has to pay for the item (Bajari et al. 2004). Third, there is the presence of naïve bidders eBay who do not understand the proxy-bidding mechanism, and hence bid incrementally in response to competitors' bids (Ockenfels et al. 2006). The last-minute bidding is a best-response by rational bidders against such naïve bidders. According the above explanations about late bidding, late bidding seems to be a rational behavior. However, it is notice that not all of bidders enter online auctions late. Some may enter early, and place an early bid.

Jump bidding Jump bidding is entering a bid larger than what is necessary to be a currently winning bidder. Since online auctions have longer duration relative to traditional ones, bidders have difficulties in monitoring all bidding process to place their pedestrian bids. Any positive bidding cost can lead to jump bids by bidders choosing to enter, especially early in the auction, and that the extent of this jump-bidding goes up as expected competition increases (Ealsey et al. 2004). Besides, jump bidding can signal bidder's valuation and deter potential future competition. High-valuing bidders can effectively use jump bidding as a signal in common-value auctions (Avery 1998).

Shilling Shilling is an attempt by the seller to drive up the price of the good (Lucking-Reiley 2000). Although most auction sites do not allow the seller to submit bids on their own goods, the seller can register another identity to bid in his/her own auction. One disadvantage of shilling for the seller is the possibility of overshooting the high bidder's willingness to pay, and thus the auction failed.

Researchers often use common assumptions when analyzing bidder behaviors. They suppose each bidder is homogenous, and may be rational, risk-neutral, knows the value of the subject to himself clearly, and does not know others valuation. They will bid strategically to achieve their best benefits. However, the homogeneity assumption can't explain all the complex behaviors listed above and the dynamics of the interactions among bidders in the online auction well. Because of the low cost of attending an online auction, more variety of participants will be attracted. Ariely (2003) argued there is a variety of motives for bidders to participate in the online auction. Johns and Zaichkowsky (2003) also presented some factors that will influence interactions of users attending auctions and found the outcome of any auction is dependent upon variety of interbehavior dynamics, which are either intensified or diminished according to the number of bidders.

Several studies have tried to identify the heterogeneity among bidders. Bapna et al. (2000) conducted an empirical investigation of multi-unit auctions identifying three distinct types of bidders. The three types of bidders are evaluators, participators, and opportunists. Evaluators are early one-time high bidders who have a clear idea of their valuation. They usually bid higher than the minimum required bid at that time. Participators often make a low initial bid equal to the minimum required bid and progressively monitor the progress of the auction making ascending bids never bidding higher than minimum required. They derive some utilities from the process of participating in the auction itself. Opportunists are bargain hunters who place minimum required bids just before the auction closes.

Shah et al. (2003) identified common bidding patterns by analyzing data from eBay video game auctions in a hierarchical process. First, all bidders were separated into single bid engagements or multiple bid engagements. An engagement is the set of all bids by an individual bidder in an individual auction. Then Shah et al. use three variables, time from end, excess increment, and total number of bids, to identify the individual bidder's behavior. They revealed that there were four types of bidding behavior which appear frequently in collected data. The first behavior is evaluating. The bidders bid once, early, and at a high value. The second is skeptic. The bidders always bid the minimum increment over the current ask price and submit multiple bids. The third is sniping, which represents the bidders bid in the closing seconds of the auction. The last behavior is unmasking. The bidder places multiple bids in a short span of time and at least one bid in the engagement has an excess increment greater than zero. One possible rationale for this behavior is that the bidder is trying to expose the maximum bid of someone else's proxy bid.

Bapna et al. (2004) further demonstrated how the taxonomy of bidder behavior can be used. The three strategic variables, time of entry, time of exit, number of bids, were chose for classification on the criteria of being observable, theoretically relevant, and manipulable. They collected the data from a multi-unit Yankee auction website and identified five bidding behaviors by a K-means clustering approach. The five bidding behaviors include early evaluators, middle evaluators, opportunists, sip-and-dippers, and participators. The early evaluators are the bidders who place just one bid during the early stages of the auction, possibly reflecting their maximum willingness to pay. The middle evaluators are the bidders placing one maximum bid in the middle of the auction. The opportunists are late bidders differing from snipers because of the existence of a going-going-gone period in Yankee auctions. The sip-and-dippers usually place two bids. One is placed early in the auction to establish their time priority and perhaps to assess the competition. The participators usually get into the auction early, and exit lately. They bid throughout the auction representing high involvement of the auction. Bapna et al. found opportunists and sip-and dippers have significantly higher winning proportions than the others. However, although time is an important element that directly affecting bidding process (Johns et al. 2003), Bapna et al. normalized time of entry and time of exit, and aggregated data for auctions with different length. The data mining analysis assumed the types of bidders remain unchanged for auctions with different length.

3. Research Method

Clustering and classification are two ways to separate bidders from different bidding behaviors. Classification finds a rule or a formula for organizing data into predefined classes. Clustering breaks a large database into different subgroups or clusters; it differs from classification because there are no predefined classes – the clusters are put together on the basis of similarity to each other, but it is up to the data miners to determine whether the clusters offer any useful insight. For the purpose of understanding the heterogeneity of bidders' behaviors, we conducted a taxonomy of bidder behaviors using the k-means clustering method as proposed by Bapna et al. (Bapna et al. 2004). Classification analyses were further conducted to explore the types of bidders we found. Except for the three variables suggested by Bapna et al., time of entry, time of exit, and number of bids, we added a new variable, number of jump bidding, to describe bidders' jump bidding in online auction and to better explain the characteristics of different types of bidder.

The data were captured from an online auction site, www.go2hk.com, because the details of each auction are presented in this auction site. The data include the auctions listed in January to March, 2005, in the category of computer products. All of the auctions collected are English auctions with fixed ending time. To study the impact of auction listing time, only records of 7-day and 14-day auction were selected, which are the two highest proportions of all auctions. Besides, only records of auctions with more than two bids were collected. Finally, there are 72 auctions which contain 605 bidders. As one bidder may attend more than 1 auction, we viewed this bidder as different bidders. Table 1 presents the profiles of the data for 7-day and 14-day auctions respectively.

Four variables were used in the clustering analysis. *Number of Bids* (*NOB*) was defined as the total number of bids in placed by an individual bidder in one auction. *Time of Entry* captures the bidder's entry time within an auction. Because what bidders concern is time left until the auction ends, we measured time of entry by the absolute entry time from the end of the auction (*ENT*). *Time of Exit* captures the bidder's exit time within an auction and was measured by the absolute exit time from the end of the auction (*EXT*). Finally, *Jump Bidding* refers to the frequency of entering a bid larger than what is necessary to be a currently winning bidder. We regarded proxy bidding as a kind of jump bidding although the bidder don't have to reveal the price he/she is willing to pay, the bidder has shown the others that he/she is willing to pay more than the current highest price in proxy bidding. We measured jump bidding by the number of jump bids (*NOJB*). The four variables used were defined as followed:

ENT = the auction's ending time - a bidder's first bidding time in the auction (in sec)
EXT = the auction's ending time - a bidder's last bidding time in the auction (in sec)
NOB = a bidder's total bidding numbers in the auction
NOJB = a bidder's total jump bidding numbers in the auction which include proxy bidding numbers

Table 1. Number of Bids and Bidders

	Day-	Auctions	Mean	Minimum	Maximum	Sum
Number of Bids	7	49	17.183	2	46	842
Number of Bidders			7.918	2	21	388
Number of Bids	14	23	23.608	2	83	543
Number of Bidders			9.434	2	28	217

Because the cluster analysis is quite sensitive to differing scales or magnitude among the variables, the four variables were standardized before applied the k-means algorithm. As suggested by Milligan and Cooper (1988), because all variables' minimum value are almost the same and equal to zero, we used the transformation Z = x/max(X) to standardize these variables.

4. Clustering analyses

Clustering is a division of data into groups of similar objects (Berkhin 2002). In this study, k-means algorithm, one of the non-hierarchical methods, was chosen because the pattern of bidder's behavior is unknown. In the cluster analysis, multicollinearity between pair of variables will bias the clusters due to the high correlations between variables. For this reason, multicollinearity was tested between variables. We regressed X_i on the remaining X' to obtain variance inflation factor (VIF), i =1 to 4. We examined multicollinearity for all of the variables and found all VIFs in both 7-day and 14-day samples are less than 10, which means there is no multicollinearity between these variables.

Before conducting the k-means algorithm, the number of clusters, k, must be supplied as a parameter in the analyses. In order to decide "k" properly, we used the kappa coefficients to find the optimal number of clusters (Brown et al. 2003). First, the data were split into two parts randomly, S1 and S2. The k-means algorithm was undertaken in S1, for a given number of clusters. Using the cluster centroids obtained from the initial solution, cases from the S2 were classified according to each solution by their Euclidean distance from the cluster centroid vectors. Then we did k-means clustering in S2 to extract another solution. The two solutions were compared by cross-tabulation to determine the chance-corrected of agreement, kappa, between the corresponding solutions. The optimal number of clusters, "k", was decided based on the largest value of kappa. We calculated the Kappa for k =3 to 6 and found that when k is equal to 4, the kappa is the largest one for both 7-day and 14-day auctions. As a result, we applied k-means algorithm with the parameter k = 4.

K-means algorithm partitioned the 388 bidders in 7-day auctions into 4 groups, which have 87,13,113, and 175 bidders respectively. Also, k-means algorithm partitioned the 217 bidders in 14-day auctions into 4 groups, which have 112, 4, 59, and 42 bidders respectively. Table 2

Table 2. Result of clustering – 7-Day auctions

	N	%	ENT	EXT	NOB	NOJB
Clus1	87	22%	4.47[a]	1.96	2.16	0.89
			1.38[b]	1.45	1.32	0.93
			(2.41, 7.00)[c]	(0.00, 4.38)	(1, 7)	(0, 4)
Clus2	13	4%	5.85	2.46	10.92	6.00
			1.56	2.21	3.38	1.68
			(2.03, 6.97)	(0.00, 5.79)	(7, 18)	(4, 9)
Clus3	113	29%	0.76	0.51	1.80	0.58
			0.75	0.63	1.37	0.69
			(0.00, 2.74)	(0.00, 2.11)	(1, 9)	(0, 3)
Clus4	175	45%	6.31	6.05	1.77	0.77
			0.63	0.78	1.38	1.08
			(4.45, 7.00)	(3.90, 7.00)	(1, 9)	(0, 5)
Pair comparison			4,2>1>3	4>2,1>3	2>1,3,4	2>1,4,3

a: mean; b: standard deviation; c: (minimum, maximum)

Table 3. Result of clustering - 14-Day auctions

	N	%	ENT	EXT	NOB	NOJB
Clus1	59	27%	8.52[a]	4.69	3.34	1.63
			2.56[b]	2.70	2.86	1.93
			(4.60, 13.99)[c]	(0.00, 9.12)	(1, 13)	(0, 10)
Clus2	4	2%	11.39	11.04	14.00	2.50
			1.84	1.86	5.94	2.08
			(9.54, 13.03)	(8.97, 13.03)	(9, 22)	(0, 5)
Clus3	42	19%	1.72	0.66	1.71	0.83
			2.01	1.11	1.24	1.06
			(0.00, 6.06)	(0.00, 3.68)	(1, 6)	(0, 6)
Clus4	112	52%	12.89	12.34	1.95	0.79
			1.17	1.55	1.57	1.26
			(9.56, 13.99)	(7.12, 13.99)	(1, 7)	(0, 7)

and 3 show the results of the cluster analyses. The values present descriptive statistics of the data in each cluster. For understanding easily, we transferred *ENT* and *EXT* from second into day.

After performing cluster analysis, the validity of the results should be evaluated. A good clustering must have high intra-cluster similarity and low inter-cluster similarity. As Aldenderfer and Blashfield (1984) suggested, we examined the null hypothesis that no significant differences existing among the clusters through ANOVA. The ANOVA tests rejected the null hypotheses and indicated the four strategic variables, consisting of *ENT*, *EXT*, *NOB*, and *NOJB*, differed significantly across clusters. The analyses indicated that the clustering models have good validity. We also performed post hoc tests for the pair comparison of clusters. The results are shown in the last row in table 2 and 3. In the 7-day auctions, the variable *ENTs* in cluster 4 and 2 are significantly larger than in cluster 1, then larger than in cluster 3. *EXT* in cluster 3 is significantly smaller than *EXTs* in the other clusters, and *EXT* in cluster 4 is significantly larger than *EXTs* in other clusters. As for the variable *NOB* and *NOJB*, the bidders in the cluster 2 placed significantly more bids and jump bids than the other bidders.

Pair comparison	4,2>1>3	4,2>1>3	2>1>4,3	1>4

a: mean; b: standard deviation; c: (minimum, maximum)

In the 14-day auctions, results of the pair comparisons of *ENT* are the same as the results in 7-day auction. Results of the pair comparisons of *EXT* are also the same as the comparisons of *ENT*. *NOB* in cluster 2 is significantly larger than *NOBs* in the other clusters, and *NOB* in cluster 1 is significantly larger than *NOBs* in cluster 3 and 4. Finally, *NOJB* cluster 1 is significantly larger than *NOJB* in cluster 4. Although *NOJB* in cluster is the largest, the differences are not significant. The characteristics of 4 groups in 14-day auctions are similar with them in 7-day auctions. We named each cluster of bidders according to their characteristics of the four parameters. Hence, we identified four types of bidders called early player, opportunist, adventurer, and observers. Features of the four types of bidders are shown in the table 4.

Early Player (Cluster 4) This group contains 45% of sample in 7-day auction, which is the largest group. The bidders in this cluster often enter the auction at the 6.31th day which is counted from the end of the auction, and exit the auction at the 6.05th day counted from the end of the auction. Besides, 1.77 bids and 0.77 jump bids are placed averagely in one auction. In 14-day auction, this group comprises 52% of the sample. The bidders often place bids in the early phrase of the auction; they often enter the auction at the 12.89th day which is counted from the end of the auction, and exit the auction at the 12.34th day. Besides, 1.95 bids and 0.79 jump bids are placed averagely in one auction. These bidders often place bids in the early phrase of the auction, as a result, we call these bidders early players. Only 2 early players in the samples had won the auction.

Opportunist (Cluster 3) In this cluster the bidders enter the auction very late. This cluster comprises 29% of the sample in 7-day auction, and 19% in 14-day auction. In 7-day auction, bidders in this cluster enter the auction at 0.76th day and exit at 0.51th day. 1.8 bids and 0.58 jump bids are placed averagely in one auction. In 14-day auction, bidders in this cluster enter the auction at 1.72th day and exit at 0.66th day. 1.71 bids and 0.83 jump bids are placed averagely in one auction. These bidders often place their bids at the time which is close to the end of the auctions. They enter the auction very late and this may because they want to avoid bidding wars with incremental bidders or other like-mined bidders. As followed by the

Table 4. Features for observer, adventurer, opportunist, and early player

Cluster1 (Observer)	**Cluster2 (Adventurer)**
♦ These bidders enter and exit the auction in the middle stage of the auction. ♦ They often stay a long time during the auction. ♦ They place few bids and jump bids. ♦ The winning likelihood in this cluster is the second high, less than the opportunists.	♦ These bidders enter the auction early, and exit the auction in the middle stage of the auction. ♦ They often stay a long time during the auction. ♦ The number of bids is very large in this cluster, and so is jump bid.
Cluster3 (Opportunist)	**Cluster4 (Early Player)**
♦ The entry time of these bidders is close to the ending time of the auction. ♦ They are late bidders. ♦ The winning likelihood in this cluster is the highest among the others.	♦ These bidders often place bids in the early phrase of the auction. ♦ They place few bids and jump bids. ♦ The often enter the auction early, and exit the auction early, too. ♦ They stay in the auction for a short period.

previous study (Bapna et al. 2004), these bidders are named opportunists. The result of ANOVA test showed the opportunist has the highest likelihood of winning among all clusters.

Adventurer (Cluster 2) This cluster is the smallest one. In 7-day auction, the bidders in cluster 2 enter the auction at the 5.85th day and exit the auction at the 2.46th day. The number of bids and jump bids are 10.92 and 6. In 14-day auction, the bidders in cluster 2 enter the auction at the 11.39th day and exit the auction at the 11.04th day. The number of bids and jump bids are 14 and 2.5. These bidders often place more jump bids than the other groups to deter potential future competition. Consequently, we called these adventurers. But none of adventurers in our samples had won the auction.

Observers (Cluster 1) This group, which comprises 22% of the in 7-day auction, is most likely to the cluster 2, adventurers, except for the number of bids and jump bids. They enter the auction at the 4.47th day of the auction, and exit the auction at the 1.96th day from the end of the auction. 2.16 bids and 0.89 jump bids are placed averagely in one auction. In the 14-day auction, this group contains 27% of the sample. The bidders enter the auction at the 8.52th day from the end of the auction, and exit the auction at the 4.69th day. 3.34 bids and 1.63 jump bids are placed averagely in one auction. These bidders often place a few bids and also a few jump bids during the long staying time. This may because these bidders have lower bidding cost and we named them as the observer. The observer has the second high winning likelihood among all bidders.

5. Classification analysis

A lack of explanation about the nature of the clusters leaves us responsible for much of the interpretation about what has been found. Therefore, we also used a supervised data mining tool, decision trees, to help us gain insight into the nature of the clusters formed by unsupervised clustering algorithms (Roiger et al. 2003). Decision trees are constructed using only those attributes best able to differentiate the concepts to be learned. We used the C5.0 algorithm, which is a successor to the well-known decision tree algorithm C4.5 (Quinlan 1993), to find the rules that can discriminate different bidder behaviors properly.

Table 6. Alternative classification rule for 14-day auctions

Classification rules	Accuracy*
IF *ENT* > 4.39 day, *EXT* < 9.12 day, and *NOB* < 8, THEN the cluster of the bidder = 1 (Observer)	108/112=96.42%
IF *ENT* > 4.39 day, *EXT* < 9.12 day, and *NOB* > 8, THEN the cluster of the bidder = 2 (Adventurer)	3/4=75%
IF *ENT* < 4.39 THEN the cluster of the bidder = 3 (Opportunist)	59/59=100.00%
IF *EXT* > 9.12 day and *ENT* >4.39 THEN the cluster of the bidder = 4 (Early Player)	37/42=88.09%

*Accuracy= the number of bidders which can be classified correctly through the classification rule/ the total number of bidders for each cluster

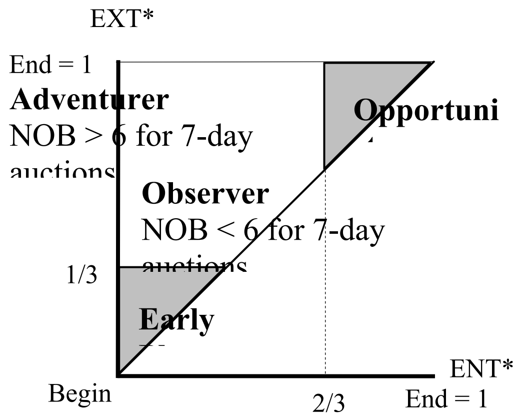
We randomly split our samples in the 7-day auctions into two groups. Group 1 contains 201 bidders and group 2 includes 187 bidders. We used group 1 to train our model, and used group 2 to evaluate the model. The result from group 2 shows that 182 (97.33%) bidders were classified correctly. 217 samples in the 14-day auctions were also randomly split into two groups. Group1 contains 105 bidders and group2 includes 112 bidders. 103 (91.96%) bidders in the group 2 were classified correctly. These results indicate our models have high validity and the classification rules derived can discriminate bidder behaviors effectively, both for samples of 7-day and 14-day auction. Table 5 summarized the classification rules and the accuracy for the whole samples in both the 7-day and 14-day auctions.

For comparing the classification rules between 7-day and 14-day auctions, we replaced the classified variable *NOJB* in the 14-day auctions with *NOB*, the same as in the 7-day auctions. As shown in the table 6, the new rules also resulted in good accuracy and the rules for the 14-day auctions are similar with the rules for the 7-day auctions. In the 7-day auctions, the opportunist will not enter the auction or place his first bid until the auction has processed about 67.14% of the total time. In 14-day auction sample the opportunist will not appear until

Table 5. Classification rules for bidders' behavior

Classification rules	*Accuracy**
7- day auctions	
IF *ENT* < 2.3 day, THEN the cluster of the bidder = 3 (Opportunist)	111/113=98.23%
IF *ENT* > 2.3 day and *EXT* >4.37 day, THEN the cluster of the bidder = 4 (Early Player)	168/175=96%
IF *ENT* > 2.3 day, *EXT* <4.37 day, and *NOB*< 6, THEN the cluster of the bidder = 1 (Observer)	86/87=98.85%
IF *ENT* > 2.3 day, *EXT* <4.37 day, and *NOB*> 6, THEN the cluster of the bidder = 2 (Adventurer)	10/13=76.92%
14-day auctions	
IF *ENT* > 4.39 day, *EXT* < 9.12 day, and *NOJB* < 3, THEN the cluster of the bidder = 1 (Observer)	107/112=95.53%
IF ENT > 4.39 day, *EXT* < 9.12 day, and NOJB >3, THEN the cluster of the bidder = 2 (Adventurer)	3/4=75%
IF *ENT* < 4.39 day, THEN the cluster of the bidder = 3 (Opportunist)	57/59=96.61%
IF *EXT* > 9.12 day and *ENT* > 4.39 THEN the cluster of the bidder = 4 (Early Player)	37/42=88.09%

*Accuracy= the number of bidders which can be classified correctly through the classification rule/ the total number of bidders for each cluster



* ENT and EXT are reversed and count from the begin of the auction

Figure 1. The classification of four clusters

the auction has processed about 68.64% of the total time. On the other hand, the early player in the 7-day auctions will exit the auction before about 37.57% of the total time has passed, and in the 14-day auctions, will also exit the auction before about 34.86% of the time of auction has passed. We further simplified the models by replacing the criteria of *ENT* and *EXT* with 1/3 and 2/3 of the total time. Figure 1 shows the rules of the classification of the four clusters. Opportunists are bidders who don't enter the auction until 2/3 of the total auction time has passed. Early players are bidders who will leave the auction before 1/3 of the auction time has passed. For those bidders who will enter before 2/3 of the total auction time and leave after 1/3 of the time, adventurers are bidders who bid more than 6 times in 7-day auctions, and more than 8 times in 14-day auctions, and observers are bidders who bid less than 6 times in 7-day auctions, and less than 8 times in 14-day auctions. The new rules also resulted in good validity of classification.

6. Conclusions

In this study, we first used the k-means clustering method to classify online bidders according to their bidding behavior. Then we used the C5.0 decision tree learning algorithm to generate the classification rules that can differentiate different types of bidders and to make us understand how these bidders behave easily. The taxonomy identifies four distinct bidding behaviors, which includes observers, adventurers, opportunists, and early players. The ANOVA tests verified that significant differences exist among these bidders. The sample size of 72 auctions in this study is somewhat small. Although the unit of analysis is actually bidders and the samples contain 605 bidders, the analyses resulted in some clusters with only a few bidders. So the characteristics of these clusters may not be correctly revealed. However, similar results were obtained both in the samples of 7-day auction and 14-day auction, further confirmed the validated of our model. Several findings of this study should be noticed.

First, the classification rules can be simplified as the one third rules as we proposed. This result suggests the pacing of the auction can affect bidding behavior in online auction. As the pacing theory proposed by Gersick that suggests a major transition occurs in a work team while the project has passed half of its time (Gersick 1988; 1989), this study also found something might happen in bidders' mind while one third and two thirds of the auction time have passed. Probably attracted by the low price of the item and the bidding appears easy and risk free (Ariely et al. 2003), early players will enter the auction in the first period but will leave before one third of the auction has passed. The proportion of the early player is the greatest among all groups. On the other hand, opportunists will not enter the auction until two third of the auction time have passed. The reasons behind this phenomenon should be examined further in the future.

Second, the opportunists who enter the auction in the last one third period are similar with the snipers who bid late to protect their private information or to avoid competition. However, previous studies about late bidding observed the late bidding by examining the last bidding time of each bidder (Roth et al. 2002), and in our study, we observed the late bidding referring to each bidder’s first bid. This criterion is more consistent with the reasons of late bidding been proposed. According to our narrow definition, late bidding is less severe and bidders are more varied than in the previous perspective.

Finally, although we added a bidder’s total jump bid number in the model as a classifying variable, it was not used in the final classification rules. The number of jump bid seem to be related to the number of bid and their explanation power seem to be duplicated. Observers are bidders who stay long but with few times of both bidding and jump-bidding. On the other hand, Adventurers will both bid and jump bid many times in the auction. Therefore, high bidding cost can’t explain jump-bidding well because those bidders will bid many times in the auction (Ealsey et al. 2004). Although it is also suggested the purpose of jump bidding is to show his/her will and to deter competition (Avery 1998), this study found that none adventurer had won the auction. Raising the auction price seems to be the only reasonable cause of adventurers.

References

Aldenderfer, M. S., and Blashfield, R. K. *Cluster Analysis* SAGE Publications, London, 1984.

Ariely, D., and Simonson, I. "Buying, Bidding, Playing, or Competing? Value Assessment and Decision Dynamics in Online Auctions," *Journal of Consumer Psychology* (l3:1), 2003, pp. 29-40.

Avery, C. "Strategic Jump Bidding in English Auctions," *Review of Economic Studies* (65), 1998, pp. 185-210.

Bajari, P., and Hortacsu, A. "Economic Insights from Internet Auctions," *Journal of Economic Literature* (42:2), 2004, pp. 457-486.

Bapna, R., Goes, P., and Gupta, A. "A Theoretical and Empirical Investigation of Multi-Item on-Line Auctions," *Information Technology and Management* (1), 2000, pp. 1-23.

Bapna, R., Goes, P., Gupta, A., and Jin, Y. "User Heterogeneity and Its Impact on Electronic Auction Market Design: An Empirical Exploration," *MIS Quarterly* (28:1), 2004, pp. 21-43.

Berkhin, P. *Survey of Clustering Data Mining Techniques.* Accrue Software, Inc., 2002.

Brown, M., Pope, N., and Voges, K. "Buying or Browsing? An Exploration of Shopping Orientations and Online Purchase Intention," *European Journal of Marketing* (37:11), 2003, pp. 1666-1684.

Ealsey, R. F., and Tenorio, R. "Jump-Bidding Strategies in Internet Auctions," *Management Science* (50:10), 2004, pp. 1407-1419.

Gersick, C. J. G. "Time and Transition in Work Teams: Toward a New Model of Group Development," *Academy of Management Journal* (31:1), March 1988, pp. 9-41.

Gersick, C. J. G. "Marking Time: Predictable Transitions in Task Groups," *Academy of Management Journal* (32:2), June 1989, pp. 274-309.

Johns, C. L., and Zaichkowsky, J. L. "Bidding Behavior at the Auction," *Psychology & Marketing* (20:4), 2003, pp. 303-322.

Klein, S. "Introduction to Electronic Auctions," *Electronic Markets* (7:4), 1997, pp. 3-6.

Lucking-Reiley, D. "Auctions on the Internet: What's Being Auctioned, and How?" *Journal of Industrial Economics* (48:3), 2000, pp. 227-252.

McAfee, R. P., and McMillan, J. "Auctions and Bidding," *Journal of Economic Literature* (25:2), 1987, pp. 699-738.

Milligan, G. W., and Cooper, M. C. "A Study of Variable Standardization," *Journal of Classification* (5), 1988, pp. 181-204.

Ockenfels, A., and Roth, A. E. "The Timing of Bids in Internet Auctions: Market Design, Bidder Behavior, and Artificial Agents," *AI Magazine* (23:3), Fall 2002, pp. 79-88.

Ockenfels, A., and Roth, A. E. "Late and Multiple Bidding in Second Price Internet Auctions: Theory and Evidence Concerning Different Rules for Ending an Auction," *Games and Economic Behavior* (forthcoming), 2006.

Pinker, E., Seidmann, A., and Vakrat, Y. "Managing Online Auctions: Current Business and Research Issues," *Management Science* (49:11), 2003, pp. 1457-1484.

Quinlan, J. R. *C4.5 Programs for Machine Learning* Morgan Kaufmann, San Mateo, CA, 1993.

Roiger, R. J., and Geatz, M. W. *Data Mining: A Tutorial-Based Primer* Addison-Wesley, Boston, MA, 2003.

Roth, A. E., and Ockenfels, A. "Late-Minute Bidding and the Rules for Ending Second-Price Auctions: Evidence from Ebay and Amazon on the Internet," *American Economic Review* (92:4), 2002, pp. 1093-1103.

Shah, H. S., Joshi, N. R., Sureka, A., and Wurman, P. R. "Mining for Bidding Strategies on Ebay," in: *Lecture Notes in Computer Science*, Springer-Verlag, 2003, pp. 17-34.