EVALUATING LONGITUDINAL ASPECTS OF ONLINE BIDDING BEHAVIOR

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Abstract: Online auctions have become a major e-commerce strategy in terms of both number, diversity of participants and revenue. Recent research has characterized online auctions as synchronous interactive computer systems, considering successive interactions as a "loop feedback" mechanism, called *reactivity*, where the user behavior affects the system behavior and vice-versa. Although some factors that explain user behavior in terms of instantaneous bidding conditions are identified by previous research, there has been no effort to study how bidders' behavior changes over time. This work presents a longitudinal analysis of bidding behavior over a series of auctions. The results show bidding behavior evolves over time and these changes are not random. The identifiable evolution patterns can be partially explained by the presence of instantaneous reactivity patterns that bidders experience throughout the series of auctions they participate. Bidders learn from these reactivity instances and adapt their future participation.

1 INTRODUCTION

Online auctions are becoming a major electronic commerce strategy in terms of both number and diversity of participants and revenue. Some recent studies, which we are going to discuss in this paper, have considered online auctions as synchronous interactive computer systems, that is, systems with which users interact continuously, getting and providing information. For example, users interact through their bids while competing for an item, waiting to see how the auction evolves, or giving up.

These studies consider interactions within an auction as a sequence, where successive interactions become a "loop feedback" mechanism, called **reactivity**, where the user behavior affects the system behavior and vice-versa. These papers describe a characterization methodology for online auctions, considering reactivity. By concentrating on relevant periods of bidding activity, they capture some important attributes that characterize reactivity and use them to identify auction negotiation patterns as well as bidding behavior. Although they identify some factors that lead a user to behave as observed in terms of instantaneous surrounding conditions they have not studied bidders' behavior evolution over time. We expect the user's interactions with the system to evolve due to change in objectives but more importantly, due to learning that takes place. With participation comes acquired knowledge that can directly impact the bidder's future bidding strategy.

In this paper we present a longitudinal analysis of bidding behavior considering reactivity. We focus on how the bidding behavior exhibited by auction participants evolves over time reflected in the bidder-auction interactions. In this context, there are some important questions we want to investigate:

1. *Are there changes in the bidding behavior over time? What are these changes?*
2. *Are these random changes? Are there trends?*
3. *Does reactivity affect these changes over time?*

In order to answer these questions we develop a model of bidding evolution behavior and use a real case study of eBay. This work is based on previous works (Pereira et al., 2007b; Pereira et al., 2007c; Pereira et al., 2007a).

Our analysis and results have wide applicability for activities such as defining seller's strategies, calibrating economic models of bidding, designing decision-support (Brown et al., 2005) and simulating e-markets.

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2 RELATED WORK

In this section we first discuss previous research related to temporal evolution in other contexts such as social networks. Then, we present some traditional work of characterization of online auctions and bidding behavior. Finally we show some studies of characterization of reactivity in online auctions.

A social network consists of people who interact in some way such as members of online communities sharing information via the WWW. To learn more about how to facilitate community building, e.g., in organizations, it is important to analyze the interaction behavior of their members over time (Falkowski et al., 2006). This paper proposes two approaches to analyze the evolution of two different types of online communities on the level of subgroups: The first method consists of statistical analysis and visualizations that allow for an interactive analysis of subgroup evolutions in communities that exhibit a rather membership structure. The second method is designed for the detection of communities in an environment with highly fluctuating members. For both methods, the authors discuss results of experiments with real data from an online student community.

In another context, with the rapid development of e-commerce, the topic of mining and predicting users' navigation patterns has attracted significant attention due to applications such as personalized services in E-commerce (Tseng et al., 2006). Although a number of studies have been done on this topic, few of them take into account the temporal properties of web user's navigation patterns. This work proposes a novel method named Temporal N-Gram for constructing prediction models of Web user navigation by considering the temporality aspects.

Menascé and Akula have several works in characterization of online auctions. (Menascé and Akula, 2003) provides a workload characterization of auction sites including a multi-scale analysis of auction traffic and bid activity within auctions, a closing time analysis in terms of number of bids and price variation within auctions, some analysis of the auction winner and unique bidder. In this work they use data from Yahoo! Auctions site (Auctions, 2003) and present some interesting overall conclusions about online auctions. In (Akula and Menascé, 2007) they present a two-level (site and user level) workload characterization of a real online auction site.

There are some studies on bidding behavior analysis. Using data from ubid.com, Bapna et al. (Bapna et al., 2004) develop a cluster analysis approach to classify online bidders into five categories: early evaluators, middle evaluators, opportunists, sip-and-dippers, and participators. Moreover, they argue that bidders pursue different bidding strategies that realize different chances of winning and different levels of consumer surplus. However, these studies are still limited regarding how they explain bidding behavior over the entire sequence of bids, as opposed to simply outcome summaries (e.g., final prices, and number of bids) in an auction (Ariely and Simonson, 2003).

Our work is fundamentally different in the sense that we start from the fact that the bidder's behavior changes across time and auctions, motivating us to understand the intra-auction interactions, that is, the factors that characterize the auction negotiation. We believe that it is the knowledge acquired in these intra-auction interactions that affect the bidder, who then adapts his/her behavior in the subsequent auctions.

3 AUCTION CHARACTERIZATION

This section briefly describes the characterization methodology presented in (Pereira et al., 2007b), showing a real case study of online auctions (Pereira et al., 2007c; Pereira et al., 2007a), that is the basis for our work. First we describe the dataset for this case study.

The dataset consists of 8855 eBay auctions comprising 85803 bids for Nintendo GameCubes from 05/25/2005 to 08/15/2005. eBay (Bajari and Hortacsu, 2003; EBay, 2007) employs a complex mechanism of second price auction, hidden winner, and hard auction closing. Because of its inherent complexity, we find it provides a good online auction environment to demonstrate the applicability of the characterization models and later, to show the evolution of bidding behavior over time. From the original dataset, we consider auctions that achieve success (selling the item) that represent 75.7% of the dataset.

3.1 Auction Representation

This section presents the basic components of the hierarchical model and characterization methodology (Pereira et al., 2007b). The premise of the characterization is to capture the relevant information about the auction negotiation features to understand its dynamics. These criteria analyze the auction at various levels of granularity and are organized as a hierarchy.

Reactivity can be defined in the context of *agents* who react to *events* through *actions* thus affecting the *state* of the system. In online auctions, agents are bidders, their actions are their bids, and events are bids from other bidders, which change the auction negotiation state. In online auctions, there are two fundamental concepts that play roles in analyzing reactivity: activity and synchronicity. As a consequence of the auctions' long duration and the bidders' habits in terms of how frequently they check an auction in which they are participating, it is possible to observe

Table 1: Description of Auction Model Hierarchy.

Auction	Starting Price	The minimum bid value previously set by the seller for the auction negotiation.	
	Duration	The auction negotiation duration.	
	Seller	The owner of the auction.	
Sequence	Time-Locality	Initial (I)	The first sequence of the auction.
		Intermediary (M)	An intermediary sequence of the auction.
		Final (F)	The last sequence of the auction.
	Competition	No competition (N)	Does not present competition, only one bidder's session.
		Successive competition (S)	There is a competition, but no overlap between bidders' actions.
		Zigzag competition (Z)	Characterizes a more direct competition, where two or more bidders compete with each other in more than one time.
	Winner's Impact	Do not change winner (w)	The sequence does not change the last winner bidder.
		Change winner (W)	The sequence changes the last winner bidder.
Session	Size	One (O)	Has just one bid.
		More (M)	Has more than one bid.
	Activity	Non-Trigger (t)	Does not initiate the sequence's activity.
		Trigger (T)	Initiates the sequence's activity .
	Recurrence	Non-Recurrent (r)	The session is from a bidder who has not bid before in this auction.
		Recurrent (R)	The session is from a bidder who has already bid in this auction.
	Winner's Impact	Do not change winner (w)	The session does not change the last winner bidder.
		Change winner (W)	The session changes the last winner bidder.
Bid	Time	The time that each bid is placed during auction negotiation.	
	Price	The bid value.	
	Bidder	The participant who places this bid.	

that online auctions present long periods of inactivity, during which no bids are submitted.

They propose a four-level characterization: bid, session, sequence, and auction, as shown in Table 1. The bid is the finest grain level, representing the bidder's action. It is characterized by the time it is placed, the bid value, and the bidder. A session is a group of one or more bids from the same bidder, in which the time interval between any two consecutive bids is below a threshold θ_{ses}. The session attributes are intended to capture the reactivity the bidder exhibited towards the auction within the defined session interval: number of bids placed, the existence of competition, if the session impacted the sequence it is inserted in, and if the bidder is a recurrent one from previous sessions. The sequence is a set of one or more sessions, where the inactivity period between two consecutive sessions is below a threshold θ_{seq}. They quantify the following sequence attributes that are related to reactivity: the time locality in terms of overall auction span, the amount of competition and whether the sequence resulted in a winner change. The auction is composed of one or more sequences.

The eBay auctions from this case study have a small average number of sessions per sequence, just 1.53, since it is common to find one or more sequences with just one session in all auctions. On the other hand, the average number of sequences per auction shows that the dynamics of the negotiation is rich, which motivates their analysis. Another aspect they analyze is the active and inactive times of the auctions. The active time is the total time during which the auction has activity, that is the sum of the sequence times. They expected a short active time per auction, since there are usually long intervals between sets of bids, but an active time of just 1.72% is much lower than their initial expectation. This motivates the auction representation they provide through their hierarchical model.

Table 1 presents the hierarchical characterization. Based on the sequence attribute values, there are 15 valid combinations (since the 3 possibilities of *Time-Locality* = I and *Winner's Impact* = w are not valid because all initial sequences change the winner) to describe patterns of auction's sequences. Considering the session's characterization, all the 16 possible patterns are valid. In order to simplify the sequence and session patterns representation, we adopt letters (lowercase or uppercase) as labels. For example, the sequence pattern IZW (initial sequences, with zigzag competition and winner changing) and the session pattern OtrW (session with one bid, non-trigger, non-recurrent, and winner changing). Each criterion of both the sequence and session has mutually exclusive values.

This detailed characterization of bids, sessions, sequences and auctions provides a new approach for understanding the negotiation patterns and bidding behavior. By focusing on the sequences that comprise an auction, we can better understand the negotiation patters that evolved in the auction. Similarly, when we focus on the sessions that an individual bidder participated in throughout an auction, his bidding behavior in that auction emerges. The next subsections present the characterization methodology for auction negotiation (Pereira et al., 2007c) and bidding behavior (Pereira et al., 2007a).

3.2 Auction Negotiation Characterization

As previously mentioned, each auction is composed of a set of one or more sequences and can therefore be described by a vector, whose 15 components are the types of possible sequences, and the values are the relative frequency of each sequence pattern.

To identify auction negotiation patterns, they group together vectors that exhibit similar distribution of sequence patterns by applying clustering algorithms (Bock, 2002), more specifically the k-means

(Hartigan, 1975). The ideal number of clusters is determined through the metric beta-CV, as described in (Menascé and Almeida, 2000). The analysis pointed out 7 as the best number of clusters for auctions.

Table 2: Distribution of Cluster's Sequences.

Sequence	Clusters						
	A0	A1	A2	A3	A4	A5	A6
(I-N-W)	0.0	0.0	20.0	47.2	0.0	15.5	15.6
(I-S-W)	0.0	40.8	0.7	0.0	0.0	1.1	1.1
(I-Z-W)	0.8	0.0	0.4	0.0	8.7	1.4	0.2
(M-N-w)	0.0	3.3	8.6	1.1	0.0	36.3	10.1
(M-S-w)	0.0	0.7	1.1	0.8	0.0	1.9	1.2
(M-Z-w)	0.0	0.0	0.0	0.0	0.0	0.0	0.1
(M-N-W)	0.0	5.8	14.0	1.1	0.0	16.4	44.2
(M-S-W)	0.0	5.6	31.6	0.0	0.0	5.6	7.7
(M-Z-W)	0.0	3.0	2.6	2.7	0.4	2.7	2.9
(F-N-w)	0.0	6.4	2.8	11.5	0.0	3.0	2.2
(F-S-w)	0.0	2.2	1.0	1.5	0.0	1.1	0.8
(F-Z-w)	0.0	0.5	0.3	0.3	0.0	0.1	0.1
(F-N-W)	99.2	10.5	5.1	16.6	0.0	4.7	4.8
(F-S-W)	0.0	12.7	6.5	11.1	90.9	5.1	5.4
(F-Z-W)	0.0	8.5	5.3	6.1	0.0	5.1	3.6
Freq.(%)	19	4	16	12	1	20	28

Table 2 shows the frequency distribution of the 15 possible sequences for the clusters. The last row of the table shows the percentage of auctions that falls in each cluster. Based on this result, we can describe each cluster. Due to lack of space, we present only some examples:

A0: auctions with very small number of sequences, almost all of them unique and without competition. All of them change the winner, as expected, once the first sequence always do it in eBay.

A3: a set of auctions with characteristics similar to *A1* in terms of the number of auction sequences and winner changing. However, most of their sequences do not present competition (77.4%).

Table 3: Auction analysis.

Aspects	Clusters						
	A0	A1	A2	A3	A4	A5	A6
St. Bid (US$)	71.4	36.4	20.9	47.1	43.3	16.9	17.7
Duration (days)	2.7	4.5	5.1	4.9	4.9	5.7	5.8
#Bids	1.1	9.7	16.3	4.8	5.4	15.8	17.1
#Bidders	1.0	5.0	7.5	2.7	3.0	7.1	7.5
1st Price (US$)	72.1	67.3	73.5	64.3	57.3	82.7	81.2
2nd Price (US$)	71.9	65.6	71.8	59.9	56.2	80.3	79.3

Once determined the seven auction clusters, they analyze the relationships between auction inputs and outputs with the negotiation. Table 3 shows some important aspects for each cluster. It presents two auction negotiation inputs (aspects defined before negotiation starts - starting bid and duration) and four outputs (aspects determined after negotiation ends - number of bids and bidders, 1st and 2nd Prices).

A0 has the highest *starting price* and the shortest *duration*. Although we previously identified low activity and competition, it is interesting to note that these auctions achieve a high winner price (the *average 2nd price* is US$71.9). These can be explained by the fact that they present a very high *starting price*, very close to the final price obtained.

A3 and *A1* have similar characteristics, but different behavior in terms of competition profile. It is important to note that they produce different results: the average number of bids and bidders for *A3* is almost half of *A1*, which can be demonstrated by the competition level. Moreover, the final negotiation price is almost 10% higher for auctions of *A1*.

3.3 Bidding Behavior Characterization

In their approach, the bidding behavior can be characterized by a distribution of session patterns, that is, a frequency of occurrence of each valid session pattern. Therefore, the bidding behavior exhibited by each bidder in an auction is represented by a vector with the following components: 16 session patterns resulted from the combination of attributes (*Size*, *Activity*, *Recurrence*, and *Winner's Impact*) described in Table 1 and 9 other values inherited from the sequence the session is inserted in (considering *Time-Locality* and *Competition*). Combining these 16 session patterns and these 9 session attributes inherited from its sequence, there are 144 possibilities.

They then augment the vector by adding two additional variables: *ToE* and *ToX*. These two variables were used in (Bapna et al., 2004) and stand for the time of entry and time of exit of the bidder in the auction and are measured through the timestamp of the first and last bid respectively. They decide to consider these timing attributes, since it is very important to identify in which part of the auction negotiation a bidder starts and ends her/his participation.

Similarly to the classification of auction patterns, they also use a clustering technique to determine groups of similar bidding behaviors. The analysis pointed to 16 as the best number of clusters. Due to lack of space, we present only some examples:

B0: bidders who act in initial (53%) and intermediary (44%) negotiation sequences, in sequences with 70% of competition, from which more than 80% have successive type. Most of their sessions have only one bid (57%), are triggered (63%), non-recurrent (74%), and change winner (76%). They act during the earliest stages of the auction negotiation (24-33% of duration time), placing 2.6 bids in average. These bidders represent 4.3% of bidding behaviors.

B1: these bidders mainly act in intermediary sequences of the auction (91%) and in competitive situations (91%) with successive type predominance. Most of their sessions have more than one bid (89%), are triggered (91%), non-recurrent (76%), and change winner (92%). They act late in the auction negotiation (85-88% of duration time), placing 3.4 bids in average. They represent only 1.8% of the bidders.

B2: act in the last auction sequences, 74% with competitive situation (40% of zigzag type). Their sessions have more than one bid in 68%, are triggered in 76% and change winner in 65%. Moreover, they are bidders who have not participated in the negotiation yet, called non-recurrent bidders. They represent 11.5% of the bidding behaviors, act after 99% of auction negotiation timing, placing 2.4 bids in average.

B3: bidders that act typically in intermediary sequences (93%), in scenarios with no competition (85%). In general, their sessions have only one bid (89%), are triggered (88%), and change winner (89%). Only 28% of them have already participated in the current negotiation before (recurrent). They act typically after the middle of the auction negotiation, from 72 to 78% of negotiation timing duration. They are a popular class, occurring in 12.9% of the bidding behaviors. They place 1.7 bids in average.

Based on the results obtained in these previous works, in the next section we present an analysis of bidding behavior evolution over time.

4 EVALUATING TEMPORAL ASPECTS

As previously mentioned, in this section we discuss each question presented in section 1. This section's analysis are based on the characterization presented in last section. We divide this section in subsections that analyze each one of the questions.

4.1 Behavioral Changes

Here we address the questions: *Are there changes in the bidding behavior over time? What are these changes?* In order to understand how bidder behavior evolves over time, we capture the temporal series of bidding profiles that each bidder displayed in each auction he participated in. We also capture each transition between pairs of profiles i and $i+1$, $i+1$ and $i+2$ etc. This characterization is like a dominoes game, where each piece represents a bidder behavior transition, and can be represented by a directed graph.

A directed graph or digraph G is an ordered pair $G = (V,A)$ where V is a set of vertices or nodes, and A is a set of ordered pairs of vertices, called directed edges, arcs, or arrows. An edge $e = (x,y)$ is considered to be directed from x to y; y is called the head and x is called the tail of the edge. Each bidding behavior profile is a vertex and each transition (that represents a temporal change in the bidder's profile) is an edge.

We called this graph as a *Bidding Behavior Model Graph* (BBMG), that is based on Customer Behavior Model Graph (CBMG) (Menascé and Almeida, 2000). This is a state transition graph that has one node for each possible bidding behavior and the edges are transitions between these profiles. A probability is assigned to each transition between two nodes, representing the frequency at which these two profiles occur consecutively.

Since we are interested in finding typical bidding behavior and how they evolve over time, more than identifying the probability of transition from one bidding behavior to another one, we want to quantify how a state (bidding behavior) is being reached from source states. In order to do this, we create a matrix of bidding behavior profiles, which consolidates all transitions by all bidders. Each row shows the number of transitions from source state to any other one, including itself. This matrix is showed by Table 4.

In the matrix, the sum of all transitions of each row represents the state's outdegree, which quantifies all the transitions from a profile to any other one. Analogously, each column has all transitions into each profile. The sum of each column is the profile's indegree.

We analyze each profile, observing the most frequent transitions from and to each of them, represented by measures of indegree and outdegree. Then, we group these profiles by transition similarity and find the following groups of longitudinal behaviors.

- **I**: bidders who keep the same profile and/or change to other similar profiles, such as group II. Group I consists of profiles *B0* and *B5*. This group represents 9.5% of bidding behaviors.
- **II**: this group presents significant incidence of bidding profiles from group I. This group changes to profiles of group III and also present similar incidence of these profiles. Moreover profiles of group II migrate much to group IV, besides receiving some bidders who were group IV. These profiles are very frequent, representing 44.3% of the occurrences. It is composed by bidders from *B3*, *B6*, *B7*, *B9*, *B11*, and *B13*.
- **III**: this group has bidders that typically migrate to profiles in groups II and IV. It also receives an equivalent number of transitions from these groups, establishing an exchange relation with them. These profiles represent 10.0% of bidding behaviors. *B1*, *B8*, *B10*, *B12* and *B15* belong to this group.
- **IV**: this group has profiles that have high incidence (indegree). They tend to keep in behaviors from themselves (group IV). Although they also exchange with behaviors from groups II and III, their outdegree to these groups is smaller than their indegree. This group is composed by bidders from *B2*, *B4* and *B14*. Together they represent 36.2% of bidding behaviors.

Analyzing these groups and transitions between them, we identify some temporal trends in bidding behavior. Group I tends to migrate to II and, with small frequency, to IV. Group II presents a strong trend to change to IV and has an exchange relation

Table 4: Bidding Behavior Profiles - Matrix of Transitions.

From / To	B0	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	OutDegree
B0	114	7	28	78	53	106	53	41	29	43	13	25	12	34	17	11	664
B1	9	16	42	46	79	18	34	22	6	41	11	10	20	52	21	4	431
B2	44	39	516	182	553	46	51	73	17	107	62	101	72	203	322	26	2414
B3	112	37	200	637	358	160	132	235	42	167	75	175	64	300	129	51	2874
B4	84	84	553	373	926	61	146	181	24	196	119	158	142	431	342	82	3902
B5	107	11	34	141	54	266	41	63	40	45	16	34	4	38	50	10	954
B6	56	21	70	141	135	57	108	98	26	115	29	57	38	81	25	19	1076
B7	77	23	79	281	172	122	98	266	28	79	67	81	20	140	46	36	1615
B8	23	4	15	55	24	39	13	21	21	35	5	17	3	15	12	2	304
B9	94	39	138	183	214	70	115	78	18	163	26	71	56	102	45	17	1429
B10	22	13	54	79	116	15	30	62	6	28	55	23	18	80	34	22	657
B11	50	19	86	153	135	89	43	80	24	55	35	121	20	89	90	17	1106
B12	22	18	79	49	116	6	25	16	8	41	17	28	33	79	28	8	573
B13	65	29	243	330	405	47	75	143	20	104	74	112	47	281	148	39	2162
B14	19	6	176	82	250	30	20	32	3	29	17	43	14	75	294	12	1102
B15	11	3	30	51	72	14	22	50	5	19	20	22	9	44	13	16	401
InDegree	909	369	2343	2861	3662	1146	1006	1461	317	1267	641	1078	572	2044	1616	372	21680

with group III. Group II is a very popular group: almost all bidders have already belonged to it. Group III is a group of transient behaviors. Finally, group IV represents typical end states, since there is a strong flow into it, mainly from group II. We can conclude from this analysis that, besides the isolated trends of each group, there is a typical trend to evolve to bidding behaviors of group D. Moreover, considering the amount of transitions that come to and leave from group I (without the reincidences), it can be seen as an initial state, that often migrate to II. Despite the differences from groups II and III, both of them are intermediary states of the typical trend observed in the analysis.

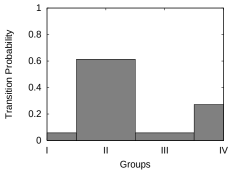
In order to enrich this analysis, it is important to investigate the typical characteristics of each group, using semantic aspects of the negotiation. To do this, we consider the aspects related to how they act in the negotiation, that is, the reactivity aspects inherited from the methodology presented in Section 3.3. An analyze of these semantic aspects of each group is presented following:

- **I:** they act during the earliest stages of the auction (24-33% of duration time). Bidders here have not participated in the negotiation yet; they are the so-called non-recurrent bidders. As expected from the previous characteristics described in section 3, their sessions are typically triggered (76%) and change winner (65-95%).
- **II:** they act typically after the middle of the auction negotiation, (72 to 80% of duration). In general, these bidders participate in scenarios with no competition. Cluster B13 is an exception; its bidders act late (91-93% of duration time) with competition (94%), predominating successive type.
- **III:** usually act after the middle of the auction negotiation, close to the end of it (82 to 94% of negotiation duration). An exception is the cluster B8 that act during all auction. They act typically in situations with successive competition type. They represent the rarest bidding behavior profiles.
- **IV:** bidders who act very late in the auction, close to 99% of auction negotiation timing. In general, these bidders act in scenarios with competition (successive and zigzag types). Most of them are non-recurrent bidders and change winner.

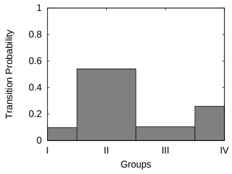
From these observations, it is possible to identify similar semantic characteristics for each of these four groups, which describe some interesting behavioral changes over time.

As previously explained, group I can be seen as an initial state. Thus, initially, bidders act during earliest stages of the auction negotiation and almost always become the auction winner. However, they rarely remain winners until the end. Bidders of group I often migrate to II, an intermediary state of the observed trend. In group II, bidders change to profiles of the same group or migrate with high frequency to IV. Therefore, bidders start to act very close to the final of auction in scenarios with high competition. This improves their chances to win the auction, since they are close to the end. Group II also presents a exchange relation with III that act close to the end with successive competition type. However, both of them are intermediary states of the typical trend, tending to change to IV. Bidders from group I also tend to migrate directly to IV with low frequency.

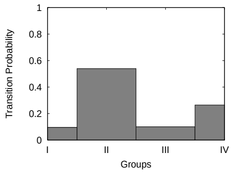
As we can observe in these analysis, there are some changes in bidding behavior over time. Initially, bidders tend to act during earliest stages of the auction negotiation. Later, when they acquire more experience they start acting close to the end of auction. This trend sometimes is fast (I migrating directly to IV), however it usually occurs gradually, where bidders first pass through intermediary states, acting in the middle of the auction negotiation. Another trend is correlated with competition. Initially, bidders act in situations without competition, then in scenarios with successive competition type, and later with high competition (successive and zigzag types). This can be explained by the increasing trend of the bidders to act at the end of the negotiation, thus increasing the competition at the end of the auction negotiation.



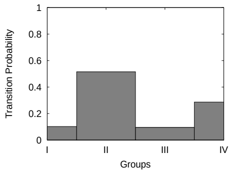
(a) Group II - May



(b) Group II - June

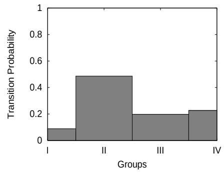


(c) Group II - July

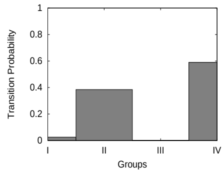


(d) Group II - Aug.

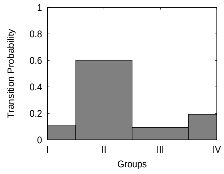
Figure 1: Transition Probability Histogram. - Time Scale.



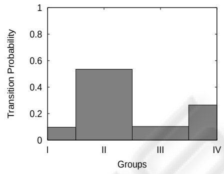
(a) Group II - A2



(b) Group II - A3



(c) Group II - A6



(d) Group II - All Actions

Figure 2: Transition Probability Histogram.

4.2 Time Scale Analysis

We now investigate the second main question presented in section 1: *Are the changes random? Are there trends?* In order to do this, we divide the dataset in four months: May, June, July and August.

We apply the same approach presented in the last section to create the bidding behavior matrix for each period. By analyzing these matrices, we investigate each profile, finding the most frequent transitions from and to each of them, represented by measures of indegree and outdegree. We identify the same four typical groups of bidding behavior presented in last section and the same trend.

In order to illustrate this trend, we group the profiles that belong to the same group and compute the transition frequency histogram of each group in different periods. Due to lack of space, we presented in Figure 1 only histograms for group II. As expected, we can observe the histograms are very similar. This occurred in the same way for the other groups, that is, they present the same trend.

We can observe that the bidding behavior changes over time are not random; the trend really exists. We also observed some additional differences. There are some bidders that evolve faster while others evolve more slowly. Others differences occur between profiles within the same group, for example, different number of bids and in some profiles, bidders change the winner more frequently than others. Our hypothesis is that these differences occur motivated by different negotiation patterns due to the user reactivity to different environment conditions (auction negotiation characteristics).

4.3 Reactivity in Behavioral Changes

We now present an analysis to answer the last question presented in section 1: *Does reactivity affect these changes over time?* In order to do this, we group the profiles that belong to the same group and compute the transition frequency histogram of each one of the four groups in different auction negotiation patterns, introduced in section 3.1. The goal is to identify whether these histograms are similar or not. Due to lack of space, in Figure 2 we present only the histograms for the auction negotiation patterns A2, A3, A6 and for all dataset for group II.

As we can observe in Figure 2, the behavioral trends are different for the auction negotiation patterns. For example, the trend of bidders from A6 is very similar to the average trend for all dataset. However, the bidders from A2 and A3 present different trends. Bidders from A2 tend to migrate to group IV slower than A3, and many bidders from group II migrate to III. For bidders that act in A3 there is a short faster to migrate from group II directly to group IV.

In this analysis we consider the behavioral changes between successive auctions of the same auction type. However we ignore the auctions of other categories in which bidders had participated between these successive auctions. This process is analogous to sequence mining patterns (Agrawal and Srikant, 1995). That is, given a sequence pattern like $I_1;:::$ $;I_n$ that I_i is a item, we want to find relevant subsequences in this pattern, without the need to be adjacent.

Despite this simplification, our approach is able to answer the third question, that is, the reactivity affects the changes over time. For a more accurate evaluation of how reactivity influences the evolution trend and which factors are more relevant, we need to perform a more detailed analysis, which is part of ongoing work.

5 CONCLUSIONS

In this work we developed a longitudinal analysis of bidding behavior considering reactivity patterns through bidder-auction interactions. In order to do this, we first apply a reactivity characterization methodology for online auctions, presented in recent research, to identify auction negotiation patterns as well as bidding behavior in a real case study of an online auction's service (eBay).

We then analyze the bidding behavior evolution over time by considering the sequence of exhibited bidding behavior by each bidder. We represent these sequences as a directed graph (*Bidding Behavior Model Graph*) in which each bidding behavior profile is a vertex and each transition (that represents a temporal change in the bidder's profile) is an edge.

Analyzing this graph we identify some changes in bidding behavior over time. We observe that initially bidders tend to act during earlier stages of the auction negotiation without competition. Later, when they acquire more experience they start acting close to the end of the auction with high competition. We proceeded to divide the longitudinal dataset in different periods and apply this same approach on each period. We observe the same trend in each sub-period of the dataset, and conclude that the patterns of changes are not random. We also apply this approach using different previously established auction negotiation patterns to demonstrate that the negotiation influences the evolution of bidder behavior. We are able to demonstrate that the reactivity patterns that bidders are subject to during negotiation affect the bidding behavior evolution.

The results can be applied to define seller's strategies, forecasting of economic models, or to design decision support tools for e-commerce, for example.

As future work, we want to conduct a detailed analysis of how reactivity influences bidding behavior evolution, identifying the main factors that affect it. Since auctions involve both bidders and sellers, we also plan to generate insights on how sellers learn over time.

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