ANALYZING EBAY NEGOTIATION PATTERNS

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Abstract: Online auctions have several aspects that violate the common assumptions made by the traditional economic auction theory. An online auction can be seen as an interactive economic information system, where user-system interactions are usually very complex. It is important to note that the interactions are not isolated, but successive interactions become a loop-feedback mechanism, that we call reactivity, where the user behavior affects the auction negotiation and vice-versa. In this paper we describe a new hierarchical characterization model for online auctions and apply this model to a real case study, showing its advantages in discovering some online auction negotiation patterns. The results demonstrate that our characterization model provides an efficient way to open the auction dynamics's "black box". We also propose an abstraction named Auction Model Graph (AMG) which enables the temporal analysis of the negotiation. This work is part of a research to analyze reactivity in e-business, that may contribute to understand the business dynamics and has wide applicability to activities such as designing recommendation agents, service personalization, and site interaction enhancement.

1 INTRODUCTION

Online auctions have several aspects that violate the common assumptions made by the traditional economic auction theory. The auction duration is typically much longer than in traditional auctions; bidders may enter and exit at any time; bidders are geographically dispersed all over the world; they have very distinct backgrounds and it is hard to predict how many bidders will end up participating in the auction.

An online auction may be seen as an interactive economic information system, where user-system interactions are usually very complex. It is important to note that the interactions are not isolated, but successive interactions become a loop-feedback mechanism, which we call reactivity, where the user behavior affects the auction negotiation and vice-versa.

An online auction is a rather complex e-business application to characterize because of its many attributes and dynamic aspects. It has an initial state defined by its input parameters, such as the beginning date and the starting bid. Its intermediary state is the phase when the negotiation occurs through bids. The final state occurs after the negotiation and is characterized by its output parameters, such as the winning price, the winner bidder, and the number of bids.

In this paper we describe a new hierarchical characterization model for online auctions. Despite the existence of other characterization models (Roth and Ockenfels, 2002; Bapna et al., 2004; Easley and Tenorio, 2004), none of them is capable of understanding the factors that explain the auction dynamics (Achtert et al., 2005), which is the basis of our research. Moreover, we apply this model to a real case study, showing the advantages of our model in order to discover the online auction negotiation patterns.

This work is part of a research to analyze reactivity in e-business, which has wide applicability for activities such as designing recommendation agents, service personalization, and site interaction enhancement (Chelcea et al., 2005).

The key aspect of reactivity is how users, or bidders in the case of online auctions, react to system's or application's behavior. The behavior may mean

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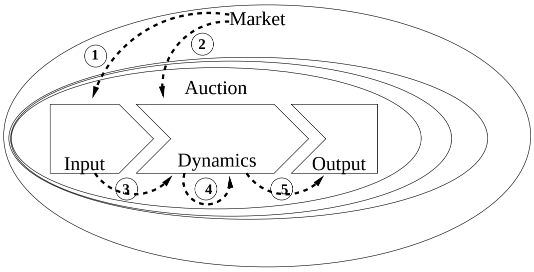

1) How the market affects the input?
2) How the market affects the dynamics?
3) How the input affects the auction dynamics?
4) How the auction dynamics affects itself?
5) How the auction dynamics affects the output?

Figure 1: Auction Dynamics - Reactivity.

the performance of the system in the case of a physical level analysis, or business rules and dynamics in a logical level view. At the physical level, we have modeled reactivity (Pereira et al., 2004) and quantified its impact (Pereira et al., 2006b) on the performance of Internet services. The logical view of the service, e.g., how the business dynamics affect the user behavior, is the current focus of our research. We chose online auctions as the application to analyze, sine it is a popular, rich and complex online service.

Figure 1 shows a high-level representation of the auction. There are five different reactivity dimensions to analyze, as illustrated by the numbered questions.

The paper is organized as follows. Section 2 provides an overview of related work in the realm of online auctions. Section 3 presents the hierarchical characterization model. Section 4 describes our case study of eBay, showing the main results through the application of our model. Finally, Section 5 presents the conclusions and outlines ongoing work.

2 RELATED WORK

Online auctions have been studied extensively lately. Many studies focus on validating concepts from the classic economic theory of auctions in the online environment. For example, Lucking-Reiley (Lucking-Reiley, 1999) checks the validity of the well-known results of revenue equivalence. Bajari and Hortacsu (Bajari and Hortacsu, 2003) address how the starting bid set by the seller affects the winner's course. Gilkeson and Reynolds (Gilkeson and Reynolds, 2003) show the importance of a proper starting bid price to attract more bidders and make an auction successful.

The growing popularity of auction sites on the Internet and the increasing importance of online auctions as exchange mechanisms have attracted the attention of academic researchers who have studied such issues as the effect of auction formats (Lucking-Reiley, 1999), the last-minute bidding phenomenon (Roth and Ockenfels, 2002) and the value of seller reputation (Melnik and Alm, 2002). However, these studies are still limited to how they explain bidding behavior over the entire sequence of bids, as opposed to simply summary outcomes (e.g., final auction prices, and number of bids) in an auction (Ariely and Simonson, 2003; Chakravarti et al., 2002).

For addressing the issue of reactivity in online auctions, it is important to take into account the work that has been done on analyzing bidders' and sellers' behavior in online environments (Easley and Tenorio, 2004). Roth and Ockenfels (Roth and Ockenfels, 2002) study the timing of bids, and the impact of different methods of specifying auction deadlines. By comparing eBay and Amazon auctions, they find evidence that auctions held with a "soft" ending time discourage late bidding (also known as "sniping"), a common behavior observed on eBay. Using data from ubid.com, Bapna et al. (Bapna et al., 2004) develop a cluster analysis approach to classify online bidders into four categories: participators, evaluators, opportunists, and sip-and-dippers. In another paper, Bapna et al. (Bapna et al., 2003) develop a simulation model emulating bidders' behavior to analyze their impact in the outcome of the auctions.

Although there are several detailed studies of online auctions, none of them deals with reactivity. We believe that this concept will allow a better characterization of online auctions and other distributed applications, qualifying and quantifying temporal and sequencing aspects.

3 CHARACTERIZATION METHODOLOGY

This section presents our hierarchical characterization model, which applies the concept of reactivity to gain a better understanding of the dynamics of online auctions.

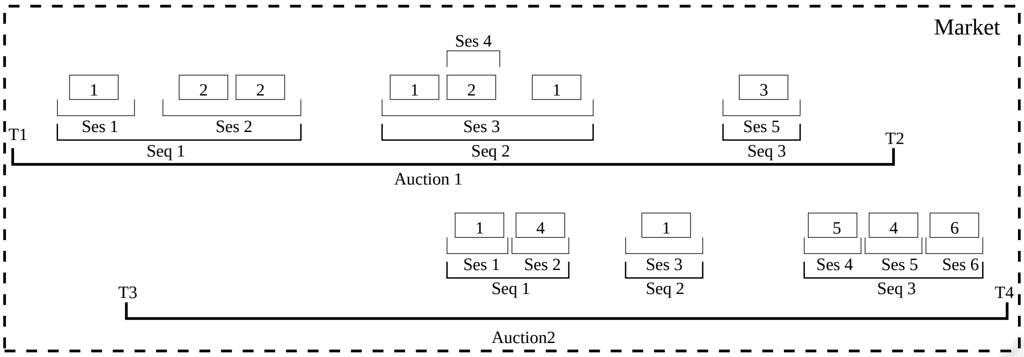

Figure 2: Auction Hierarchy.

Previous auction characterizations (Bapna et al., 2004; Bapna et al., 2003; Roth and Ockenfels, 2002) consider mainly the static aspects, as discussed in Section 2. We propose a novel model that is able to capture the relevant information about the auction features to understand its dynamics. These criteria analyze the auctions at various levels of granularity and are organized in a hierarchy.

A reactivity model defines *agents* who react to *events* through *actions* (Pereira et al., 2006a). In the online auctions environment, agents are bidders, their actions are their bids, and events are bids from other bidders. Another important concept in the reactivity model is the *time to react*. In online auctions, because of its long duration, the intermittent nature of the bidders' visits to the sites, and their own behavior characteristics, the time to react induces the occurrence of both synchronous and asynchronous reactivity periods. Synchronous in our model means two actions occurring during the same period of activity.

In our characterization model we have incorporated these ideas in the definition of the basic components of the model. The important objectives are to isolate, measure and understand periods of synchronous and asynchronous reactivity, how reactivity leads to competitiveness, and the instantaneous impact on the auction winning price, and the winner. These are basic components necessary to understand the auction dynamics.

There are two key concepts for modeling reactivity: activity and synchronicity. One auction is active if bid occurred within a time threshold θ_{ses}. One auction is synchronous when it is active and more than one bidder submitted a bid within θ_{ses}.

As illustrated in Figure 2, our characterization model is organized as a five-level hierarchy: bid, session, sequence, auction, and market. The bid (represented by rectangles containing a number that identifies the bidder) is the finest grain level, representing the bidder's action. 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 delimits activity intervals for each bidder. The sequence is a group of one or more sessions, where the inactivity period between two consecutive sessions is below a threshold θ_{seq}. Notice that $\theta_{ses} \leq \theta_{seq}$. Each auction is modeled by a group of sequences and the market is the set of all auctions. In Figure 2, the labels $T1$ and $T3$ represent the beginning of two auctions, and the end is defined by $T2$ and $T4$. In the case study presented in this work, we adopt θ_{ses} and θ_{seq} as 90 minutes. We choose this threshold after an analysis of the inter-bidding time of the auctions.

Table 1 shows our proposed characterization criteria for sequences and sessions. According to this sequence characterization, there are 15 valid combinations to describe patterns of auction's sequences. Considering the session's characterization, there are 32 valid patterns. In order to simplify the sequence and session patterns representation, we adopt letters (minuscule or capital) as labels, such as the sequence pattern IZW (initial sequences, with zigzag competition and winner changing) and the session pattern OStrW (session with one bid, serial competition, non-trigger, non-recurrent, and winner changing). It is important to emphasize that each criterion of sequence (e.g., Time-Locality) and session (e.g., Size) is mutually exclusive.

The next section presents a case study that applies this characterization model to actual data.

4 CASE STUDY: eBAY

This section presents our case study. We apply our model to an actual dataset that consists of 8855 eBay auctions comprising of 85803 bids for Nin-

Table 1: Description of Auction Model Hierarchy- Sequences and Sessions.

Sequence	Time-Locality	Initial (I)	It is the first sequence of the auction.
		Intermediary (M)	It is an intermediary sequence of the auction.
		Final (F)	It is the last sequence of the auction.
	Competition	No competition (N)	The sequence does not present competition, only one bidder's session.
		Successive competition (S)	Exists a competition, but there is no overlap between bidders' actions.
		Zigzag competition (Z)	Characterizes a more direct competition, where one or more bidders compete with each other in more than one occasion in the sequence.
	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)	The session has just one bid.
		More (M)	The session has more than one bid.
	Competition	Serial (S)	The session does not overlap with any other one.
		Parallel (P)	The session is concurrent with other(s), defining a parallelism.
	Activity	Non-Trigger (t)	The session does not initiate the sequence's activity.
		Trigger (T)	The session 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.

tendo GameCubes from $05/25/2005$ to $08/15/2005$. eBay (EBay, 2005; Anderson et al., 2004; Bajari and Hortacsu, 2003) employs a non-trivial mechanism of second price auction, hidden winner, and hard auction closing, in a typical complex online auction environment that demands characterization models that allow more detailed analysis.

A statistical study of this dataset finds that the number of distinct sellers is high (5453), which shows that auctions are not concentrated among a small number of sellers. The number of distinct bidders is also high (18073), indicating high level of competition. On the other hand, from this set of bidders, just very few of them become winners (735); the mean variation of price between new and used products is small, however the standard deviation of the prices is very high; and there is a significant number of average bids per auctions (11.59), which suggests the level of competition during the negotiation. This is confirmed by the average number of unique bidders per auction, which is greater than 5.

Table 2 presents some auction information that is important to better understand its dynamics. From the original dataset, we consider auctions with bids that achieve success in the negotiation, selling the item. This group represents 75.7% of the complete dataset. We can see that the average number of sessions per sequence is small, just 1.53, since it is common to find one or more sequences with 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 our analysis. Another aspect we 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. We 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 beyond our expectations.

According to our characterization model, each auction is composed by a set of one or more sequences, therefore we can describe each of them as a distribution of sequence patterns, that is, a frequency of occurrence of each valid sequence pattern (see Table 1). For example, if an auction has four sequences, from which two of them are IZW and the other two are ISw, then this auction is represented by 50% of IZW, 50% of ISw and 0% of other sequence patterns.

Amongst the diversity of auctions observed in our dataset, some of them exhibit similar distribution of sequence patterns. To analyze the auction negotiation patterns in our case study, we use a data mining technique called clustering (Bock, 2002) which partitions the analyzed data into clusters of similar data. More specifically we use the clustering algorithm k-means (Hartigan, 1975). This type of algo-

Table 2: Auction Characterization - General Statistics.

Auctions	#Seq	#Ses	#(Ses/Seq)	#(Seq/Auct)	#(Ses/Auct)	T_{act}	T_{inact}
6707	29575	45201	1.53	4.41	6.74	1.72%	98.28%

Table 3: Distribution of Cluster's Sequences.

Sequence Patterns	Clusters							
	0	1	2	3	4	5	6	7
1 (I-N-W)	17.53	0.00	18.28	0.00	47.19	0.00	0.00	21.61
2 (I-S-W)	0.12	12.85	0.19	0.00	0.00	44.74	0.00	0.02
3 (I-Z-W)	0.04	6.15	0.10	8.76	0.00	0.00	0.87	0.07
4 (M-N-w)	8.77	14.77	37.45	0.00	0.00	1.42	0.00	8.71
5 (M-S-w)	1.31	1.49	2.01	0.00	1.04	0.44	0.00	1.18
6 (M-Z-w)	0.08	0.07	0.08	0.00	0.00	0.00	0.00	0.00
7 (M-N-W)	43.10	24.12	14.99	0.00	1.15	2.94	0.00	12.65
8 (M-S-W)	7.91	13.99	5.22	0.00	0.00	3.59	0.00	31.15
9 (M-Z-W)	3.47	3.39	3.13	0.00	3.44	2.12	0.00	2.90
10 (F-N-w)	2.20	2.97	3.67	0.00	10.32	5.99	0.00	2.71
11 (F-S-w)	0.82	1.11	0.94	0.00	1.62	2.67	0.00	1.09
12 (F-Z-w)	0.13	0.15	0.12	0.00	0.32	0.44	0.00	0.33
13 (F-N-W)	5.02	3.58	4.89	0.00	16.57	11.90	99.13	5.21
14 (F-S-W)	5.66	4.97	5.28	91.24	11.72	13.94	0.00	6.92
15 (F-Z-W)	3.86	10.39	3.67	0.00	6.63	9.80	0.00	5.45
Frequency (%)	22.90	7.53	16.25	1.45	11.70	4.56	18.75	16.85

rithm is a technique well known to partition a heterogeneous group of entities (in the case, online auctions) into clusters that have similar characteristics. In our case study, we want to determine clusters of auctions that present the same probability distribution of sequence patterns. The ideal number of clusters is determined through β-CV, as described in (Menascé and Almeida, 2000; Menascé; et al., 1999). In our datasets we found eight clusters.

Table 3 shows the probability distribution of sequences for the clusters. We have the frequency of occurrence for each of the 15 sequence patterns and also the percentage of auction in each group (the last row of the table). This result is very interesting, showing different negotiation patterns for each group of auctions. We can describe each cluster as:

- cluster 0: represents auctions with a high number of sequences with the presence of initial (I), intermediary (M) and final (F) patterns. They have only 23.5% of competition, divided in 2/3 of successive and 1/3 of zigzag competition. Almost 87% of sequences change the winner.
- cluster 1: consists of auctions with high activity, high level of competition (54.5%) from which 37% is zigzag type. Almost 80% of the auction sequences changes the winner.
- cluster 2: group of auctions with a large number of sequences, but with low competition level (20.7%). It is similar to cluster 0, however the number of sequences that changes the winner is much smaller, just 55.7%.
- cluster 3: represents auctions with predominance of low level of activity (sequences). Most auctions in this cluster have just one sequence. The competition level is maximum, with 91.2% of successive and 8.8% of zigzag competition types. As expected , all sequences change the winner.
- cluster 4: consists of auctions with medium level of activity, most of them with two activity moments. Most sequences do not present competition (75.2%) but change the winner (86.7%).
- cluster 5: a set of auctions with similar characteristics of cluster 4 in terms of number of auction sequences and winner changing. However these auctions present a high competition level (77.7%), from which 85% is successive.
- cluster 6: group of auctions with very small number of sequences, almost all of them unique and with no competition. All of them change the winner, as expected, once the first sequence always changes the winner in eBay.
- cluster 7: has auctions with high activity, a significative amount of competition (49%), with predominance of successive type (8 in each 10 sequences with competition). Moreover, 86% of

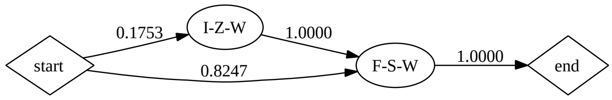

Figure 3: AMG - cluster 3.

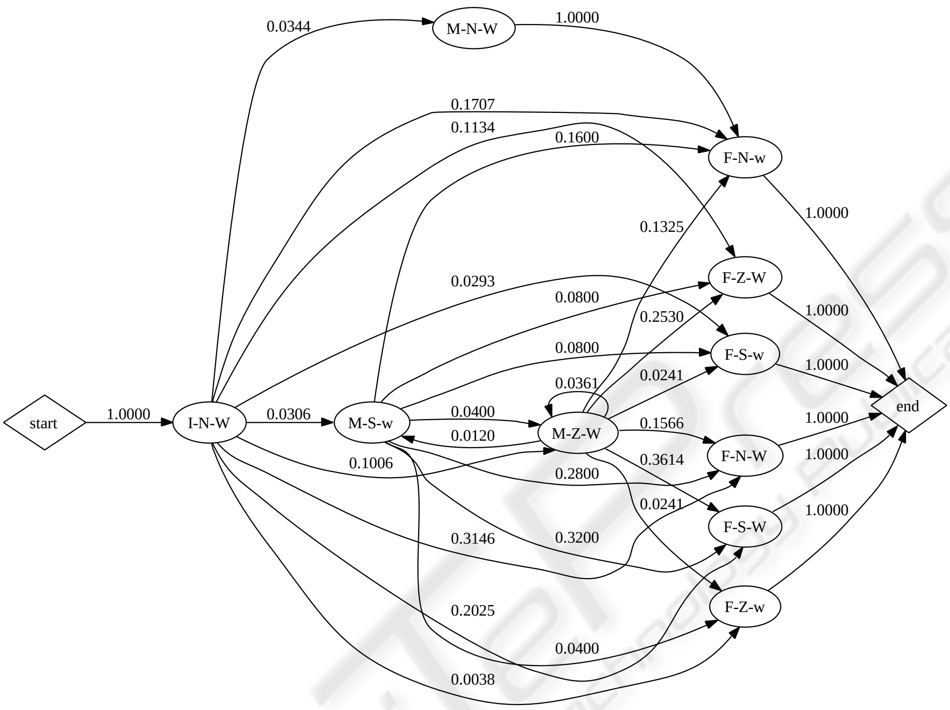

Figure 4: AMG - cluster 4.

auction sequences changes the winner.

Table 4 shows some important aspects about auctions for each cluster. It presents two auction negotiation inputs and four outputs. AVG means the average value of the attribute. This is an example of the reactivity analysis introduced in Figure 1, in which we start to explore the relationships between inputs and reactivity and between reactivity and outputs. Cluster 1 has the lowest *starting price*, the highest *duration*, and the highest *2nd price*, that represents the auction winner price in eBay. It is interesting to emphasize that cluster 1 presents high competition level and activity. Cluster 3 has an average duration of 5 days and an average starting price of US$41.32. In these set of auctions we identify very low activity and high competition level. The mean number of bids is only 5 (associated to 3 bidders). This cluster has the lowest *2nd price*, that can be explained in part by its low activity, that occurs mainly at the end of the negotiation. Clusters 4 and 5 have similar characteristics, but different behavior in terms of competition profile, as previous explained. However it is very interesting to note that they produce different results: the average number of bids and bidders for cluster 4 are almost half of the cluster 5, which can be explained by the competition level. Moreover, the final negotiation price is almost 10% higher for auctions of cluster 5. Cluster 6 has the highest *starting price* and the shortest *duration*, that are negotiation inputs. In terms of its dynamics, we previously identified low activity and competition. However, it is interesting to note that these auctions achieve a high winner price (the *AVG 2nd price* is US$71.99). These can be explained by the fact that these auction's sellers set a very high *starting price*, very close to the final price obtained. It is important to emphasize that we do not exhaust the inumerous possibilities of analysis, however these preliminar analysis shows how interesting and promising is our novel

Table 4: AMG analysis.

Aspects		Clusters 0	1	2	3	4	5	6	7
Inputs	AVG Starting Price (US$)	18.78	11.91	17.39	41.32	46.92	38.55	71.4	20.27
	AVG Duration (days)	5.9	4.8	5.8	5	4.9	4.5	2.7	5.3
Outputs	AVG #Bids	16.75	19.76	15.29	5.04	5.15	9.21	1.16	16.07
	AVG #Bidders	7.35	8.34	6.88	2.98	2.87	4.78	1.05	7.48
	AVG 1st Price (US$)	81.21	82.29	82.22	55.31	65.02	68.05	72.2	74.12
	AVG 2nd Price (US$)	79.32	80.62	79.68	54.3	60.67	66.09	71.99	72.33

work.

The frequency distribution of sequence patterns allow us to understand the overall auction negotiation patterns, however it is not possible to analyze the temporal aspects of the negotiation, that is, how the auction develops across time. This aspect is important to complement the analysis and also to allow the possibility to generate an online auction synthetic workload. In order to provide a way to do this complementary analysis, for each identified cluster of auctions, we create an Auction Model Graph (AMG). AMG, that is based on Customer Behavior Model Graph (CBMG) (Menascé and Almeida, 2000; Menascé; et al., 1999). This is a state transition graph that has one node for each possible sequence pattern and the edges are transitions between these sequences. A probability is assigned to each transition between two nodes, representing the frequency at which these two sequences occur consecutively in a cluster.

Due to lack of space we present in this paper only two AMGs, to illustrate the usefulness of this approach and as the wealth of details that it provides. Figures 3 and 4 show the AMG of clusters 3 and 4, respectively.

The AMG presented in Figure 3 is very simple. In this cluster, 17.53% of the initial sequences of the auction is represented by zigzag competition and they are succeeded by final sequences with successive competition. The other group denotes auctions with unique sequences of type F-S-W.

The AMG of Figure 4 is more complex than the previous AMG and through its analysis it is possible to understand details of the auction negotiation pattern. We can realize that there is not any auction with unique sequence and that all of them begins with the sequence pattern I-N-W. About 83% of the auctions from this group has a second period of activity where the negotiation determines the end of the auction. In these auctions sequences, 49% has already defined their winners in the initial activity period while 51% has determined the winner in the last auction's sequence. The other 17% of auctions have at least one more intermediary sequence before the auction resumes. Moreover, it is interesting to note that the competition arises at the end of the auctions (final sequences), where we observe 43% of competitive sequences and the predominance of zigzag competition type.

As we can see, the details presented in these graphs are so rich, and through them its possible to model an online auction workload and design new service personalization policies.

This analysis is an example of how our model can help the understanding of the auction dynamics and is the basis for reactivity modeling, as we explained in Section 1.

The application of our characterization model to an eBay dataset demonstrates that our proposal provides a way to open the auction dynamics's "black box". We are aware that these results must be validated against a larger dataset and realize that we should characterize auctions using sequences, and bidders through sessions. By doing this, we will have a better semantic characterization, since the current work shows that it is difficult to explain some specific behavior through a general data analysis. In the next section we present our conclusion and ongoing work.

5 CONCLUSION

This work presents a new hierarchical characterization model for online auctions, which provides novelties in order to model and understand the factors that characterize and explain the auction dynamics, differently of other characterization models (Roth and Ockenfels, 2002; Bapna et al., 2004; Easley and Tenorio, 2004). Moreover, we apply this model to an actual dataset that consists of 8855 eBay auctions, showing the advantages of our model in order to discover the online auction negotiation patterns.

Applying a data mining technique called clustering, which sorts the analyzed data into clusters of similar data, we found out eight clusters in our datasets. This result is very interesting, showing different negotiation patterns for each group of auctions considering not only static and aggregated measures, but the auction dynamics, a novelty for online auctions research. We also introduce the Auction Model Graph (AMG) to analyze the temporal aspect of the negotiation. This aspect is important to complement the analysis and can also be used to generate an online auction synthetic workload.

This work is part of our ongoing research to analyze reactivity in e-business. We hope that, by understanding the reactivity patterns in relation to the negotiation features and specific business rules that govern the auction environment, we will be able to conceptualize and design a comprehensive framework to model reactivity. Also, studying reactivity may benefit the economic analysis of Web-based environments, such as marketplaces.

As future work we are going to characterize the bidders. Characterizing both bidders and auctions will allow us to conduct in-depth analysis of reactivity patterns that emerge in auction negotiations.

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