Reactivity in Online Auctions

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Abstract. Interactive computer systems, that is, systems in which users cyclically interact by getting and providing information, have already a widespread and increasing use in all areas of our society. One characteristic of such systems is that the user behavior affects the system behavior and vice-versa. There is strong evidence that much of the user behavior is reactive, that is, the user reacts to the instantaneous conditions at the action time. This paper presents the reactivity concept and describes a framework to model it in interactive systems, in particular Internet-based systems. We analyze an online auction within the framework. Based on *eBay* data, we identify attributes that affect the winner bidders' behavior, such as the auction time to finish. This paper presents the first findings towards the formal description and understanding of reactivity patterns in an e-commerce application, which will be useful in improving the application and building novel mechanisms.

1 Introduction

Interactive computer systems, that is, systems in which users cyclically interact by getting and providing information, have become very useful in our society. From bank transactions to cell phones, we are continuously interacting with systems and even with other users through these systems. A significant part of the interactions is synchronous, that is, users submit information to the system and wait for a response, then submit more information and so on. The Web is an example of such a rich environment for interaction pattern.

User-system interactions are usually complex and intriguing. It is quite hard to determine exactly the factors that lead a user to behave as we may observe. The information we have about users is sparse and variable, in terms of both the instantaneous conditions surrounding the observed behavior and the users' background. It is important to note that the interactions are not isolated, but successive interactions become a loop feedback mechanism, where the user behavior affects the system behavior and vice-versa.

There is strong evidence that a significant part of the user behavior is reactive, that is, the user reacts to the instantaneous conditions. As a consequence, user behavior varies according to some factors related to the server and the application.

This work presents the reactivity concept, describing how to model it in interactive systems, in particular Internet-based systems. We propose a framework to model reactivity in interactive systems and present a case study of applying it to online auctions, based on *eBay* data.

The paper is organized as follows. Section 2 provides an overview of related work in the realm of online auctions. Section 3 explains the concept of reactivity, discussing how it may be modeled. Section 4 presents our case study showing the reactivity modeling online auctions. Finally, Section 5 presents the conclusions and outlines ongoing work.

2 Related Work

An auction is the process of buying and selling goods by offering them up for bid, taking bids, and selling the item to the highest bidder. In economic theory, an auction is a method for determining the value of a commodity that has an undetermined or variable price. Online auctions present 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 can come 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. Instantaneous reactivity in such environments plays an important role, which we plan to address in our research.

Online auctions have been studied extensively lately. Many studies focus on testing results from the classic economic theory of auctions in the online environment. For example, Lucking-Reiley [1] tests the well-known results of revenue equivalence. Bajari and Hortacsu [2] address how the starting bid set by the seller affects the winner's course. Gilkeson and Reynolds [3] show the importance of a proper starting bid price to attract more bidders and make an auction successful.

The widespread use of reputation and feedback systems and their impact on the outcome of online auctions has also received considerable attention. Resnick and Zeckhauser [4] and Ba and Pavlou [5] examine the effects of bidder and seller reputations on auction outcomes, concluding that seller reputations are correlated with auction success on eBay.

In addressing the issue of reactivity in online auctions, it is important to consider the work that has been done on analyzing bidders' and sellers' behavior in online environments. Roth and Ockenfels [6] study the timing of bids, and the impact of different methods of specifying auction deadlines. Comparing eBay and Amazon auctions, they find evidence that auctions held with a “soft” ending time discourage late bidding or “sniping”, common on eBay. Using data from ubid.com, Bapna et al. [7] develops a cluster analysis approach to classify online bidders into four categories: participators, evaluators, opportunists and sip-and-dippers. In another paper, Bapna et al. [8] develop a simulation model emulating bidders’ behavior to analyze their impact in the outcome of the auctions.

Looking at sellers’ strategies, Anderson et al. [9] find that various types of sellers have diversified strategies for PDAs listed in eBay. They also show that sellers with higher feedback scores are more likely to release more information about the items for sale. Kauffman and Wood [10] model opportunistic sellers’ behavior in coin auctions in eBay because of information asymmetry.

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, for instance, temporal aspects. We have already studied reactivity in system’s performance. In [11] we model reactivity in this context and [12] quantifies its impact on the performance of Internet services.

Reactivity has been widely studied in the database context [13, 14], and more recently has been applied also in Web semantic research [15]. Also, event-condiction action (ECA) paradigm [16, 17] is an interesting topic in this context.

Our reactivity concept can be considered in any Web-based systems characterized by user-system interactions. The reactivity concept we are presenting in this paper has a novel semantic, once its objective is to model the dynamics of e-business applications, like online auctions. In this context, there are not specific related works.

3 Reactivity Modeling

This section introduces our concept of reactivity. Reactivity emerges naturally whenever there is the possibility of a feedback on the user-system interaction. Our approach is based on the concepts of action and perception. Actions are all activities performed by users while interacting with the systems. On the other hand, perceptions are the set of criteria through which the user evaluates the service being provided.The goal of our analysis is to correlate actions and perceptions, as a means of identifying the user behaviors.

We define reactivity as the set of pairs perception-action associated with each user, that is, we model how the user acts as a function of his/her perception of some criterion. We classify reactivity according to two dimensions: (1) Performance: in this case, the user action considers performance measures, such as response time; (2) Business Rules: in this case, the user action considers business rules, such as the negotiation parameters of an e-business application.

Our approach may be divided into three steps: (1) the framework is instantiated for an application and reactivity dimension; (2) application-related data is translated into framework elements; and (3) behaviors are characterized in terms of action-perception pairs.

In this paper we focus on Internet-based services where the business-rules dimension is important. One example of such service is an auction, where the negotiation characteristics may affect directly the bidder's behavior.

We model the reactivity as a tuple $< App, Ses_{App}, S, E, Ac, P, PC >$, where App is the application, Ses_{App} is an application session (an instance of the application by a user), S is the set of states that the application may assume, E represents the set of entities that participate, Ac is the set of actions that may be executed by the entities, P is the application protocol, and PC is the set of perception criteria that characterize the reactivity.

App describes the service or object being provided. The Ses_{App} is adopted once it describes the set of actions performed by the entities that will define the interaction process. P represents the protocol, that is, the application functioning - rules that define which actions can be executed by the entities according to the application states. Each rule has the form: Source State $\xrightarrow[Action]{Entity}$ Target State. The protocol rules define the state transition graph.

Once we have a reactivity model, we can try to identify some correlation between the perception criteria (PC) and the set of actions that an entity may execute. This function will be used to add the reactivity concept to the traditional interactivity model. Once we instantiate the framework, we translate observations in terms of the framework components, so that we may analyze them.

4 Case Study: On Line Auction

In an auction there are two entities, the buyer and the seller. The English auction [18, 19] is an ascending-price auction. Each auction instance is a session of the auction engine, that is, the sequence of bids related to the sell of a given item. Thus, the seller putting an item for sale is the start of a session. The last bid delimits the end. There are many states in which an auction session may be: *Active*, *Active with Bids*, *Active with Buy-it-now Option*, *Active with Bids and Buy-it-now Option*, *Cancelled*, *Ended with Buy-it-now Option*, *Ended with Sale*, and *Ended without Sale*. The seller may create an auction session, cancel it, and set the "Buy it now" option. The buyer may bid, the most common action, or perform a "Buy it now" offer. During the auction, the "Buy it now" option permits an immediate purchase. There are many attributes that may affect the buyer's action, such as: the number of bids, the current price, the seller's feedback, and the payment method. It is important to stand out that we are interested in this work in business rules as reactivity dimension, that is, we analyse how the business rules tailor user actions. Instantiating the reactivity framework to this scenario we get the result presented in Table 1.

App	Auction Engine
Ses_{App}	Each Auction Instance
S	Created , Active, Active with Bids, Active with Buy-it-now (BIN) Option, Active with Bids and Buy-it-now (BIN) Option, Cancelled, Ended with Buy-it-now (BIN) Option, Ended with Sale, Ended without Sale
E	Buyer, Seller
Ac	Buyer: MakeBid, MakeBuyItNowOffer Seller: Cancel, SetBuyItNow
P	Created $\xrightarrow[Cancel]{Seller}$ Cancelled Active $\xrightarrow[MakeBid]{Buyer}$ Active with Bids Active $\xrightarrow[SetBuyItNow]{Seller}$ Active with BIN Option Active with Bids $\xrightarrow[MakeBid]{Buyer}$ Active with Bids Active with Bids $\xrightarrow[SetBuyItNow]{Seller}$ Active with Bids and BIN Option Active with BIN Option $\xrightarrow[MakeBid]{Buyer}$ Active with Bids and BIN Option Active with BIN Option $\xrightarrow[MakeBuyItNowOffer]{Buyer}$ Ended with BIN Option Active with BIN Option $\xrightarrow[Cancel]{Seller}$ Cancelled Active with Bids and BIN Option $\xrightarrow[MakeBid]{Buyer}$ Active with Bids and BIN Option Active with Bids and BIN Option $\xrightarrow[MakeBuyItNowOffer]{Buyer}$ Ended with BIN Option Active with Bids and BIN Option $\xrightarrow[Cancel]{Seller}$ Cancelled
PC	Number of Bids, Current Price, Seller's Feedback, Starting Bid, Seller Location, Item's Condition, Shipment Fee, Item's Pictures, Shipment Insurance, Payment Method

Table 1: Reactivity Model - Auction

eBay [20] was founded in 1995. eBay boosters claim that, in terms of revenue growth, eBay [9, 2, 4] is among the fastest-growing companies of all time. It has revolutionized the collectible market by bringing together buyers and sellers world-wide in a huge, never-ending yard sale and auction. As of June 2005, there were over 15,000 members in the eBay Developers Program, comprising a broad range companies creating software applications to support eBay buyers and sellers as well as eBay affiliates.

Information	Product			Total
	Nintendo	Sony	Xbox	
# Auctions	8855	17234	9928	36017
# Bids	85803	179057	120021	384881

Table 2: Basic information about the eBay dataset

Statistics	Product		
	Nintendo	Sony	Xbox
Number of auctions with winner	6103	10884	6466
Number of unique sellers	5453	9340	6466
Number of unique buyers that win	735	795	548
Number of unique buyers	18073	39026	26358
Average winner price (overall)	US$ 32.04	US$ 44.21	US$ 49.63
STD winner price (overall)	37.04	51.36	58.87
Average winner price (new)	US$ 35.32	US$ 48.71	US$ 52.97
STD winner price (new)	37.53	60.26	66.10
Average winner price (used)	US$ 31.90	US$ 41.71	US$ 50.34
STD winner price (used)	38.14	49.09	58.12
Average number of bids per auction	11.59	12.38	14.13
STD number of bids per auction	9.43	10.82	11.27
Average number of unique bidders per auction	5.39	5.71	6.48
STD number of unique bidders per auction	3.58	4.23	4.57

Table 3: General statistics about the eBay dataset

This case study is based on eBay data. The data consists of auction data of three different products: Nintendo GameCube, Sony PlayStation 2, and Microsoft Xbox System. The data was collected from $05/25/2005$ to $08/15/2005$, almost three months. Table 2 presents basic information about the auction data, where we can see that there is a significative number of auctions and bids to analyze.

Table 3 presents general statistics, concerning the number of buyers and sellers that participate in the auctions, the auction pricing, the average number of bids per auction, and the average number of unique bidders per auction. STD represents the standard deviation. As can be observed, the STDs are big, showing there are significant variations over the data. This aspect motivates even more the reactivity analysis, once it can be used to explain them. A first analysis on these statistics shows that:

- The number of successful auctions varies from 63% to 69%.

- The number of distinct sellers is high, showing that auctions are not concentrated among a small number of sellers. The top seller has created 186 Nintendo, 223 Sony, and 116 Xbox auctions for each product.
- The number of distinct buyers is also high, guaranteeing high level of competition in this e-market. On the other hand, from this set of buyers, just very few of them become winners.
- The mean variation of price between new and used products is small, however the standard deviation of the prices is very high.
- There is a significant number of bids per auctions, which indicates the level of competition during the negotiation. This information is confirmed by the average number of unique bidders per auction being greater than 5.

The following two aspects are important to reactivity in online auctions, once they are related to dynamic aspects of the auction bids: (1) The inter-bidding time (IBT), i.e., the time between two consecutive bids; and (2) The price difference, i.e., the difference of price between two consecutive bids.

Due to space constraints, only the characterization of Nintendo auctions is presented here. Figure 1 shows the difference of price and time between each consecutive bid for Nintendo. As can be seen, there exists a huge concentration of points where the IBT and the difference of price have small values. However the variation of these two metrics shows that there exists a significant variation over them. In the case of IBT, this variation is very high. Moreover it is not possible to identify a clear correlation between these two metrics. This observation holds for the three different auction products.

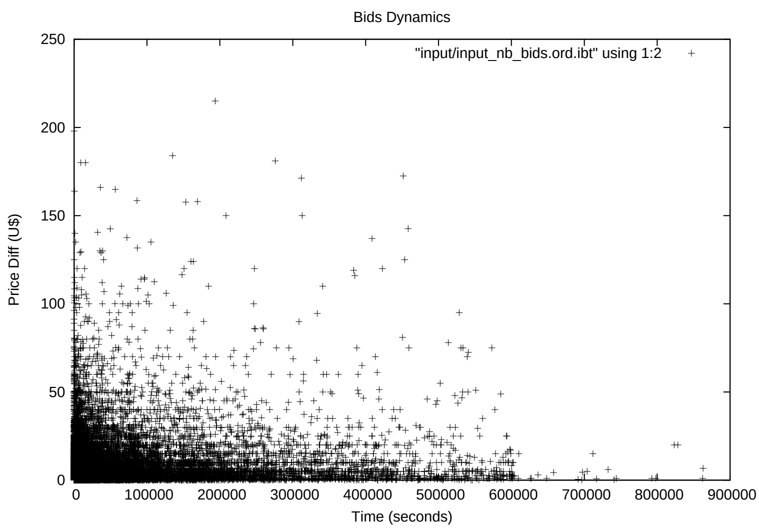

Fig. 1: Bid Dynamics - Nintendo

We analyze the histogram of auction duration for Nintendo, Sony and Xbox. The three sets of auctions present similar duration behavior. Nintendo has more than 40% of auctions during a week and around 15% of them during one day. For Sony and Xbox, the number of auctions with 7-day duration is 40% and 1-day is 20%. The other durations are similar: 20% of three days long and 15% of five days long. Around 5% of the auctions has durations of 2, 4, 6 and 10 days. As can be noted, duration of odd number of days predominate.

In order to analyze the bidders' behavior, we classify them isolating the winner attribute to evaluate how some attributes affect the result of the auction. Initially, we identify the most relevant attributes using an attribute selection algorithm. From 31 attributes, all of them related to business-rules dimension, we select the following attributes to apply the classification technique: BIDDER BIDS REL (Relative Quantity of Bidder Bids), ACTIVE TIME REL (Relative Time between the First and Last Bidder's Bid), BID ENTRANCE REL (Relative First Bid Date), BID LEFT REL (Relative Last Bid Date), AVG DELTA TIME REL (Relative average time difference between two bids of the same bidder in an auction), and AVG DELTA PRICE REL (Relative average price difference between two bids of the same bidder in an auction).

Figure 2 presents the classification tree for the Nintendo auctions dataset. This decision tree is a simple structure where non-terminal nodes represent tests on one or more attributes and terminal nodes reflect decision outcomes. From its analysis it is possible to identify some interesting results:

- 43% of winning bidders make the last bid almost at the end of the auction, their bids represent less than 90% of auction bids, and their average relative delta price consists of small values.
- 34% of winning bidders have made more than 90% of the bids of the auction.
- 9.3% of winning bidders present a small average relative price difference between bids (less or equal than 0.02), a small average relative delta time between bids (less or equal than 0.0145), make less bids than 38.5% of the total number of the auction bids, and make the last bid almost at the end of the auction (BID_LEFT_REL $>$ 0.9993).
- 8.5% of winners present an average relative delta time between bids greater or equal than 0.0145, make less bids than 38.5% of the total number of the auction bids, and make the last bid almost at the end of the auction (BID_LEFT_REL $>$ 0.9996).

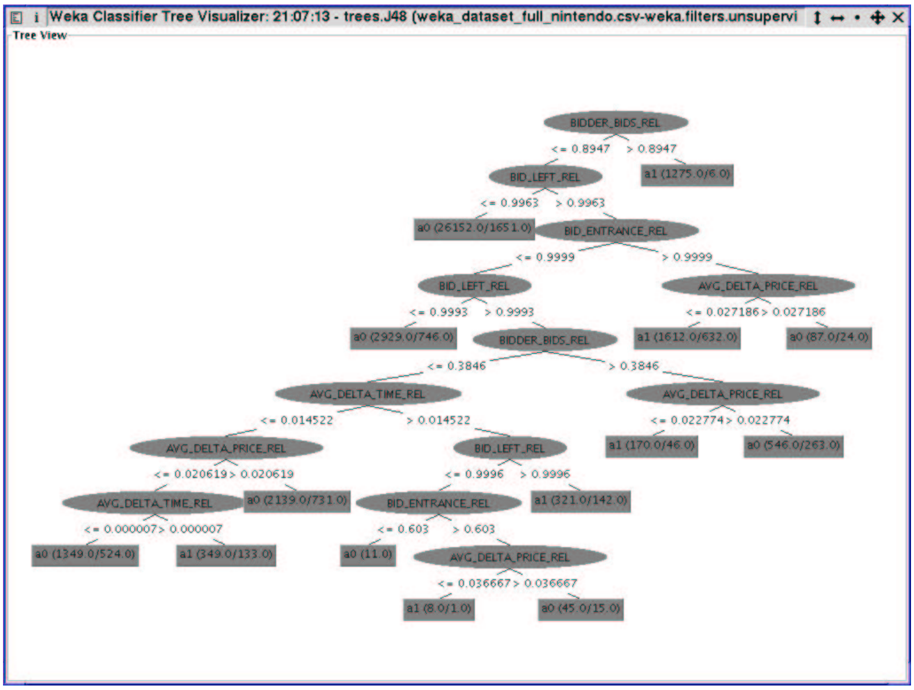

Fig. 2: Classification Tree - Nintendo

– 4.5% of winners present a small average relative price difference between bids (less or equal than 0.0227), make 38.5% to 89.5% of the total number of the auction bids, and make the last bid almost at the end of the auction (BID_LEFT_REL > 0.9993).

From the results of this case study it is possible to identify that there are some aspects that affect the winning bidders' behavior, such as the auction time to finish. Another interesting aspect is that most of the winning bidders make a large amount of bids and/or present a small inter-bidding time. As an expected result, the winning bid has been made near the end of the auction.

The results of the classification for Sony and Xbox auctions are similar to Nintendo. From this analysis, we conclude that is of interest to divide the auction duration in periods to analyze separately. These will help us to understand which factors directly affect the result of the auction, such as the correlation between inter-bidding time and bidding price difference. It will also help in identifying reactivity determinants that explain bidders' behaviors at different stages of the auction.

5 Conclusions and Ongoing Work

This work presents the reactivity concept, describing how to model it in interactive systems, in particular Internet-based systems. We present a case study of an online auction, based on *eBay* data. Although there are some related works of online auctions, none of them models reactivity.

The case study shows some aspects that affect the winner bidders' behavior, such as the auction time to finish and the number of bids of each bidder according to the total amount of auction bids. We identify that winners make a large amount of bids and/or presents a small inter-bidding time.

As ongoing work we divide the auction duration in periods and analyze them separately. These will help us understand which factors directly affect the result of the auction, such as the correlation between inter-bidding time and bidding price difference. This case study motivates us to continue working on improving the reactivity characterization of e-commerce environment.

Modeling reactivity in online auction can contribute to understand the business dynamics and to design more complete automatic agents. We are also confident 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 can benefit the economic analysis of Web-based environments, such as marketplaces.

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