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# Online Bargaining as a Form of Dynamic Pricing and the Sellers' Advantage from Information Asymmetry<sup>1</sup>

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## ABSTRACT

Among the means of implementing dynamic pricing strategies in e-commerce, online bargaining is found to be better than revenue management and online auction, because each deal actually reaches a “win-win” situation for both the buyer and the seller in the sense that the mutually agreed deal price is higher than the seller’s reserved price but lower than the buyer’s reserved price. Such feature brings profit to the seller, as well as savings to the buyer. Meanwhile when bargaining online, there is an information asymmetry between the seller side, i.e. the company side, and the buyer side, which grants a great advantage to the sellers over the buyers. This information asymmetry can be captured and exploited for financial gains through adopting a properly designed online bargaining algorithm.

## Keywords

Information Asymmetry, Online Bargaining, Online Auction, Revenue Management, Intelligent Agent, Dynamic Pricing.

## INTRODUCTION

Dynamic pricing strategy is superior to fixed pricing strategy because prices can be changed in a fairly timely manner when necessary. It has been gaining popularity in the era of digital commerce. The high availability of the data about demand and supply, consumer behaviors, and consumer preferences, etc. provides a basis for dynamic pricing strategies. Meanwhile, digital commerce has drastically reduced of the cost of changing prices in real time.

Online bargaining, as compared to revenue management and online auction, is a very under-researched topic in the field of dynamic pricing. To our best knowledge, only a very few studies have conducted in relation to online bargaining (e.g. Lang and Doong, 2000; Lin and Chang, 2001). However, online bargaining can be the best form of dynamic pricing strategy, in the sense that 1) it takes into account different customers’ valuations toward the same product or service; 2) both the buyer side and the seller side have equal control over the price movement during bargaining; and 3) bargaining can involve multiple dimensions of a product or service, such as price, delivery time, warranty, etc.

When bargaining online, there exists a phenomenon of information asymmetry between the seller side and the buyer side. Such information asymmetry is actually beneficial to the seller side and the seller side can certainly take advantage of it to obtain higher profit gain. A framework of an agent-based online bargaining system is therefore designed to exploit such information asymmetry for the sell side

The paper is organized as follows. First, following a brief introduction to different pricing strategies, we argue that online bargaining is superior to online auction and revenue management in implementing dynamic pricing strategy in e-commerce. Second, we reveal the information asymmetry during bargaining processes. Third, an online bargaining system based on intelligent software agents is proposed to help the seller side capitalize on such information asymmetry. Last, conclusions and future research directions are provided at the end.

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### **FIXED PRICING STRATEGY – A “LOSE AT LOW, LOSE AT HIGH” STRATEGY**

In the traditional commerce market, companies sell their products to customers at a fixed “menu” price, customers could either take it or leave it. Such pricing strategy is called “fixed pricing” strategy. The mass production using rigid but efficient assembly lines and widespread delivery of goods through railways or alike reaching every corner of the world made price negotiation impractical (Wurman, 2001). Besides, the cost associated with changing price at a high frequency throughout the whole distribution chain could be discouraging in the traditional brick-and-mortar business environment.

Fixed pricing strategy assumes that all the customers are the same, i.e. they all have the same utility function towards a product or service. This is certainly not true in the real world. A fan of Britney Spears is probably willing to pay more for a ticket to a Spears’ concert than a non-fan for the same ticket, because the fan usually gains more pleasure from attending the concert than the non-fan. This example illustrates that different consumers do have different utility functions towards the same product or service. In fact, a buyer’s utility function towards a product or service is an important determinant of the price the buyer is willing to pay. A buyer is unlikely to purchase something at a price that is higher than his or her valuation towards it. Otherwise, it becomes a case of “Pay More, Get Less”, which is irrational.

An obvious drawback of fixed pricing strategy is that, if a product with a cost of \$50 is fix-priced at \$100, 1) it loses \$20 of revenue if it is sold to a customer who is actually willing to pay as high as \$120; or 2) it, too, loses \$20 of revenue from a potential customer who is only willing to pay \$70 for the product, because a \$100-priced product won’t be sold for \$70 under the fixed pricing strategy even though it still means a profit of \$20 if sold.

### **DYNAMIC PRICING AND ITS FORMS**

The use of the Internet in commerce has made the pricing strategy much more flexible and dynamic. Technically, it is possible now for companies to dynamically fine-tune pricing strategies in response to changes in demand and supply, i.e. to adopt the “dynamic pricing” strategy. As a matter of fact, dynamic pricing strategies have been increasingly seen on many e-commerce websites. For example, buy.com continuously searches its competitors’ website for low prices and then sets its own prices even lower (Smith, Bailey and Brynjolfsson, 2000). Amazon.com once tried to offer different prices to different customers (Baker, Line, Marn and Zawada, 2001). Under dynamic pricing strategy, the price of a product or service can be changed from customer to customer, from transaction to transaction or even within a transaction (Kannan and Kopalle, 2001).

#### **Revenue Management – A “Self-Centered” Strategy**

Dynamic pricing is not a new invention of today’s information age. It has been in the business world for many years. Dynamic pricing was common, in the form of *revenue management*, in industries like airlines, hotels and electric utilities even before the era of e-commerce. Dynamic pricing methods were used to arrange the sales of these goods and alike to maximize the yield or revenue. One of the important features of these goods is that the sales information of these goods during the sales can be collected and sent to a central location for analysis and prediction in a fairly timely manner, through the use of information technology.

The dynamic pricing practice used in revenue management does not address the issue of different buyers’ different utility functions towards the same product or service either. It narrowly focuses on how to optimally segment products or services to maximize revenue. In a hypothetical airline with particularly simple inventory structure, the revenue management would concentrate on how many tickets should be allocated to Y, M, B, and Q classes respectively with Y-class tickets carrying no purchase or return restrictions and a high price, and M, B, Q-class tickets carrying various degrees of restrictions (Boyd and Bilegan, 2003). The allocation of tickets to different classes is dynamically based on the historic or current sales data, but does not take buyers’ own valuations towards a flight ticket into account. Buyers of tickets in the same class pay same price.

#### **Auction – An “One Party’s Game” Strategy**

*Auction* is another well-known form of the historic dynamic pricing strategy. The price dynamics of auction is reflected in the different deal prices for the same product or service in different auction processes.

Auction has many variations, such as 1) English auction, where the price of a product being auctioned keeps being bid up until no further bids are tendered; 2) Dutch auction, where the price keeps dropping automatically from the high until a bidder stops it; 3) reversed auction, where a buyer names the price and the sellers decide whether to accept or not.

Using auction to implement dynamic pricing method does address the issue of different buyers’ different utility functions towards the same product or service. Buyers who value the product or service high are willing to pay more, and so bid high. The high price paying buyers will outbid the low price paying buyers. The drawback of English and Dutch auction is that it is

the bidding buyers who determine the final deal price; the seller side has little to do with it, other than setting a reservation price before an auction begins. After an auction process starts, the seller side is completely taken out of the process. The final deal price is solely determined by the buyers' biddings; the seller has no control over it. In reversed auction, though the seller side gets to choose whether to take an offer or not, the offer price is still decided by the buyer side indeed.

### Bargaining – A “Win-Win” Strategy

Price bargaining is a process through which a buy and a seller seek a mutually acceptable price for a product or service. A bargaining process ends when both parties agree on a price or either of them quits. The deal price for the same product or service but in different bargaining processes can be different.

Bargaining goes further in using dynamic pricing methods to address the issue of different buyers having different utility functions towards the same product or service. Buyers who value the product or service high are willing to push their offers higher and higher until reaching their valuations, i.e. the reserved price, or until the seller side accepts the offer, whichever comes first. In a bargaining process, the market demand and the valuations of both buyer side and seller side towards the product or service are fully reflected through the prices exchanges through offers and counteroffers. Besides, in bargaining, the seller side is an active, rather than passive, participant in the whole process. It has the equal role in influencing the price movement, i.e. the speed and direction of price changes, based on its own perception towards market dynamics when bargaining.

Using bargaining to implement the dynamic pricing strategy can lead to “win-win” cases for both the buyer side and the seller side, because each final deal price is mutually agreed by both parties. This implies that the seller sells the product or service at the price he or she is willing to sell, and the buyer buys the product or service at the price he or she is willing to buy. Figure 1 is an illustration of a general bargaining process in which the seller gradually decreases his or her offer/counteroffer prices and the buyer gradually increases his or her offer/counteroffer prices, all by following their own price change strategies, until they reach a consensus. Any premium above the seller's reserved price, i.e. the seller's minimum acceptable price, is regarded as the profit gain for the seller. And, any price room below the buyer's reserved price, i.e. the buyer's maximum acceptable price, is regarded as the savings for the buyer. In fact, all deal prices fall in-between both parties' reserved prices in bargaining, otherwise there won't be a deal, so each deal is a win-win situation for both parties.

Due to these superior features, bargaining can be an excellent means for companies to conduct sales in e-commerce. Prior empirical research has also found that consumers prefer online retailing websites that offer bargaining opportunities even though they may not end up getting the lowest price (Liang and Doong, 2000). This further indicates that companies having online retailing web store will be better off if they could offer online bargaining services through their website. However, hiring a large number of sales staff to bargain with customers online could be very costly for companies. Intelligent software agents can be good replacements for online human sales bargainers in such circumstances.

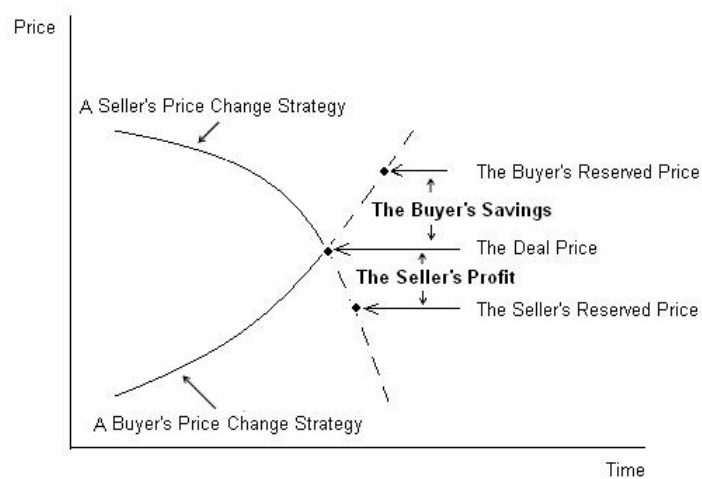


Figure 1 A General Bargaining Process

## INFORMATION ASSYMMTRY BETWEEN SELLERS AND BUYERS DURING BARGAINING

Not only an agent-based online bargaining system could save personnel cost for a company, it also provides the company, i.e. the seller side, valuable real-time information during bargaining processes. And some of the information is only available to the seller side, so it asymmetrically exists. Examples include, but not limited to, 1) how many buyers are currently bargaining with the company on a particular product at a given time? 2) what are the past and current bidding/deal prices on a particular product? and 3) how many deals have been made on a particular product in the recent past?

Such information describes the current market demand, bargainers' valuations towards the products under bargaining, and bargainers' behaviors, which is quite valuable for the company in determining its own bargaining strategies to bargain with buyers. Information asymmetry like this gives the seller side greater advantages over the buyer side during online bargaining. The seller side certainly can capitalize on it to maximize its profit gain. An agent-based online bargaining system built on this idea to exploit such advantages is proposed next.

## A FRAMEWORK DESIGN OF AN AGENT-BASED ONLINE BARGAINING SYSTEM

An agent-based online bargaining system supporting dynamic price change strategy can be modeled after an agent-based decision support system (DSS). According to Hess, Rees and Rakes (2000), an autonomous software agent is "a software implementation of a task in a specified domain on behalf or in lieu of an individual or other agent." (p.6) The advent of autonomous software agents, which are goal-oriented, persistent and reactive, leads the DSS to its second generation (Hess *et al.*, 2000). One of the primary benefits of using agent-based system, as compared to nonagent-based implementation, is to reduce human interactions (Bradshaw, 1997; Maes, 1994).

An autonomous software agent empowered with intelligence allows it to fulfill its task in a more efficient and effective way with less assistance from users. In this case, intelligent selling agents are the replacements of human online sales bargainers. Once an intelligent selling agent is created or activated, it immediately engages in a bargaining process with a potential online buyer with the goal of selling the product to the potential buyer at a price as high as possible. During a bargaining process, the real-time asymmetrical information that the seller side collects can be quantified to form an aggregated variable named *Popularity Index (PI)* of the product currently under bargaining. The *PI* is the measure of the market demand and buyers' valuation toward the product under bargaining. The reactivity of the intelligent selling agents is manifested through their reactions to the change of the *PI* of the product under bargaining. When the *PI* moves up, a selling agent should drop price more slowly or even increase price so as to sell products to high price paying customers, i.e. going after higher profit per item. When the *PI* moves downwards, a selling agent should drop price more quickly so as to sell more products to low price paying customers, i.e. going after higher sales volume. The agents' shifts among different price change strategies (speeds and directions) are autonomous and no human interaction is needed.

The real-time change of a seller's bargaining strategy during bargaining is essential, because it represents the selling agent's prompt reactivity to the market dynamics. Other systems, for instance the one designed by Lin and Chang (2000), do not have such responsive feature. In their system, a selling agent picks a bargaining strategy when it first engages in a bargaining process; the strategy, once chosen, does not change along with the changes of market dynamics.

The following is a modeling of the *Popularity Index*. It is built upon three variables describing the market dynamics, the number of bargainers of the product currently under bargaining (*numBargainers*), the number of recent deals made on the product recently (*numRecentDeals*) and the deal prices (*RecentDealPrices*). This modeling only uses the parameters describing the market dynamics. Certainly, parameters involving bargainers' behaviors, preferences and motivations could be included as well to construct more complicated models.

$$\text{Popularity Index} = w_{nb} * \frac{\text{numBargainers}}{\text{scale}_{nb}} + w_{nd} * \frac{\text{numRecentDeals}}{\text{scale}_{nd}} + w_{np} * \frac{\text{RecentDealPrices}}{\text{scale}_{np}}$$

, where  $w_{nb}$ ,  $w_{nd}$  and  $w_{np}$  are the weight factor and  $\text{scale}_{nb}$ ,  $\text{scale}_{nd}$  and  $\text{scale}_{np}$  are the scaling factors for *numBargainers*, *numRecentDeals*, and *RecentDealPrice* respectively. The values of these weight and scaling factors vary from product to product and company to company; they can be decided through experiments.

Figure 2 shows the framework design for the agent-based online bargaining system supporting the dynamic price change strategy. It is modeled after Hess *et al.*'s agent-enhanced general DSS framework which consists of three systems: the Dialog Generation Management System (DGMS), the Model Based Management Systems (MBMS), and the Database Management System (DBMS) (Hess *et al.*, 2000). The DGMS is responsible for managing the dialogs, i.e. the interactions, with the DSS

users; the MBMS is to manage the different modeling tools and packages for DSS; and the DBMS manages the data involved in DSS.

In our system, the Interface Agents make up the DGMS. These Interface Agents are in charge of the interactions with potential online buyers, such as presenting merchandise information in HTML format, taking offers from buyers, displaying counteroffers from the intelligent selling agents, etc. Interface Agents have been widely used in many agent-based systems involving human contact (e.g. Ba, Kalakota and Whinston, 1997; Hess *et al.*, 2000). An intelligent Interface Agent with learning ability can organize the human-computer interface fitting to the individual buyers' personal preferences to give the buyers a personal touch.

The Intelligent Selling Agents in the MBMS get inputs, i.e. the *PI*, from the Popularity Monitoring Agents and choose an appropriate price change strategy/model from the Model database to make offers and counteroffers. Model Database stores all the price change models. Meanwhile, Intelligent Selling Agents also update the Real-Time Bargaining Information Database to record all the bargaining activities, such as offer prices, counteroffer prices, duration of a bargaining process, deal prices, unsuccessful bargains, etc. The Popularity Monitoring Agents query the Real-Time Bargaining Information Database to supply the popularity information of certain merchandise to the Intelligent Selling Agents upon request.

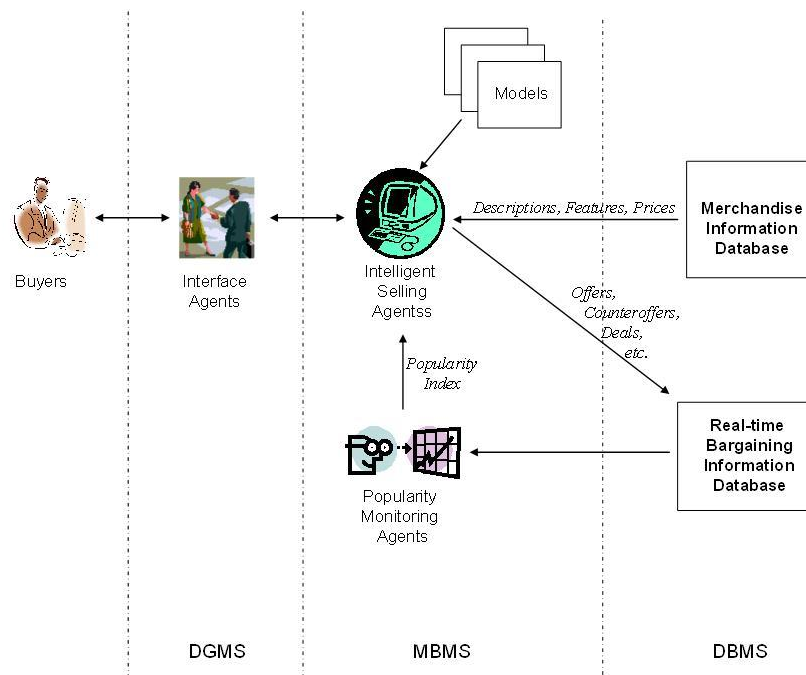


Figure 2 A Framework of an Agent-based Online Bargaining System to Capitalize on Information Asymmetry

The DBMS has two databases: the Merchandise Information Database and the Real-Time Bargaining Information Database. The Merchandise Information Database stores the information about merchandise to be sold, such as merchandise descriptions, features, specifications, starting bargaining prices, reserved prices, etc. The Real-Time Bargaining Information Database records all the bargaining activities of all the Intelligent Selling Agents as discussed earlier. Popularity Monitoring Agents analyze this database to determine the popularity of a particular kind of merchandise, such as the number of online bargainers of certain merchandise, the number of deals made on certain merchandise in the near past, etc.

**FUTURE RESEARCH DIRECTIONS**

In order to examine the real performance of the agent-based dynamic bargaining proposed above, detailed bargaining algorithms based on the *Popularity Index* need to be developed. And computer simulations can be used to study the effects of the algorithms before implementation<sup>2</sup>. Simulation is the preferred method in the cases where mathematical reasoning and modeling are very complicated or even impossible. A bargaining process is indeed fairly complicated because it involves many factors, such as the distribution of buyers' reservation prices, the distribution of the buyers' arrival to the market, the

<sup>2</sup> The work of algorithm development and simulation is currently underway.

buyers' negotiation patience and aggressiveness, etc. Computer simulation is a very good method to study behaviors of the bargaining market and its outcomes. DiMicco, Maes and Greenwald (2003) used computer simulation to study their dynamic pricing strategies under different models. The Information Economics group at IBM Research also used simulation to investigate the potential impact of widespread use of shopbots on prices (see Kephart, Hanson and Greenwald, 2000).

## CONCLUSIONS

Dynamic pricing strategy is superior to fixed pricing strategy because prices can be changed in a fairly timely manner when necessary. In bargaining, each deal is a "win-win" situation for both the buyer and the seller. This is achieved through a mutually agreed deal-price that is higher than the seller's cost but lower than the buyer's valuation towards the product or service being bargained. In addition, both the buyer and the seller are actively involved in the whole process to reach the ultimate deal price, and multiple dimensions of a product or service can be included in a bargaining process. In this sense, online bargaining is a better choice than online auction or revenue management in implementing dynamic pricing strategy in e-commerce.

While hiring human sales personnel to bargain with customers online is not economically practical for a company, intelligent software agents can be good candidates to serve the role of online human sales bargainers for the company. Meanwhile, there is an information asymmetry between the seller side and the buyer side, which gives a great advantage to the seller side over the buyer side. Properly designed online bargaining systems can capture such information asymmetry for financial gains.

Last, we perceive that there is a lack of research undertaken in the arena of online bargaining, while there are plenty of issues in relation to online bargaining waiting for answers or solutions. Examples include 1) different bargaining strategies for both the seller side and the buyer side; 2) learning-based bargaining where an agent is able to learn what kind of buyer it is currently deal with, a stingy one or a lavish one; 3) memory-based bargaining where a bargaining system "remembers" and uses a buyer's previous bargaining records to learn the buyer's bargaining strategy, etc. Many topics are actually across multiple disciplines, so we call for collective research in this area.

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