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A Brief Survey on Dynamic Pricing

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Abstract: Dynamic pricing is the alteration of prices dynamically to consumers depending upon the value these customers' property to a product or service. Today's world of e-commerce is ready for dynamic pricing; however, recent research has ushered that the prices will have to be familiar in moderately advanced ways. Based on mathematical models one can infer the gains of dynamic pricing. Dynamic pricing can be formally defined as the buying and selling of products where prices vary quickly in response to need fluctuations.

Keywords:Dynamic pricing, e-commerce, Price optimization,.

I. INTRODUCTION

e-Business companies are currently grappling with the complex task of determining the right prices to charge a customer for a product or a service. This task requires that a company knows not only its own operating costs and availability of supply, but also how much the customer values the product and what the future demand would be [1,2]. A company, therefore needs a wealth of information about its customers and also be able to adjust its prices at minimal cost. Advances in Internet technologies and e-commerce have dramatically increased the quantum of information the sellers can gather about customers and have provided universal connectivity to customers making it easy to change the prices. This has led to increased adoption of dynamic pricing and to increase interest in dynamic pricing research.

There are various dynamic pricing methods; however, they have some characteristics in common. First, pricing strategies should be simple and easy to be implemented in switches and routers. Second, they need to allow dynamic in-session user adaptation because there are significant variations over short and long durations of time for internet traffic. So, the demand for a resource is likely to change during the lifetime of an active flow and a good pricing scheme should reflect the current demand, and let the user be able to respond to these variations. Finally, there should be a stable transmission rate while maximizing its consumer surplus.

This research work covers a wide range of issues in dynamic pricing whereas the above research works are more focused discussing specific issues.

II. FROM FIXED PRICING TO DYNAMIC PRICING

There is a trend in pricing that promises to significantly change the way goods are marketed and sold. Sellers now offer special deals, tailored for individual customers, and are beginning to compute the right price to the right customer at the right time. This change has been largely due to the wiring of the economy through the Internet, corporate networks, and wireless networks. Buyers are now able easily, quickly and compare products and prices, putting them in a better bargaining position. At the same time, the technology is allowing sellers to collect detailed data about customers' buying habits, preferences, even spending limits, so they can customize their products and prices [5]. In the past, there was a significant cost associated with changing prices, known as the menu cost. For a company with a large product line, it could take months for price adjustments to filter down to distributors, retailers, and salespeople. The emergence of network technology has reduced the menu cost and time to near zero. As buyers and sellers interact in the electronic world, the resulting dynamic prices more closely reflect the true market value of the products and services being traded.

2.1 FACTORS AFFECTING THE PAST USE OF DYNAMIC PRICING

For consumer goods, dynamic pricing has occurred in the case of products such as hotel rooms and air travel, because these product classes:

1) Cannot be stored: A loss in potential revenue is incurred if any vacancies occur.

2) Can be classed and priced differently: The possibility of charging different people different rates either for the same product or different product configurations.

3) Centralized order processing: Sales for hotel chains are centralized for some while they are decentralized for others. But all information is available centrally. Consequently, it is possible to track differences in supply and demand for different product configurations at different prices. Hence, a single point of storage and access of information supports a dynamic pricing environment.

4) The high value differential between incremental revenue and incremental cost: Incremental cost of the product, if it is used, is relatively low compared to the revenue generated. Consequently, profitability can be increased through changes in pricing that optimize the tradeoff between high utilization and high average rate per available asset.

5) Temporary and sudden increases/decreases in demand: The potential for periodic increases in revenue due to specific events creates the potential for increased profit through monitoring demand and changing the price accordingly. The advantage of dynamic pricing is that it allows for the management of a firm to vary prices, thereby increasing the difference between price and cost in comparison to firms that use a static pricing model.

III. METHODS FOR COLLECTING DYNAMIC DEMAND DATA

There are a number of different ways to collect demand data to identify and respond to changes in the price-demand relationship with potential customers. In this section, the different possibilities for collecting dynamic demand data—auctions, exchanges, offers to purchase, online surveys and focus groups—are briefly considered here. After these methods of demand data collection are considered, the challenges associated

By all of these alternatives are discussed, followed by a summary of under what circumstances, each method appears to offer the greatest potential.

The Internet fundamentally alters the customer–supplier relationship, empowering both the customer and supplier, by removing the transaction costs associated with imperfect information and vendor search. The Internet is also a viable channel for marketing and selling to customers. Customers no longer need to purchase based only on low cost best- brand association or vendor location [9]. Having considered the Internet as an enabler of dynamic pricing and the advantages of dynamic pricing, the specific methods for collecting dynamic pricing data over the Internet are considered [7]. The methods are: auctions, reverse auctions, exchanges, negotiations and bundle pricing. See Fig.1 for a depiction of these methods.

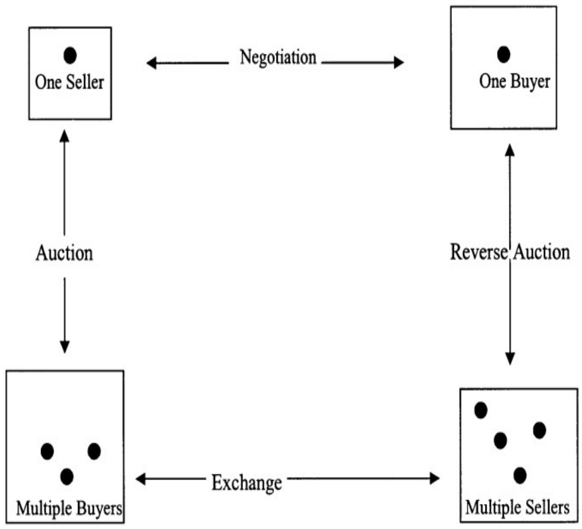

Fig. 1 Model of related interactions used in dynamic pricing.

3.1 AUCTIONS

Interest in auctions has increased as a result of the Internet’s ability to simultaneously reduce the cost of running an auction and increase, by orders of magnitude, the number of potential participants.

Theoretically, the auction offers a forum in which individuals will continue to increase their offering price until they have reached the maximum price they are willing to offer, at which point they drop out of an auction. By collecting data on at what price people cease to bid, one identifies the individual’s demand for a product. This process allows for the identification of the demand for every individual in the auction, except the highest bidder. Auctions such as eBay, allow for bidders to place a confidential maximum bid in the auction, this allows for automatic bidding. The collection of this data also identifies the maximum price that the individual is willing to pay. Auctions hold great potential if it is possible to have a large number of people to bid on the products. Auctions have excellent potential for collecting demand data on expensive and/or unusual products.

3.2 REVERSE AUCTIONS (OFFER TO PURCHASE)

The concept of offers to purchase has also been extended by the use of the Internet. Reverse auction is a transaction format that allows the buyer to procure goods and services at the lowest possible price. In a reverse auction, prospective buyers can list any items they wish to buy, and then sellers bid to provide the best price. The buyer decides the exact specifications of each item, instead of the specifications being dictated by the seller.

The offer to purchase‖ approach has great potential if the time to participate does not outweigh the value of the potential savings. Consequently, to collect data using this method, it may be necessary to offer incentives to obtain participation. For example, free collection and delivery of goods would make such an approach attractive to many people in income brackets that would not normally participate in such a scheme. The offer to purchase and reverse auction approaches offer great potential for a variety of commodities or clearly definable products, but it is unclear for which product it is possible to operate the collection of demand and pricing data on a sustained basis.

3.3 EXCHANGES

Exchanges existed long before the Internet. However, the Internet has increased the number of exchanges serving existing sectors. An exchange involves the transaction of goods or services between multiple buyers and suppliers. Exchanges offer value by inexpensively linking buyer and seller of products in real time. This is being accomplished on the Internet at the expense of brokers and other middlemen that historically have charged a commission or fee to link buyers and sellers profiting from their superior market knowledge. Exchanges exist in a variety of different markets, including: chemicals, steel, and energy [8]. The current belief is that the low entry cost and potential profitability of exchanges has resulted in an oversupply and the number of exchanges will decline over time. This is likely since an exchange value is dependent on the number of buyers and sellers that utilize it. Every new buyer is a potential customer to all sellers and every new seller is a potential supplier to every buyer. Products sold on exchanges are typically commodities that are sold or purchased in either large quantities or smaller quantities on a regular basis with great time specificity. Data from these exchanges could provide useful information on the shifts in demand for a commodity product, assuming that increases in demand by large purchases are indicative of the demand for the purchase of smaller quantities.

3.4 NEGOTIATIONS

Negotiation involves the agreement on terms of a purchase of good and/or service between buyer and seller. Unlike an auction, negotiations typically involve a single buyer and a single supplier. For a supplier, the negotiation begins with his or her first contact with a buyer. Buyers might, however, view a negotiation as an end to a process. For example, in software negotiations, a software supplier helps a buyer to be aware of a number of factors that drive the supplier as well as the motivation of the sales person. Suppliers often study their customers (annual reports, competition, websites) before they engage in a transaction. The terms and conditions are explicitly provided for this auction. These would provide important clues for determining if there is congruence between the buyer and the supplier. Some ―driving‖ factors that might be part of the terms and conditions may include issues such as functionality, initial price, and general business practices.

IV. MODELS USED IN DYNAMIC PRICING

A variety of mathematical models have been used in computing dynamic prices. Most of these models, formulate the dynamic pricing problem as an optimization problem. Depending on the specific mathematical tool used and emphasized, we provide a list of five categories of models.

4.1 MACHINE LEARNING – BASED MODELS

Inventory-based models: These are models where pricing decisions are primarily based on inventory levels and customer service levels.

Data-driven models: These models use statistical or similar techniques for utilizing data available about customer preferences and buying patterns to compute optimal dynamic prices.

Game theory models: In a multi-seller scenario, the sellers may compete for the same pool of customers and this induces a dynamic pricing game among the sellers. Game theoretic models lead to interesting ways of computing optimal dynamic prices in such situations.

Machine learning models: An e-business market provides a rich playground for online learning by buyers and sellers. Sellers can potentially learn buyer preferences and buying patterns and use algorithms to dynamically price their offerings so as to maximize revenues or profits.

Simulation models: It is well known that simulation can always be used in any decision making problem. A simulation model for dynamic pricing may use any of the above four models stated above or use a prototype system or any other way of mimicking the dynamics of the system.

Machine learning has recently emerged as a popular modeling tool for dynamic pricing in the business. In a typical market, the environment constantly changes with demands and supplies fluctuating all the way. In such a scenario, it is impossible to foresee all possible evolutions of the system. [6] The amount of information available is also limited (for example, a seller does not have complete information about the pricing of the competing sellers). With learning based models, one can put all available data into perspective and change the pricing strategy to adapt better to the environment.

The latest and probably most important application of Machine Learning is dynamic pricing. Here, the goal of the pricing process is to maximize the price not in relation to a quantity and consequently to a price elasticity model, but rather to the likelihood of a customer completing a purchase; the model identifies the features or configurations of the product or channel that will maximize the value for the customer, setting a premium price.

4.2 MACHINE LEARNING

ML focuses on developing systems that learn from the data. This involves a training phase where the system learns to complete certain tasks (predictive or classification) using a given data set contains information representative of the problem. After the training phase, the system is able to analyze new data having the same set of parameters and suggest a prediction. Unfortunately, there is no perfect method that is able to solve a particular problem, as there are several that offer best hits and forecasts easily [14] being dependent on the study area. This is an aspect that should be considered before developing a system based on these models and we will review.

A. Logistic regression

The Logistic regression (LR) seeks to achieve the influence of independent variables in predicting categorically the dependence of a variable (which has a number of limit values). This technique is commonly useful for identifying in a dataset the most discriminating variables and its output can only assume predefined values (ex. Positive or negative). These models tend to be less robust than the Artificial Neural Networks (ANN) and Support Vector Machine (SVM) when we are dealing with a complex set of data. However, they use simple linear models to process quick decisions as it is easier to interpret the output and how the decision was made [14].

B. Artificial neural networks

This mathematical model, known as artificial neural networks (ANN), is conceptually similar to SVM [14], interpret the learning process in the human brain using artificial neurons interconnected in a network that identifies patterns in data [15]. A neural network has some inputs and produces one or more outputs applying incremental learning algorithms to process and modify the intensity of the links between inputs, outputs and hidden layers of the network, with observed patterns among the data [14]. The adoption of neural models has several advantages. They are implemented without much statistical training, are endowed with skills which implicitly detect nonlinear relationships between complex, dependent and independent variables and the ability to detect all possible interactions between predictor variables [14]. The disadvantages focus on rational behavior. The perception and the decision is implemented through the hidden layers which is trivial for the user to realize what was decided and why, which does not prone to possible adjustments (because the model describes the error and the random noise rather than the underlying relationship the data) [10]. However, there have been efforts in the perception of this limitation [11].

C. Support vector machines

The Support Vector Machine (SVM), presented by Vapnik [12], is powerful and complex instruments that fit particularly when the classification task is difficult [13]. Examples of an SVM model are a set of data points in space as to become divided into different categories for the widest possible space [14]. These instances are mapped getting divided with regard to its category, space and forecasting using the kernel trick [13]. It is an efficient method for problem solving in pattern recognition and regression and the analysis of handwritten documents, images and time series forecasting. [12].

V. CONCLUSION

Price discrimination is the strategy of charging different prices to different customers for the same product or service offering. One type of price discrimination is based on setting different prices for different groups of customers. Dynamically changing prices is now being viewed as a profit maximizing strategy for companies who garner the power of the Internet to conduct business.

Future research should consider whether demand and pricing data collected over the Internet are generalizable to buyers that are not Internet-based. Reverse auctions have been noted as the data collection method that appears to be most promising for the collection of dynamic pricing and demand data, this being the case, it is of great value to determine for what product categories can the data collection process be operationalized. That is, at what point does transaction costs prevent sufficient potential buyers from participating so that the results are biased and of reduced or little value. Once these two concerns are addressed, testing and validation of the proposed build-to order and build-to-forecast models is recommended. The efficacy of our proposed approach should be quantified by comparing profits for the products under consideration before and after model implementation. An econometric model that estimates profits for those products as a function of factors not under control in our models should be generated. This would ensure that our before-after implementation comparisons are adjusted for different before-after economic conditions.

Further study is required to see if the users will accept these pricing schemes and if any specific scheme can be broadened to handle more applications and scenarios. The former requires users to test different charging schemes to collect opinion.

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