European Journal of Operational Research 237 (2014) 555–565

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Decision Support

Pricing to accelerate demand learning in dynamic assortment planning for perishable products

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A R T I C L E I N F O

Article history:
Received 17 March 2013
Accepted 21 January 2014
Available online 3 February 2014

Keywords:
Assortment planning
Demand learning
Bayesian updating
Stochastic dynamic programming
Retailing

A B S T R A C T

Retailers, from fashion stores to grocery stores, have to decide what range of products to offer, i.e., their product assortment. Frequent introduction of new products, a recent business trend, makes predicting demand more difficult, which in turn complicates assortment planning. We propose and study a stochastic dynamic programming model for simultaneously making assortment and pricing decisions which incorporates demand learning using Bayesian updates. We show analytically that it is profitable for the retailer to use price reductions early in the sales season to accelerate demand learning. A computational study demonstrates the benefits of such a policy and provides managerial insights that may help improve a retailer's profitability.

1. Introduction

The retail industry plays a central role in connecting manufacturers with consumers. Retailers are at the end of the supply chain and form an essential element in a manufacturer's distribution strategy. Assortment planning is integral to a retailer's business and have a significant impact on a retailer's bottom line. While retailing was not one of the pioneer industries in applying operational research (Higgins, 1981), new retailing concepts and practices has made the use of quantitative methods necessary.

Because of its importance, assortment optimization have received significant attention in the operations management and operations research literature. The majority of research in this area assumes that the relationship between a retailer's assortment decisions and the consumers' purchase decisions is known. In other words, demand – the major factor affecting assortment decisions – is assumed to be a known function of the assortment. However, this full information setting is becoming increasingly uncommon in practice. Mass customization and shorter product life cycles because of rapidly changing consumer preferences, are just two factors driving the frequent introduction of new products, for which it is hard to predict demand. Because it is becoming more common that there is insufficient historic data for forecasting future demand, it becomes necessary to put greater emphasis on "exploration" of the market as opposed to "exploitation" of the market. That is, demand learning has to become an integral part of effective assortment management, which is the focus of our research. With learning also comes dynamic decision making. In the presence of full information making decisions once works well, but when demand is learned over time decisions have to be reviewed and revised frequently.

We focus on the size of the market, or the customer arrival rate, as the unknown parameter of the demand function. The size of the market represents the number of people who are interested in a product and are considering purchasing it. Whether they purchase the product or not depends on the price of the product. Our premise is that the distribution of market size can be learned by observing sales, unlike the exact size of the market which is inherently uncertain and cannot be learned. Thus, we advocate and analyze a loop in which at the end of a period demand learning occurs based on observed sales in the period, and the estimate of the demand function is updated before decisions about the assortment for the next period are made. In practice, a substantial amount of uncertainty about the demand process is resolved through early sales information.

One of the most prevalent learning methods is Bayesian updating. Bayesian updating can be used in situations where observations come from a fixed distribution and are used to update information, represented in the form of a prior distribution. In the retailer's context, a manager's belief about the demand function is updated after observing new sales data. Thus, Bayesian updating utilizes both the manager's initial estimate of demand and the observed sales data to revise the demand forecast. We use parametric Bayesian, where the shape of the demand function is assumed to be known, but some of its parameters are unknown.

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http://dx.doi.org/10.1016/j.ejor.2014.01.045
0377-2217/

More specifically, we consider a retailer who has the option to sell a number of different product families and has to decide what assortment of product families to offer and what prices to charge for them. Since we focus on assortment planning at the product family level, we assume that demands are independent and there is no need to consider substitution. This seems reasonable as product families are well differentiated and customers are likely to go to a competitor if a product family is not offered. An assortment decision still has to be made, because insufficient space is available to sell all product families. For presentational convenience, we will use product family and product interchangeably in the remainder.

The retailer does not have full information about the market size of each product. Therefore, the retailer uses observed sales in the early periods of the sales season to update its demand estimates. As the retailer observes the early sales and updates its belief about the demand function, its decisions regarding price reductions also change.

The retailer faces a dilemma when making assortment and pricing decisions if it wants to learn more about demand at the same time. On the one hand, the retailer wants to maximize the revenue based on its current belief about demand by charging the optimal price and choosing the most profitable product families, i.e., it wants to exploit the market. On the other hand, the retailer wants to maximize the learning of the true size of the market by manipulating prices and offering different product families, i.e., it wants to explore the market. We develop a stochastic dynamic programming model that optimally balances the exploitation and exploration of the market.

Our main innovation is the use of pricing to accelerate demand learning. Our computational experiments demonstrate that offering carefully chosen price markdowns for the express purpose of speeding up demand learning can outperform state-of-the-art demand learning strategies. That is, we investigate the benefits of using pricing to influence the observed sales. Note that there is full information about price-response function and, as a result, the optimal price. However, we show that the retailer is better off charging prices below the optimal price to learn about the market size.

There is some practical evidence that pre-season price reductions are beneficial. Sen (2008), for example, reports that "In some merchandise categories, retailers charge introductory low prices for a short period of time before the start of the season. For example, at LDS [the disguised name of a major retail chain], the preseason sale for the winter season is held in late August, and each garment is marked 25% of regular price, or comes with two price tags: one with the regular in-season price and another with a 25% marked down price with a purchase date limitation. The resulting increased store traffic allows the retailer to gather information about the popular colors, styles and garments early enough for appropriate replenishments within season.".

We carefully distinguish between passive and active learning. In passive or off-line learning, the retailer observes sales and uses the observed sales to adjust its belief about the demand and then uses this adjusted belief about demand to optimize assortment and price decisions. In this setting, no assortment or price decisions are taken with the specific intent to learn about demand. Learning takes place, as observed sales are used to update the belief about demand, but it happens in a passive way. In active or on-line learning, assortment and price decisions may be taken with the specific intent to learn about demand, e.g., including a product family in the assortment to observe the effect on sales or setting a lower price to observe the effect on sales. Our analysis and empirical study shows that both passive and active learning are effective strategies in environments in which there is uncertainty about the size of the market, that active learning is more effective.

The remainder of the paper is organized as following. In Section 2, we discuss assortment, pricing, and learning in more detail and review relevant literature. In Section 3, we propose a stochastic dynamic programming model, discuss its approximate solution, and derive some asymptotic results. In Section 4, we present results of a computational study. Finally, in Section 5, we present final remarks and discuss future research opportunities. For convenience, we will use the term product instead of product family from now on.

2. Related literature

Assortment planning, also known as product line selection and product portfolio optimization, is concerned with the problem of choosing which products to offer or display or "put on the shelf". Assortment planning is a key element in retail merchandizing, and as Alan (1993) indicates in an early review, it is a vital factor in the final profitability of retailers. Displaying or offering a larger variety of products increases market share, as it attracts a more heterogenous set of customers and satisfies customers' variety-seeking tendencies (see for example Tang (2006)). The need to choose arises because there is a limit on the number of products that can be offered or displayed, i.e., there is "limited shelf space".

Assortment planning is not limited to traditional bricks-and-mortar stores, which have to decide which products to carry in the store. It is crucial too for modern on-line retailers, which have to decide how to allocate the available screen space on their websites. Similar decision situations arise when space to hold safety stocks is limited or when trained and knowledgeable sales staff is in short supply. In the airline industry, and more generally service industries, assortment planning manifests itself in the selection of fare classes to offer. Of course in this case it is not only the shelf space that is limited, i.e., a limited number of fare classes can be offered, but product inventory, i.e., the seats, itself is bounded.

The value of assortment planning is clearly illustrated by Kök and Fisher (2007), who develop an optimization-based methodology and report that their recommendations for a grocery store chain, when compared with the existing approach, result in profit increases of more than 50%. Similarly, Rajaram (2001) use a nonlinear integer programming model for assortment planning in a large catalog retailer specializing in women's apparel, and report a profit increase of 40%.

Russell and Urban (2010) extend assortment planning by not only deciding a product's allocated space, but also its location: it has been shown that the location of a product affects its sales. They consider a setting in which products are categorized as part of a family, and the integrity of a family should be maintained.

An important aspect of the research in the above-mentioned papers, and much of the assortment literature, is modeling product substitution. Product substitution occurs when a customer's preferred product is not offered and the customer decides to purchase a different, but similar product. See van Ryzin and Mahajan (1999), Mahajan and van Ryzin (2001), Li (2007), Gallego, Ratliff, and Shebalov (2011) for more on product substitution using Multinomial Logit models, Smith and Agrawal (2000) for more on product substitution using exogenous models, and Gaur and Honhon (2006) for more on product substitution using locational choice models. Most of the research related to product substitution in assortment planning assumes that the demand distribution is known in advance and can thus be categorized as *static* assortment planning. We refer to Kök, Fisher, and Vaidyanathan (2009) for an extensive review of the static assortment planning literature with an emphasis on its practical aspects as they arise in retail supply chain management. An exception is Bernstein, Kok, and Xie (2011),