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Markdown optimization for an apparel retailer under cross-price and initial inventory effects

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ABSTRACT

Apparel Retailers have been using markdowns as a means of revenue maximization with an increased frequency. Parallel to this increase, several authors have studied single product markdown optimization problem under various settings or assumed that the products are independent in case of multi-products.

In this paper, we address the simultaneous determination of markdown prices and optimal initial inventory levels under the cross-price effects in a random demand setting for multi-product groups for an apparel retailer chain in Turkey. First, we formulate the problem as a Markov Decision Process that considers price-based substitution and complementary effects among products and maximizes the expected total profit over a finite horizon. Then, we find the approximate markdown policies of each product by using Approximate Dynamic Programming algorithm. We investigate how cross-price elasticity affects the markdown policies of each product by considering several relationships among them, such as the products are all substitute or all are complement or some are substitute and some are complement. In addition to this, we provide insights on how they affect the expected revenues when non-optimal and optimal initial inventory levels are considered. When cross-price effects are considered in case of non-optimal initial inventory levels, average revenue increases about 32% while it increases to 50% when optimal initial inventory levels are in case.

1. Introduction

Markdowns are permanent price reductions such that once the price of a product is marked down, it may not be brought up to the same price level again in the same selling season. The properties of products in which markdowns are common are: i) product orders are placed only once during the selling season because of long manufacturing lead times, ii) As the selling season progresses, the perceived value of the product, and hence customers' willingness to buy the product decrease. A typical example of such products is fashion products with short selling season [18]. The prior studies on markdown optimization have focused only on single product markdowns. However, consideration of multi-product optimization may lead to significant revenue increases since there may be a significant crossprice elasticity among products. Cross-price elasticity measures the percent change in one product's demand when the price of another product increases. It may be either positive or negative depending on whether the demand of a product increases or decreases when the price of another product goes up. If the cross-price elasticity between products A and B is positive, it means that product A is the substitute of product B, since an increase in product B's price causes a demand increase in product A's demand. On the other hand, if the cross-price elasticity between products A and B is negative, then products A and B complement each other since a decrease in product A demand occurs due to an increase in product B price. If these price interactions among products are not considered and product demands are assumed to be independent, a markdown in products' price may decrease the sells of another product because the other product's price may not be marked down sufficiently enough. Such an effect is known as cannibalization in the marketing literature.

In this study our objective is threefold: (i) To develop a mathematical model which can be used in deciding how much markdown to apply when cross-price elasticity among several products is considered. (ii) To provide insights on how substitution and complementary relations among products affect a retailer's markdown policies and expected revenues. (iii) To observe the effects of optimal initial inventory levels on markdown policies and expected revenues. To the best of our knowledge, ours is the first study that

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addresses the simultaneous determination of markdown prices and optimal initial inventory levels under the cross-price effects in a random demand setting for multi-product groups.

Our work is motivated by a request by a leading retail chain in Turkey which owns over 250 stores with an annual sales of one billion dollars approximately. In their request, they asked if we can develop a markdown optimization model which considers cross-price effects among multiple products. Therefore, we consider a group of products which have cross-price elasticities among each other and their demands in a given period are random. First, we develop a Markov decision model (MDP) that maximizes the expected total revenue of the product group over a finite interval. The aim of the MDP model is to find an optimal markdown policy for each product. In the MDP model, a policy specifies the discount percentages applied to each product in each week for all possible inventory levels. However, when there is an interaction among products, MDP model becomes impossible to solve optimally since the number of products is more than two. This is called as "curse of dimensionality". Because the size of the state space makes it impossible to solve the developed MDP model by using conventional solution techniques such as value or policy iteration or their variants, we resort to Approximate Dynamic Programming (ADP) which works better than many heuristics [19]. We use point of sales data (scanner data) collected from the stores to determine the product groups, substitution and complementary effects within the group and forecast the product demands.

Section 2 gives a brief review of the literature in dynamic pricing and markdown optimization. Section 3 develops the MDP formulation. Section 4 explains the approximate dynamic programming algorithm that we developed. Before presenting numerical study, we evaluate the performance of the ADP algorithm in Section 5. In the numerical study in Section 6, our objective is to provide insights on how cross-price relations among products affect the revenue and the markdown policies. Finally, Section 7 summarizes the paper and points out some future work.

2. Literature review

A markdown optimization problem may be posed as a dynamic pricing problem with a constraint which states that consecutive period prices cannot be greater than the current period's price. Therefore, we first review the related dynamic pricing literature. We, then review the markdown optimization literature and point out the similarities and differences between the literature and our work. First studies in dynamic pricing are in the marketing literature. They aimed at understanding what kind of dynamic pricing policies should be used at certain conditions. The very first dynamic pricing problem in retail has been considered by Lazear [15]. He developed a model to explain retail pricing behavior and the time distribution of transactions. Pashigian [17] extended the model in Lazear [15], and provided analytical and experimental evidence that an increase in product assortments causes number of markdowns to increase. Since these studies focused on understanding how markdown strategies are affected by specific conditions, they didn't provide operational tools on the determination of markdowns dynamically. First study aimed at developing an operational tool is Rajan and Rakesh [23]. They considered a single product whose value decreases in time. They assumed that product demand was deterministic and determined the optimal inventory levels and pricing policy. Gallego and Van Ryzin [11] developed a continuous time optimal pricing model in which demand was described by a Poisson process. They determined the optimal prices and developed a heuristic for a single product. Gallego and Van Ryzin [12] generalized this basic model to a network (multi-product) setting where the demand for each product was a stochastic process whose intensity depended on the prices of all products. They examined the performance of heuristic methods based on the optimal solution to the deterministic version, which were shown to be asymptotically optimal. Feng and Gallego [9] developed a Markov process formulation to determine the optimal timing and duration of a single markdown. Feng and Xiao [10] extended Feng and Gallego's [9] work to policies involving multiple and reversible (nonmonotonic) price changes. Bitran and Mondschein [2] considered a similar non-monotonic price change setting and periodic pricing policies that modified prices only at prespecified times for a single product. They characterized the optimal pricing policy as a function of time and inventory. Bitran et al. [3] also considered a single product, however in more than one store. They modeled it as a dynamic program, however; due to "curse of dimensionality" they developed a heuristic and tested its performance by using retail data. The first study that uses MDP setting in markdown optimization is Mantrala and Rao [16]. They developed an MDP-based decision support system to help retailers to decide on optimal merchandize order quantities, i.e., optimal season starting inventory and markdown levels for each period. The decision support system used point of sales data as in our study, however; since it was for a single product, they did not consider the price correlations. Similar to Bitran et al. [3], Mantrala and Rao [16], Heching, Gallego and van Ryzin [13] also analyzed historical demand and pricing data from various firms in order to develop an operational markdown optimization model and to generate useful insights on the likely additional revenue and the pricing policy differences if the markdown optimization model was used. An important additional step was taken in Smith and Achabal [26], and Valkov [28], which described the implementation and use of markdown optimization systems by various companies, and reported the results of markdown optimization systems. Smith and Achabal [26] considered multiple products in a deterministic demand setting, and developed a nonlinear mathematical model to determine optimal inventory levels and markdown prices for the products. Caro and Gallien [5] studied the development, implementation and use of an operational markdown optimization modeled by a leading fast fashion retailer with complete descriptions and technical details. Aviv and Pazgal [1] assumed that there was a single price reduction at a fixed time and they studied the optimal pricing of fashion-like seasonal goods, in the presence of forward-looking (strategic) customers, characterized by heterogeneous valuations that declined over the course of the season. Cachon and Swinney [4] looked at quick response in the presence of strategic customers. They considered a retailer that sold a product with uncertain demand over a finite selling season. Su [27] developed a dynamic pricing model but their model captured both markups and markdowns. In their model, there was a monopolist who sold a finite inventory over a finite time horizon. Elmaghraby and Keskinocak [8] analyzed the optimal design of a markdown pricing mechanism with preannounced prices and their suitability in the presence of strategic buyers with multi-unit demands. Reiner and Natter [24] developed markdown pricing strategies on Austrian mobile phone market. They considered different markdown strategies on two products but did not consider the correlation between products. Therefore, most of these papers consider single product or the papers consider multi products assume that the products are independent. However, we know that the most challenging subject is to observe the substitution effect among products in multi-product cases.

The substitution possibilities in retailing can be classified into three groups [14]. We consider the price-based substitution and complementary effects in this paper. When the price of a product decreases, the customer can choose this product instead of the other expensive product in the same substitutable product group. Cosgun et al. [6] investigated only the substitution and time effect on markdown policies by using Sarsa Algorithm which is one of