Retail revenue management: applying data-driven analytics to the merchandise line of business

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Keywords
Retail Revenue Management; Merchandise; Elasticity

Abstract
Recent advances in data collection technology and computing power yield opportunities to apply robust analytical methods to retail. Additional profitability can be obtained by leveraging data-mining techniques and optimization models to decisions that have heretofore been based heavily on experiential understanding. Scientific methods can be applied to the revenue-driving areas of merchandise such as assortment, pricing, placement, and promotion to obtain further insight and make more precise decisions.

Introduction
The retail industry is complex, and its decision-makers regularly encounter various challenges regarding how to best build and maintain businesses. What type of products should be offered? How should these products be priced? How and when should they be promoted? Complicating these questions are several influencing factors, which increase the difficulty of identifying straightforward solutions. Shifts in shopper behavior and competition can contribute to misleading forecasts and conclusions. Large-scale trends in the market and technology require the retailer to keep up with the

times in order to maintain profitability. The purpose of this paper is to organize and discuss analytical solutions to these challenges as well as the foundational science that can be used to make better informed, more profitable retail decisions with less risk.

The main areas of control, or strategic decision levers, at the retailer's disposal can be represented as McCarthy's (1981) four Ps: product, price, placement, and promotion. The retailer selects products to offer, their pricing and in-store placement, and how to promote them to the customer. Each of these decisions can drive profitability as well as the overall positioning of the brand image (Sayman *et al.*, 2002). It is in the retailer's best interest to be as informed as possible when making such decisions and to have the highest probability to drive long-term profitability for the success of the business.

Recent advances in data capture, storage, and computing power enhance the opportunity to apply data-driven analytics to these decisions, which have historically been based heavily on experiential understanding (Moyer, 1972). Several types of data can provide insight into business profitability and causal relationships. Categories of data that can be helpful include historical transaction-level sales, on-hand and on-order inventory, and extraneous demand drivers such as store traffic, demographics, weather, competitor information, significant events, and macro-economic conditions. Understanding the effects of demand drivers can help the retailer to proactively position the business in response to foreseen changes to the shopping environment (Morrison, 1979). Also important to track are decisions on product mix, pricing, placement, and promotions, in order to measure the effects of these changes and improve the likelihood of success for the future.

Utilizing data in analytical models can increase profitability, increase confidence in decision-making, and minimize mistakes attributed to error and subjectivity. Automated tools can be used to support decisions and drive value, while the data can also be mined to provide useful insights into the business that may not be readily apparent.

Scientific Concepts to Support Retail Decisions

Those who have booked a vacation have experienced the dynamics of revenue management from a consumer's perspective by making reservations off-season for lower hotel rates, finding the ideal combination of flights to fit the budget, or waiting for a product to be offered at a discounted price before making the decision to purchase (Kimes, 1989). But behind the scenes, revenue management is a complex science that combines marketing, analytics, and customer relationship management for increasing loyalty and profits. This science drives many decisions in modern business.

Revenue management is traditionally applied in service industries or in markets with fixed capacity and perishable inventory such as airlines and hotels; however, revenue management is gaining attention beyond these industries as economies tighten, consumer spending declines, and operating costs continue to rise (Boyd and Bilegan, 2003). Businesses are finding the need to invest in revenue management systems that apply more sophisticated, reliable analytics, advancing them beyond traditional decision-making considerations. For example, understanding seasonality leads to a more accurate prediction of demand, management of inventory, and determining prices for maximum profitability using the following concepts:

Normalization: Modeling the effects of the independent variable of interest (*e.g.*, price) can be difficult with all of the extraneous variation in demand data caused by other factors clouding the picture. Thus it is necessary to normalize for this extraneous variation by modeling the effects of each identified driver, then isolating the effect of price in order to better understand the price-demand function (Yang *et al.*, 2002). This accounts for the variation not attributed to price with the goal of isolating the effect of price.

Elasticity: Once the primary effect has been isolated as closely as possible through the modeling and normalization processes, it is then necessary to identify the elasticity of the demand to changes in price (*i.e.*, the sensitivity of a population's decision to purchase, due to changes in price).

Identification of Complementary and Cannibalistic Relationships: Once individual product elasticities have been identified, it is necessary to consider the cross-price elasticities of products that are either complementary (likely to be purchased with the current product of interest) or cannibalistic (likely to be purchased as a replacement, or in lieu of, the current product of interest; Lattin and McAlister, 1985). In this way, a more holistic view of a business's demand and optimal pricing strategies is possible.

Segmentation: Nearly every industry has market segments that behave differently and are more sensitive to price levels than others (Noone *et al.*, 2003). The travel industry, for example, might segment by leisure travelers, who usually incorporate a weekend stay, and business travelers, who typically travel during the week. The healthcare service industry may segment by urgent care and postponable care. The broadcast industry might segment by guaranteed spots, pre-emptable spots, and rotating spots.

Forecasting: Accurate demand forecasts translate directly into increased revenue in the form of higher revenues per customer, without a loss in demand (Littlewood, 2005). Increased confidence in predicting high-rate-class customer demand results in decreased risk in reserving inventory for them. The search for improved forecasting techniques continues to attract a considerable level of investment, even among companies with relatively mature revenue management programs. A potential side benefit of developing good demand forecasting capabilities for revenue management is that the customer-volume and unit-demand forecasts are often useful elsewhere in the company. Functions such as supply-ordering and staffing can often be planned more accurately with access to the detailed customer forecasts produced by a revenue management system.

Product Application

Assortment Elasticity – Customer Reaction to Changes in Product

A retailer decides upon a breadth of products to offer as well as a depth of various types within each category (Hoch *et al.*, 1999; van Ryzin and Mahajan, 1999). The portfolio of products presented by the retailer not only fulfills demand for goods, but also defines the brand essence. A section of the portfolio mix can be designated for the latter purpose, containing lower-profit products carried for the specific purpose of establishing the brand image in the consumer's mind (Upshaw, 1995). Determining the best mix of profit-driving products and "show" products requires a balance of art and science. Inventory levels must then be maintained at proper levels within each store to maximize profitability (Kök and Fisher, 2007).

Assortment elasticity is a measure of the customer's purchasing response to changes in the product portfolio (Borle *et al.*, 2005; Urban, 1998). Based on normalized demand, the assortment elasticity model measures the response of each offering within a category, and provides insight into the diminishing returns of sales for each additional offering (Chong *et al.*, 2001). The model is built and strengthened upon tests of various configurations within each category. It can provide insightful measurements of the effects of historical changes and can be utilized to determine the optimal assortment to carry.

Assortment Optimization

Pairing the diminishing returns of sales with the incremental costs for each additional offering can yield a profit function that can be used to identify the optimal assortment that drives maximum profit (Yücel *et al.*, 2009). The assortment elasticity model measures the revenue and margin side, while the carrying cost and product development functions provide the cost side (Stassen and Waller, 2002). If the profit function indicates that there is opportunity to increase the number of offerings, then the incremental profit should be greater than or equal to the product development cost (Fisher and Vaidyanathan, 2009). In this case, the additional revenue must overcome the additional costs in order for there to be an opportunity. Conversely, the profit function will indicate an opportunity to decrease the number of offerings if a category's revenue is less than its carrying cost. In this case, the cost savings for decreasing the number of offerings will overcome the lost revenue. Once an expansion or reduction opportunity has been identified for a category, the incrementality of that category must be assessed relative to all other categories in order to quantify the expected overall increase or decrease in sales.

Price Application

Price Elasticity – Customer Reaction to Changes in Price

Pricing can be one of the most powerful decision levers at a retailer's disposal (Hardesty *et al.*, 2007). It is essential to understand its effect on customer purchasing behavior in order to make informed pricing decisions that will drive the business (Schindler, 2006). The level, stratification, and timing of prices can drive quality perception and influence the overall brand image. Does the retailer want to be positioned as a premium or bargain brand (Krishnamurthi and Raj, 1991)? Overall pricing strategies can define the retailer's reputation and positioning within the competitive market, and they can draw both new and return customers. Pricing can carry a retailer through lean periods when the larger market is suffering, and it can drive large incremental profits during periods of high consumer confidence.

Price elasticity is essential to quantifying and predicting customer response to changes in price (Bijmolt *et al.*, 2005). It is a measure of the historical change in demand relative to change in price. Based on normalized demand, the elasticity model is more robust if it is based on several historical prices that have been tested in the market; the model and its output can only be as robust as the data on which it is based.

Just as important as understanding the reductionistic dynamics of the pricing effects on a single product is the holistic view of the effects to other products. These effects can be better understood via cross-price elasticity model, which quantify these effects, and lend to a more holistic view of the direct and indirect effects of pricing decisions. Including complementary and cannibalistic effects in the model for products outside the company can also help account for variability in demand attributed to changes in competitors' prices.

Price Optimization

The price elasticity model enables the retailer to predict how demand will change at new price points. Optimal prices can be determined based on these predicted responses (Kim *et al.*, 1995). The goal function of the optimization can be set to maximize volume, maximize revenue, maximize margin, or minimize overstocked inventory. The retailer's overall business goals should determine the best optimization strategy to use (Bitran and Caldenty, 2003). Maximizing revenue considers the change in demand relative to the new price. Maximizing margin considers the additional element of product cost. Changing prices in response to maximizing margin can result in a decrease in revenue but an increase in margin.

The objective is to minimize discounts during peak periods and encourage demand during off-peak times after isolating the effect of price from extraneous variation in demand. For example, a travel company may require a Saturday night stay, three-week advanced purchase, or offer a senior citizen discount during specific periods. Another example would be a product that is offered at a considerable discount if a larger-volume or higher-margin product is purchased to increase the overall ticket volume and margin. The idea is to divide existing demand according to derived product preferences and purchase behavior, and then market to those specific characteristics in order to increase your revenue potential. The expectation of lower price points is that it will encourage demand during periods when utilization of fixed capacity is projected to be low, therefore increasing overall revenue for the company. These prices would not be offered during peak periods when customers are willing to pay higher prices for a product.

The complexity increases when a constraint is introduced, such as requiring that products be priced relative to each other. An example of such a scenario may be a grocer who wishes to price each can of soup the same price. The tomato soup may be more elastic than the mushroom soup such that their respective optimization models recommend that the price of tomato soup decrease and mushroom soup increase. The optimal price for the two products, given the constraint that their prices must be identical, can be determined by solving the system of price-demand functions as a linear program. This will result in a price for each product that is optimal for the set as a whole. To further refine the model, the indirect effects on the complementary and cannibalistic products can be added to determine the total impact to the business.

Pricing for the Product Life Cycle

The optimal price of a product can change over the duration of its life cycle (Parker, 1992). An introductory price is set relative to a market benchmark or a similar sponsoring product. Once the new product has enough sales and price data to support its own model, a steady-state price can be set based on the optimization. Several price points may be tested during this period to establish a robust elasticity model and identify the optimal price. Promotional prices can also be tested as temporary solutions in order to strategically increase sales during key periods. As sales downtrend near the life cycle's end, a markdown price can be set such that profit is maximized and inventory is liquidated by the best out date identified through a life cycle analysis.

Placement Application

The location of a given product within a store plays a significant role in its sales, along with the sales of other items. Milk, for instance, is usually strategically placed at the back of a grocery store to encourage customers to walk through the location, exposing them to other products. This is an example of a destination item. Magazines, on the other hand, are usually placed at the front of the store. Most customers will not go into a grocery store with the goal of shopping for a magazine, but they may be prone to pick one up while waiting in line. This is an example of an impulse item.

Current literature available on the impact of placement on merchandise shows very promising findings. Dreze *et al.* (1994) believe that retailers should expect 4% to 5% gains in sales from better product positioning and space allocation. According to van Nierop *et al.* (2006), the location of a product is an important demand driver.

One way to analyze the location of a given product within the store is at the macro level. This level focuses on merchandise placement changes from a horizontal perspective. These horizontal moves can be based on either taking the customer to the product or bringing the product to the customer. Understanding the most common shopping route can lead to floor layout changes to allow for longer trips and more product exposure. However, rather than forcing the most common route to change, the retailer can take advantage of the additional path insight to bring products with higher margin to the customer. Sorensen's (2003) research shows that the average shopping trip only covers about 25% of the store, alluding to the fact that retailers need to take full advantage of the visited space to optimize their sales. Curhan (1973) also focuses on increasing profitability by shifting space from relatively low-profit items and assigning the space to higher-profit items.

Another level of analytics – the micro level – focuses on both the vertical and horizontal movement of merchandise within a given fixture. Desmet and Renaudin (1998) state that the position of the product on the shelf seems to be important for determining sales, supporting the micro level analytical approach. Dreze *et al.*'s (1994) shelf management research also shows micro location of products being a significant driver, with vertical placement changes having more consistent results, perhaps due to the resting position of the eye, and vertical placement having conflicting results, depending on the product category.

Visibility Elasticity – Customer Reaction to Changes in Placement

Behaving very similarly to price elasticity, placement also has an elasticity measurement as it relates to the customer's sensitivity in purchasing behavior, driven by a product's visibility. While some products will experience increases or decreases in sales due to how visible it is to the customer, other products will sell well regardless of where they are placed. Destination products, for instance, tend to be fairly inelastic; their desirability and the customer's awareness are high enough to sustain sales regardless of their location. Impulse items, on the other hand, are highly elastic – strategic placement can be a very strong sales driver for these products.

Placement Optimization

In a typical retail environment, multiple stock-keeping units (SKUs) move concurrently, making it difficult for retailers to measure and quantify the impact of their placement changes. Moreover, other demand driver changes can occur simultaneously, also causing fluctuations in product sales. To truly understand the impact of product placement changes, it is imperative to remove the effect of other demand drivers so that one can focus on measuring and quantifying the impact of a placement change.

One way to focus on measuring the impact of these placement changes, once the impact of other demand drivers is removed, is to focus on the chain reaction caused by moving a certain product either horizontally or vertically from point A to point B. In order for the placement change to take place, a second product must move or decrease its display quantity to create room for the arriving product. If the second product is moved to another location, it will create a similar reaction at its new location on a third product. This dynamic creates chains of product movement, which can be analyzed and potentially reversed if the normalized sales impact is found to be negative.

Another way of measuring the impact of product placement changes is to understand individual fixture performance. By understanding what products were moved from and to a given fixture along with increases and decreases to the number of face-outs for each product that did not move, one can measure how the fixture performed before and after the changes took place.

Placement Application to Life Cycle

Where a product is in its life cycle can alter its placement strategy within the store. For instance, products that have been recently introduced to the market are usually placed by store entrances to make the customer aware of its arrival. This ideal real estate helps the retailer better promote their new arrivals and boost sales. Products that are in the latter stages of their life cycles, on the other hand, tend to be located at the back of the store, forcing the customer to take a long route through the store to get to the markdown merchandise and therefore exposing them to additional merchandise.

Promotion Application

Just as other areas of revenue management focus on a fixed capacity, the science of promotion considers the customer's capacity of attention. The ability to capture attention is necessary for both capturing traffic into the store and also conversion of purchases once in the store (Parsons, 2003). The techniques available to create conscious or subconscious consideration for purchase can be dynamic and complementary. Examples can include price, placement, lighting, fixtures, advertisement, signage, video, sound, scent (Chebat and Michon, 2003), taste, touch, and surrounding colors. Through pulling the appropriate promotion levers, retailers can bring awareness to their product.

Visibility Elasticity – Customer Reaction to Changes in Promotion

Given the customer's capacity for attention, the ability to strategically pull the appropriate lever(s) at the best time of the shopping experience can drive additional profit. Similar to the above discussions, there exists an elasticity of a customer's visibility to a promotion, which can be measured. This elasticity measurement can provide insight into the optimal point of effectiveness for each promotion activity, given that there is a cost associated with each action. Also similar to the previously discussed elasticities, the measurement begins with normalized demand to measure the customer's response to changes in promotional activity.

Content Optimization

Recent advances in technology have allowed for environments that can change rapidly, based on forecasted demand by segment. An example of this is the recent use of electronic monitors to leverage many of the attributes of promotion into one display. By utilizing strategic images, prices, and sound, a retailer can influence guest behavior positively. Pierce (2009) reports that sales increases of five percent or more have been achieved by optimizing the promotion by product to the time of day, leveraging incrementality behavior, and bringing awareness to the products that are the most elastic with regards to visibility elasticity.

Similarly, the ability to measure any change in promotion can drive insight and ultimately value for a retailer. This measurement can be used to better understand the ability to create awareness, incentive, and ultimately demand.

Conclusion, Other Decisions, & Future Research

Conclusion

Each of the four decision levers discussed above can lead to long-term strategic directions that will benefit the retailer and drive significant value. Leveraging data through analytical solutions can decrease risk, increase accuracy of measurements and predictions, and increase profitability. With more sophisticated tools, the decision-maker can anticipate small- and large-scale trends and be in a better position for a more efficient response. Adapting these solutions can improve customer service and translate into better results on the bottom line.

Other Decisions

In addition to the four Ps, there are other decision-making areas of the retail business that can benefit from data-driven analytics. These include placement of stores, allocation of labor, and the option to include services such as free shipping, gift wrapping, or layaway. While the above discussion focuses on the revenue-maximization side of retail, there is also opportunity to leverage data-mining and analytics on the cost-minimization side, including supply chain management, sourcing, and labor allocation efficiencies.

Multi-dimensional Optimization

A key future opportunity for this approach to business insight is in harnessing the power of all four Ps simultaneously. Retailers will benefit from knowing the possible impacts of any one lever or combinations of multiple levers when making decisions on how to best accelerate the movement of product. A truly optimal strategy will consider the combination and interaction of each avenue at the retailer's disposal. As the individual workstreams mature, a holistic or global optimization will be within reach (Li *et al*, 2002).

Unconstraining Demand

A retail location is subject to various constraints on demand (*e.g.*, square footage, operations inefficiencies). These constraints result in a gap between the potential demand and that which is actually realized to the retailer. Understanding the true potential demand that exists for products can provide valuable insight, which can aid in capital planning and making decisions to capture this lost demand through various strategies. As traffic increases, pressure is increasingly put on a location's constraints. Using lower-traffic periods as a benchmark, the diminishing returns of higher-traffic periods can be better understood, and additional opportunities identified (Harrell *et al.*, 1980).

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