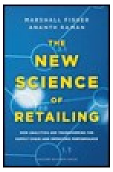

The New Science of Retailing: How Analytics Are Transforming the Supply Chain and Improving Performance

by Marshall Fisher and Ananth Raman
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Chapter Two: Assortment Planning—Mining Sales Data to Discover "Home Run" Products You Are Missing

Overview

A retailer's assortment—the set of products carried in each of its stores—defines the company for consumers. L.L.Bean may sell far more wool blankets than cross-country skis but, by stocking the skis, it announces that it specializes in outdoor recreation, not just rustic house goods.

In choosing an assortment, retailers must take into account strategic issues like whether products align with their brands: L.L.Bean isn't going to start stocking silk negligees.

But retailers must also ponder nitty-gritty operational puzzles. Best Buy, for its part, might have to choose only twenty digital cameras, among the thousands available. On top of that, it might not carry all of those twenty in each of its stores.

The rhythm of assortment planning varies across the three major retailing segments. A grocer can frequently tweak its offerings, even varying them within a single day. Albert Heijn, a Dutch supermarket chain, offers a different assortment to breakfast-time shoppers than it does to those who arrive right before dinner. Shoe and apparel peddlers, in contrast, plan around the seasons, usually spring and fall. Hard-goods retailers hew to annual cycles corresponding to their fiscal years. Pianos don't lend themselves to being shuttled on and off the showroom floor.

Assortment planning happens at two levels. At the *strategic level* , you address the amount of resources, including shelf space and purchase dollars, to allocate to each category. This kind of planning often resembles capital budgeting, especially for retailers that plan assortments annually. At the *operational level* , you drill down to the SKUs that you'll carry in each category. In both sorts of planning, you consider whether and how much to *localize* your assortment. Options here range from having a single assortment for the entire chain to unique assortments for each store.

Current Practice

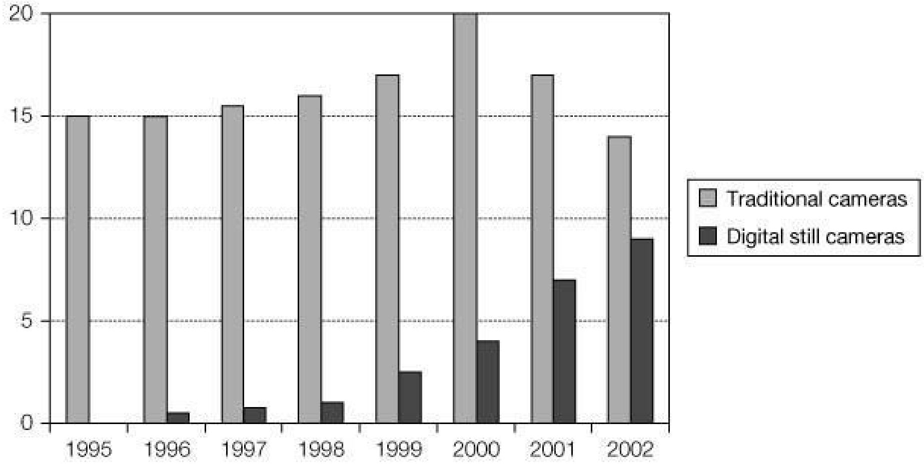
In this chapter, we examine current practice in each of these categories and then describe our experiences helping two retailers strengthen their assortment planning. [1] By giving greater care to picking their assortments, they were able to boost their sales. We suspect that you'll see the same sorts of gains by taking greater care with yours.

Strategic Planning: Thinking Big

Assortment planning begins with setting goals for each department and product category for unit sales, market share, revenue, and profit. [2]

You'll increase resources, including store space and purchase dollars, earmarked for some product categories, while decreasing them for others to reflect product, competitive, and fashion trends.

A forecast of future sales helps to decide which categories to expand and which to contract. Figure 2-1 shows Best Buy's sales of digital and film cameras for 1995 to 2002. A logical forecast for 2003 would be a decrease in the sales of traditional cameras and an increase in sales for digitals, compared with sales in 2002.



This figure is an illustrative example and the values are approximate.

Source: Kevin Freeland, chief operating officer, Advance Auto Parts, and former senior vice president for inventory management, Best Buy.

FIGURE 2-1: Historical sales of film and digital cameras

But figure 2-1 also shows the limitation of this approach. A forecast of 2001 film camera sales based on an extrapolation of historical sales would have erred high. A smarter forecast would have factored in intelligence from trade shows, conversations with vendors, observations of competitor moves, and reviews of new technology. With this information, a retailer identifies potential changes in sales for a product or category that might not be apparent from a straightforward extrapolation of sales history. In the case of cameras, these sorts of observations would've led you to predict the fast rise in the sales of digitals.

The method we'll describe relies on recent sales history to identify profitable assortment changes and therefore is most appropriate for product segments where demand patterns change slowly. Many product segments, particularly in grocery and hard lines, satisfy this requirement, but some, such as fashion apparel, do not. Urban Outfitters' CEO Glen Senk's remark that "In fashion apparel, there is nothing as boring as last season's hot seller," clearly illustrates that for fashion products, history can lead one in exactly the wrong direction. But even in the volatile world of fashion apparel, attributes can help. Urban Outfitters has developed an impressive approach to dynamically adjusting their assortment within a season by having their buyers focus on current sales and identify which product attributes are trending upwards or downwards.

Borders, the bookseller, has an even more advanced approach to strategic assortment planning. Two brothers, Tom and Louis Borders, founded the company. Tom majored in English at the University of Michigan, which explains why they based their chain in Ann Arbor. Louis studied computer science at MIT, which enabled their chain to develop sophisticated information technology in its early days.

Borders segments its books into about nine thousand categories and allows each store to carry a different number of titles in each category. [3]

To choose the number of titles in each category for each store, it relies on a measure called *relative sales per title* (RST), which equals the sales in a category in a store over a specified period, divided by the number of titles carried in the category over the same period. If RST is high for a store category in a recent period, then Borders increases the number of titles in that category. If RST is low, it reduces them. It might, for example, divide the one thousand categories in a store into upper, middle, and lower thirds of RST values and then increase the number of titles carried in the upper third by 10 percent and reduce the lower third by 10 percent. (Borders' process also takes seasonality into account, but that is outside the scope of this chapter.)

The philosophy behind Borders' approach makes sense—put resources where they can earn the greatest return. Borders' approach is on the right track, but we can do even better by understanding that as you analyze your company's assortment, what matters is the *marginal return on incremental resources* , not the average return of resources already deployed.

Figure 2-2 shows revenue versus SKU count for two hypothetical product categories. The SKUs in each category are ranked by dollar sales rate. Then the revenue is plotted as SKUs are added, one by one, in rank order. Note that the first category has higher average sales per SKU, but just a few high sellers cause this; the weakest SKUs in the category barely sell and add little revenue. By contrast, the second category has lower average sales per SKU, but all of its SKUs are equally productive. It would therefore make sense to reduce the SKU count for category 1 and increase it for category 2. You can delete half the SKUs in category 1 with little loss of revenue. If you then use the resources freed to add a comparable number of SKUs to category 2, their sales rate will probably resemble that of the SKUs currently in the category.

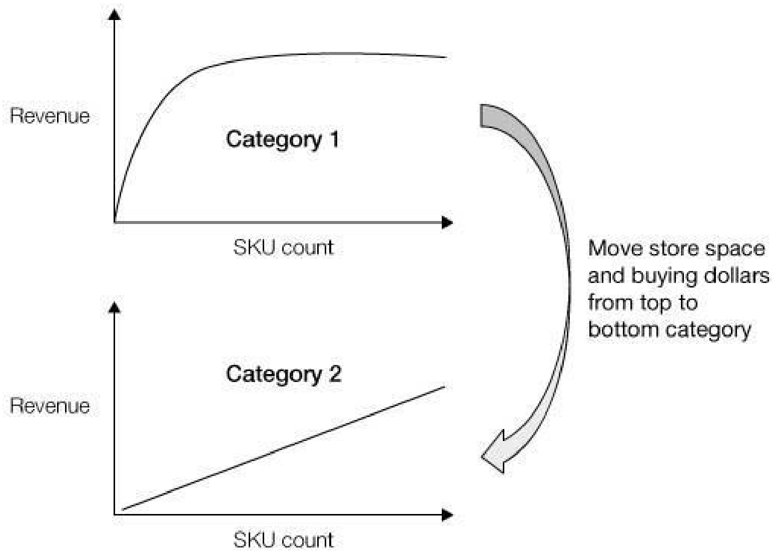


FIGURE 2-2: Enhancing the Borders approach by considering the marginally performing SKU in each category

As you apply these insights in your company, you should evaluate categories by *their marginal productivity* —that is, you should target categories where the worst-performing SKUs have relatively low sales rates, and delete them to free space to add SKUs to categories where the worst performers have relatively high sales rates, indicating potential for growth.

Operational Planning: Getting Specific

Once a retailer decides how many SKUs to carry in a category, it faces the operational problem of picking particular ones. In flat panel TVs, for example, Best Buy might stock 82 different models. The number of potential SKUs, of course, is much larger, comprising eight diagonal widths, five screen types, seven resolution levels, and nine major vendors, for a total of 2,520 (that is, of 8 × 5 × 7 × 9). Company buyers select the specific SKUs, and they incorporate many factors into this decision, including ensuring that Best Buy offers products from a variety of vendors. That way, the chain can benefit from competition when negotiating on price, and its customers have more choices.

One challenge in assortment planning is including new products; buyers will have to consider many goods for which Best Buy has no sales experience. The lack of sales histories for these thwarts analytic planning. A buyer will have little, if any, data to use in making decisions.

Be aware that assortment decisions aren't only about maximizing the profit on every single SKU. Though that's the focus of this chapter, you might also select a SKU to help sell other goods. An obvious example would be a loss leader that attracts shoppers to your store. And low-priced offerings are not the only way of enticing customers. A broad array in a category, including high-end aspirational goods, can signal that your store is the best place to buy all of the products in that category. Bike shops, for example, will often sell custom-built frames by makers like Seven and Independent Fabrication, even though the vast majority of their sales come from off-the-rack offerings like Trek and Cannondale. The custom frames give shops cachet with bike aficionados, even if many of those customers choose not to pony up that much money for a bike.

Carrying a premium-priced offering can increase the sales of other pricey products by making them look like relative bargains. In a Publix supermarket, one of us noticed a bottle of wine selling for $264—a lofty price anywhere, much less in a grocery store. The natural question for the wine manager was how much of that wine he sold. His response: "None, but we sell a lot of this $67 bottle next to it *because* we carry the $264 bottle."

Another reason to carry slow-moving SKUs is to please your best customers. Jim Halpin, former president of BJ's, tells a story that illustrates this point. [4] Soon after he became president of BJ's, he got a sales report and noticed a dessert pie

SKU at the bottom of the list: BJ's was selling a whopping three a week. So he deleted the SKU. That was a no-brainer, he thought—until he got an angry call a few days later from one of his best customers asking why he'd stopped carrying his dessert pie. Those three a month mattered to this customer, and this customer mattered to BJ's.

Grocery chains, which can obtain data on customers' baskets of purchases through loyalty cards, are ideally positioned to protect themselves from this pitfall. Before they delete a SKU, they can assess the average size of the basket of goods purchased by customers who typically bought that SKU. If they notice that caviar buyers tend to purchase $500 worth of groceries every time they visit, they should keep the slow-selling fish eggs.

All Retailing Is Local

Traditionally, a retailer would use the same assortment in all of its stores, except perhaps for eliminating less important SKUs in smaller outlets. Recently, some firms have made great efforts to localize their assortments. [5] They'll group their stores into clusters with similar demographics or sales mixes and then apply their chain-level assortment planning process to each cluster.

Though it sounds promising—after all, what's better than catering to your customers?—problems arise with this approach. It's a ton of work. Manual planning must be done not just once for the chain but for each cluster. And despite all of the toil, localization may not lift sales. One home-fabrics retailer implemented the approach for a category that it thought would benefit, and achieved an 18 percent sales increase. Pleased with the results, it tried a second category, but saw no rise. That ended its enthusiasm for localization.

Another challenge is figuring out the right number of clusters to form and picking one of the many ways of forming them.

Politics complicates localization, just as it complicates many things. If you choose to localize, you also have to decide *who gets to decide* . That is, you have to figure out how to divide decision-making authority between your headquarters and stores. The most common approach is for headquarters personnel to dictate a single common assortment to be carried by all stores. But a few retailers—Bed Bath & Beyond is one—allow their store managers considerable authority in deciding which SKUs to carry. Usually, the corporate office mandates a portion of the SKUs, and store managers choose the rest for their locations from an approved list of options. Differing offerings in each store end up, in theory, tuned to the tastes of that location's customers. Delegating a portion of the assortment decision to stores is decentralized localization, but it's also possible to make all assortment decisions centrally and still localize the assortment. The Borders approach to assortment planning described previously is an excellent example of localized assortments created centrally.

[1]Our discussion of current practice is based on Michael Levy and Barton Weitz, *Retailing Management* (New York: Irwin-McGraw Hill, 2007) and conversations with several retail executives, including Kevin Freeland, chief operating officer, Advance Auto Parts; Herb Kleinberger, principal, ARC Business Advisors; and Rob Price, chief marketing officer, CVS.

[2]Sometimes the term *merchandise planning* is used for what we are calling strategic assortment planning.

[3]This discussion is based on Zeynep Ton and Ananth Raman, "Borders Group, Inc.," Case 9-601-037 (Boston: Harvard Business School, 2003).

[4]Subsequent to BJ's, Mr. Halpin was CEO of CompUSA and is currently founder and CEO of River Bend Inc.

[5]See Jena McGregor, "At Best Buy, Marketing Goes Micro," *BusinessWeek* , May 15, 2008; Vanessa O'Connell, "Reversing Field, Macy's Goes Local," *Wall Street Journal* , April 21, 2008; Ann Zimmerman, "To Boost Sales, Wal-Mart Drops One-Size-Fits-All Approach," *Wall Street Journal Online* , September 7, 2006; and Ann Zimmerman, "Home Depot Learns to Go Local," *Wall Street Journal* , October 7, 2008, for descriptions of efforts by Best Buy, Macy's, Wal-Mart, and Home Depot to localize their assortments.

Real Experiences in Assortment Planning and Localization

By now, you probably have come to understand that SKU assortments resemble the weather: they can bollix even the best-laid plans. But as with the weather, a forecast, even an imperfect one, helps.

In this section, we'll describe a method (developed in collaboration with one of our doctoral students, Ramnath Vaidyanathan, now a professor in McGill University's business school) for making such a forecast of store-SKU demand, even for SKUs for which you have no experience. As examples, we'll use the snack cake assortment of a regional convenience chain and the tire assortment of a national tire retailer. [6] Our approach mostly left alone the overarching strategic planning process at both retailers. We just injected analytics and information technology to help the two retailers pick better items.

The best retail buyers consider their products as packages of attributes. A buyer for a home-fabrics seller, for example, will see bed sheets in terms of size, color, fabric type, and thread count. She'll try to carry a set of SKUs that includes all possible values of these attributes but will overweight the ones that customers seem to most want. If she sees that twin sheets are selling better than queens, she'll carry both but stock more twins.

Not everyone, of course, has the experience or talent to make these sorts of judgments. What we do with our analytic approach is to translate a talented buyer's way of thinking into a formulaic approach that anyone can use.

Like the talented buyer, we define each SKU as a collection of attributes. We then use prior sales to forecast market share in a store for each attribute value and use this information to forecast demand for any potential SKU. This approach lets you forecast the demand for SKUs that you haven't sold before. If you're in the home-fabrics business, you may never have sold a set of pink twin sateen 400-thread-count sheets, but you would have surely sold twin sheets and sateen sheets and 400-thread-count sheets and probably even pink sheets. You can use their sales history to estimate the percentage of customers who will buy sheets that combine all of the attributes. You simply multiply the percentage of demand for pink and the percentage of demand for twin and the percentage of demand for sateen and the percentage of demand for 400 thread count.

This approach can be applied at any level from chain to cluster to individual store. It lets you do lots of what-if analyses to answer questions like how much you'll gain by localizing your assortments.

Forecasting based on attributes lends itself to localization. Retailers typically think and talk in terms of attributes. Chat with them about what's selling and what's not, and you'll hear things like "We sell more black in Manhattan than in Madison, Wisconsin, more plus sizes in Iowa than in Florida, and more cotton in Canada than in Los Angeles."

Understand that using attributes as the basis for forecasts isn't perfect. It entails approximation because it assumes that attribute demand patterns are independent of each other. In reality, customers who buy queen-size sheets may have a greater preference for 400-thread-count ones than those who buy twins, so using sales of all sizes to estimate demand for the 400-thread-count ones might cause you to overestimate the demand for 400-thread-count twins. Nonetheless, this simplifying assumption is extremely useful because it allows you to forecast the demand for a vast number of possible SKUs from a relatively small set of parameters. Your assumptions won't be perfect, but, as you'll see in our examples, they can be good.

We make other assumptions that you should be aware of. We assume that consumer preferences for attributes are stable over time or at least trend in a predictable way. That's certainly not true for some products, such as trendy apparel, where there's nothing staler that last season's hit. But in many categories, especially hard goods and food, customer preferences change gradually, so tracking customer preferences via sales history makes sense. We also assume that if a customer doesn't find her first choice, she may substitute a different product.

Tasty Techniques in the Snack Cake Aisle

Now let's turn to Little Debbie and her competitors in the snack cake aisle and use the example of planning an assortment for a convenience store chain to illustrate this approach. The primary input that we'll use is store-SKU sales over the last six months of 2005. Table 2-1 provides an example of the data for one store. This retailer carried thirty-nine out of the sixty-eight possible brand-size-flavor combinations (two brands × two sizes × seventeen flavors = sixty-eight combinations) at this location. We can't reveal the actual names of the two brands, so we'll call them Yummy Cakes and Tiny Tina.

Table 2-1: July 1–December 31, 2005, snack cake sales in a convenience storea

	SINGLE SERVE		FAMILY SIZE		
PRICE	**$1.29**			**$3.34**	
Flavor	**Yummy Cakes**	**Tiny Tina**	**Yummy Cakes**	**Tiny Tina**	**Revenue**
Chocolate	7,246	3,100	472	456	$16,445.86
Cinnamon	3,182	1,487	551	385	$9,149.25
Butter	1,398	1,355		331	$4,656.91
Cheese	353	570		335	$2,309.57

Raspberry	3,100	1,471		398	$7,225.91
Vanilla	1,513	1,155		184	$4,056.28
Chocolate chip	2,034		185	139	$3,706.02
Fudge	2,926	563	274		$5,415.97
Butterscotch	3,009		325		$4,967.11
Peanut butter	4,780		380		$7,435.40
Honey	2,169	967			$4,045.44
Apple		224		60	$489.36
Cherry/cheese		1,596			$2,058.84
Vanilla/chocolate		2,162			$2,788.98
Oatmeal/raisin	4,049				$5,223.21
Coconut	1,827				$2,356.83
Buttercream			100		$334.00
Totals	37,586	14,650	2,287	2,288	$82,664.94
Sales shares	66%	26%	4%	4%	
a. The numbers in this table have been disguised to protect confidentiality.					

These thirty-nine SKUs generated revenue of $82,665 during the six-month period. A crucial question is whether a different set of thirty-nine SKUs might generate more sales in the future. (Prices varied slightly across the different flavors and the two brands within a size, but for simplicity, we'll use the average prices for single serving and family size of $1.29 and $3.34.)

Not surprisingly, most retailers do better at identifying poorly performing SKUs and deleting them than at identifying promising new ones and adding them. As a result, many retailers follow a "gin rummy" strategy. They discard the worst-selling SKUs from their current hand of products and randomly draw from the deck of potential new offerings. They hope that, over time, they'll identify a productive assortment.

But what if you could have an accurate sales forecast for any assortment your store might offer? Instead of guessing which products might sell, you could then choose the exact assortment that would maximize revenue. That's what we'll show you how to do now.

Our challenge in working with the convenience store chain was to use the data in table 2-1 to estimate the demand for brand-size flavors not offered. We started by estimating the shares of the four brand-sizes. We could have just used the sales shares shown in table 2-1 to estimate demand shares of the four brand-sizes. But these sales shares had been influenced by the assortment offered and thus didn't represent true demand. The chain had previously offered Yummy Cakes in more single-serving flavors than it did Tiny Tina. That inflated the sales share of Yummy Cakes: in some instances, customers really wanted Tiny Tina in a particular flavor but had to settle for Yummy Cakes. We sidestepped this problem by focusing on the two flavors where the chain had offered all four brand-sizes—chocolate and cinnamon—and where sales thus represented true demand because no customers had been forced to substitute. Table 2-2 shows the calculation of demand shares for these two flavors. Notice that, as predicted, the demand share of Yummy Cakes is lower, and that of Tiny Tina is higher, than their sales shares in single serving. This shows the impact of the assortment on sales. Demand shares for family size also differ for the same reason.

Table 2-2: Calculating brand-size demand shares using the flavors where all four brand-sizes are offered

	SINGLE SERVE		FAMILY SIZE	
Flavor	**Yummy Cakes**	**Tiny Tina**	**Yummy Cakes**	**Tiny Tina**
Chocolate	7,246	3,100	472	456
Cinnamon	3,182	1,487	551	385
Total	10,428	4,587	1,023	841
Demand share	62%	27%	6%	5%

Next we used these brand-share estimates to estimate the demand for the SKUs not offered. How much, for example, would the store sell if it offered Yummy Cakes in family-size butter flavor? It's tempting to use the 6 percent and 5 percent shares for Yummy Cakes and Tiny Tina in family size, observe that Yummy Cakes sells 20 percent more than Tiny Tina, and reason that since the store sold 331 in Tiny Tina family-size butter, it might expect to sell about 397 of Yummy Cakes.

But this logic ignores product substitution. If customers don't find what they really want, they may buy another product instead. Thus the 331 units sold of Tiny Tina might have included customers who wanted Yummy Cakes but bought Tiny Tina when they couldn't find their first choice. Studies of convenience store customers have shown that they place a much higher weight on flavor than brand in their purchase decisions for snack cakes and that they are unlikely to jump between family size and single serving. Someone seeking a midmorning snack doesn't want to lug a box of Tastykakes or Hostess Ho Hos around in his backpack for the rest of the day. We assumed that the likelihood of substitution across flavors and sizes was zero, and focused on estimating the percentage of customers who substituted between brands within a size and flavor.

How can we estimate the likelihood of substitution between brands? Notice that for four of the flavors shown in table 2-1—butter, cheese, raspberry, and vanilla—the chain carried Tiny Tina in single and family sizes and Yummy Cakes in single size. In those flavors, it didn't offer any Yummy Cakes in the family size. With this information, you can estimate the fraction of customers who substituted Tiny Tina in family size for Yummy Cakes in that size. Table 2-3 shows the calculation.

Here's the logic behind table 2-3. The sales of Yummy Cakes and Tiny Tina in single serving represent true demand since the store offered both brands, and customers didn't have to substitute. These sales totaled 10,915 (6,364 + 4,551), and, as we calculated in table 2-2, they represented 89 percent of total demand for these four flavors. This means that the total demand for the four flavors was 12,264 (10,915 / 0.89). Thus the demand for Yummy Cakes and Tiny Tina in family size can be calculated as 6 percent and 5 percent of this total value, which are the values 736 and 613 shown in table 2-3. If 613 was the true demand for Tiny Tina in family size, then you could estimate that 635 (1,248 – 613) customers preferred Yummy Cakes *but substituted Tiny Tina* when their first choice wasn't available. This means that 86 percent (635 / 736) of the customers who wanted Yummy Cakes bought Tiny Tina instead. You thus can conclude that the likelihood of a customer substituting from Yummy Cakes to Tiny Tina in family size is 86 percent.

Here's another way to think about estimating the rate of substitution. You know from the share estimations that family size represents 11 percent of demand. If everyone substituted from Yummy Cakes to Tiny Tina, then when Yummy Cakes was missing, family size would still represent 11 percent of sales. If no one substituted, then the 6 percent of sales to customers that prefer Yummy Cakes would be lost, and you'd only capture 94 percent of demand. The 5 percent of customers who buy Tiny Tina in family size would represent 5 / 94 = 5.3 percent of the total demand captured, and hence the share of family size would fall to 5.3 percent of sales. So family-size share when Yummy Cakes is missing will be between 5.3 percent and 11 percent of sales; closer to 5.3 percent indicates low substitution, while closer to 11 percent indicates high substitution. The share of family size is 1,248 units sold / 12,264 total units = 10.2 percent, very close to 11 percent and indicating a high level of substitution. In fact, 10.2 percent actual share / 11 percent maximum share = 93 percent, almost the same as the 86 percent substitution rate we calculated before, so the two viewpoints are similar.

Table 2-3: Calculation of the percentage of customers who will substitute from Yummy Cakes to Tiny Tina in family size

	SINGLE SERVE		FAMILY SIZE	
Flavor	**Yummy Cakes**	**Tiny Tina**	**Yummy Cakes**	**Tiny Tina**
Butter	1,398	1,355		331
Cheese	353	570		335
Raspberry	3,100	1,471		398
Vanilla	1,513	1,155		184
Total	6,364	4,551		1,248
Estimated demand	6,364	4,551	736	613
Substitution demand				635
Portion of customers who substitute from brand 1 to brand 2 in family size = 635 / 736 = 86%				

Table 2-4: Estimating substitution percentage from Yummy Cakes to Tiny Tina in single serving

	SINGLE SERVE		FAMILY SIZE	
Flavor	**Yummy Cakes**	**Tiny Tina**	**Yummy Cakes**	**Tiny Tina**

Apple		224		60
Estimated demand	366	160	35	30
Substitution demand		64		30
Portion of customers who substitute from brand 1 to brand 2 in single serve = 64/366 = 17%				

Applying the same logic to the fudge flavor, you can estimate that the likelihood of substitution from Tiny Tina to Yummy Cakes in family size is 20 percent. Likewise, for chocolate chip, the likelihood of substituting from Tiny Tina to Yummy Cakes in single serving is 26 percent.

Estimating the substitution percentage from Yummy Cakes to Tiny Tina in single serving is trickier because there is no flavor in which Yummy Cakes single serving is the only missing brand-size. But table 2-4 shows how you can do this calculation, using sales data of apple-flavored cakes.

Thanks to the brand-size and substitution percentages for family size that you've already estimated, you know that the 60 units sold of Tiny Tina in family size correspond to 10.16 percent of total demand for apple (5 percent + 0.86 × 6 percent). You therefore can estimate total demand for apple as 591 (60 / 0.1016). You then compute the demand estimates shown in table 2-4 as brand-size shares multiplied by this total demand estimate. Once you know the estimated demand for Yummy Cakes and Tiny Tina in the single-serving size, you can compute the substitution demand for Tiny Tina and the substitution percentage from Yummy Cakes to Tiny Tina, as shown in table 2-4.

Table 2-5 summarizes the substitution frequencies we have calculated.

In our experience, most buyers guess that some customers will substitute if they can't find what they want, but many of these buyers lack a way to estimate these values and factor those estimates into their assortment decisions. Table 2-5 shows that substitution rates can vary a lot; customers who buy Yummy Cakes in family size are not very loyal: 86 percent of them switched to Tiny Tina. This made sense to the convenience chain's buyers when we presented our findings, as Yummy Cakes was strong in single serving but had only recently begun to offer family size. These sorts of differences in willingness to substitute have a big impact on assortment planning.

You can use the estimates of brand-size shares in table 2-2 and cross-brand substitution frequencies in table 2-5 to estimate the demand for all brand-size-flavors. Table 2-6 displays these estimates. For each flavor, you know total sales, given the assortment of brand-sizes offered in that flavor. You can also compute the fraction of potential demand captured, both from customers for whom a brand-size offered is their first choice and from customers for whom it is their second choice but who are willing to substitute. Witness the 7 percent share captured by buttercream. It results from the 6 percent of customers who made Tiny Tina family-size buttercream their first choice plus the 1 percent of customers who wanted Tiny Tina but substituted Yummy Cakes (20 percent of 5 percent equals 1 percent). You can then estimate total demand for a flavor, assuming the chain offered all four brand-sizes, as total sales divided by share captured. For buttercream, for example, the estimated total demand is 1,429 (100 / 0.07). You can then multiple total demand by brand-size shares to obtain estimates of SKU demand. The 62 percent share of Yummy Cakes in single serve, for example, implies a demand estimate for Yummy Cakes single-serving buttercream of 886 (.62 × 1,429).

Table 2-5: Estimated substitution percentages

	SINGLE SERVE			**FAMILY SIZE**	
	TO			**TO**	
From	**Yummy Cakes**	**Tiny Tina**	**From**	**Yummy Cakes**	**Tiny Tina**
Yummy Cakes		17%	**Yummy Cakes**		86%
Tiny Tina	26%		**Tiny Tina**	20%	

Table 2-6: Estimated demand for all brand-size-flavors

	Sales						Estimated demand					
	Single serve		Family size				Single serve		Family size			
Flavor	Yummy Cakes	Tiny Tina	Yummy Cakes	Tiny Tina	Total	Share of demand captured	Yummy Cakes	Tiny Tina	Yummy Cakes	Tiny Tina	Total demand	Total demand estimate
Chocolate	7,246	3,100	472	456	11,274	100%	7,246	3,100	472	456	11,274	11,274
Cinnamon	3,182	1,487	551	385	5,605	100%	3,182	1,487	551	385	5,605	5,605
Butter	1,398	1,355		331	3,084	99%	1,398	1,355	187	156	3,095	3,110
Cheese	353	570		335	1,258	99%	353	570	76	63	1,063	1,269
Raspberry	3,100	1,471		398	4,969	99%	3,100	1,471	301	251	5,122	5,011
Vanilla	1,513	1,155		184	2,852	99%	1,513	1,155	173	144	2,984	2,876
Chocolate chip	2,034		185	139	2,358	80%	1,827	796	185	139	2,947	2,947
Fudge	2,926	563	274		3,763	96%	2,926	563	235	196	3,920	3,920
Butterscotch	3,009		325		3,334	76%	2,719	1,184	263	219	4,386	4,386
Peanut butter	4,780		380		5,160	76%	4,208	1,833	407	339	6,788	6,788
Honey	2,169	967			3,136	89%	2,169	967	211	176	3,524	3,524
Apple		224		60	284	48%	369	161	36	30	595	595
Cherry/cheese		1,596			1,596	38%	2,636	1,148	255	213	4,251	4,251
Vanilla/chocolate		2,162			2,162	38%	3,571	1,555	346	288	5,759	5,759
Oatmeal/raisin	4,049				4,049	69%	3,637	1,584	352	293	5,866	5,866
Coconut	1,827				1,827	69%	1,641	715	159	132	2,647	2,647
Buttercream			100		100	7%	886	386	86	71	1,429	1,429
Totals	37,586	14,650	2,287	2,288	56,811	80%	43,381	20,028	4,294	3,552	71,255	71,257

Table 2-6 shows demand estimates for each brand-size. If the convenience store offered both brands in a flavor and size, we used sales as our demand estimate. [7] In this case, customers didn't need to substitute, so sales corresponded to actual demand. We computed other demand estimates as the shares times the estimated total demand for a particular flavor.

A key question in improving this assortment is which flavors customers want most. A traditional way of answering this is to look at sales rank. But the total demand estimate column in table 2-6 gives a different—and we'd argue, better—answer. Consider the flavor vanilla/chocolate. With total sales of 2,162, this flavor ranks twelfth, near the bottom, making it a candidate for deletion. But if you take our estimates into account, its total demand of 5,759 puts it in third place, near the top of the list.

Why such a big difference? Vanilla /chocolate is offered only in single serving, and is the least popular brand for single serve to boot, and this depresses its sales relative to other flavors. Despite this handicap, if you look closely, customers love this flavor. Its sales of 2,162 ranks second only to chocolate in Yummy Cakes single serving.

This is one more example that the assortment a retailer offers distorts sales away from true demand. If you want to discern true demand, you must tease out customer insights latent in sales data. [8]

Finding an Optimal Assortment—Let's Get Greedy

To use the demand estimates in table 2-6 to find an optimized assortment, you employ a technique called a *greedy rule* . For sake of concreteness, suppose you're seeking a revenue-maximizing assortment for this store, subject to the constraint that the assortment contain no more than thirty-nine SKUs. (You could just as easily apply this approach to the chain or a cluster of stores, and you can use it to maximize unit sales or dollar gross margin.) The greedy rule chooses thirty-nine SKUs sequentially, choosing as the first SKU the one that would maximize revenue if it were the only one in the assortment. Note that the revenue of a SKU is its primary demand revenue plus any revenue from substitution demand from other SKUs. Thus the first SKU that you choose might not have the highest demand; it might be many customers' second choice. You choose the second SKU to maximize the increase in revenue *given the first SKU that you picked* . You continue to pick SKUs that maximize the increase in revenue from their selection until you've selected thirty-nine of them.

Table 2-7 shows the resulting new assortment. We estimated that this assortment would capture $99,757 in revenue, a 21 percent increase over the current assortment revenue of $82,665. Note the other ways in which the assortment has changed. First of all, our assortment drops Yummy Cakes in family size in all flavors. Recall that 86 percent of the customers who preferred Yummy Cakes in family size were willing to switch to Tiny Tina. Thus the revenue lost by dropping Yummy Cakes is only 0.11 times its 6 percent share, or .66 percent. Our assortment also drops cheese and apple, the least popular flavors. The revenue lost is again small because few customers preferred these flavors. This frees room in the assortment to add additional brand-sizes in the more popular flavors, which generates the 20 percent sales lift.

Figure 2-3 shows the results of applying the greedy rule to the demand estimates for all of the stores of this chain. Figure

2-3 gives revenue as a function of SKU count for the two extremes of assortment localization: no localization, which corresponds to one assortment for the chain; and maximum localization, which corresponds to a unique assortment for each store. To get a single chain assortment, we applied the greedy rule to sequentially choose SKUs guided by the total revenue across all stores for a SKU choice.

Table 2-7: Revised assortment—shaded cells are SKUs carried in the new assortment

	SINGLE SERVE		FAMILY SIZE			
Flavor	**Yummy Cakes**	**Tiny Tina**	**Yummy Cakes**	**Tiny Tina**	**Current**	**New**
Chocolate	7,246	3,100	472	456	$16,446	$16,225
Peanut butter	4,780		380		$7,435	$10,096
Vanilla/ chocolate		2,162			$2,789	$8,566
Cinnamon	3,182	1,487	551	385	$9,149	$8,892
Oatmeal/raisin	4,049				$5,223	$8,726
Raspberry	3,100	1,471		398	$7,226	$7,597
Butterscotch	3,009		325		$4,967	$6,523
Cherry/cheese		1,596			$2,059	$6,324
Honey	2,169	967			$4,045	$5,241
Butter	1,398	1,355		331	$4,657	$4,607
Vanilla	1,513	1,155		184	$4,056	$4,418
Fudge	2,926	563	274		$5,416	$5,294
Chocolate chip	2,034		185	139	$3,706	$3,619
Coconut	1,827				$2,357	$2,357
Buttercream			100		$334	$1,272
Cheese	353	570		335	$2,310	$-
Apple		224		60	$489	$-
Totals	37,586	14,650	2,287	2,288	$82,665	$99,757

These curves are a by-product of the greedy rule, which adds SKUs one by one, and every point on each curve is backed up by a specific assortment that is estimated to produce the revenue shown. The figure also shows a point that gives the revenue of the thirty-nine-SKU assortment currently used by the retailer. The revenue increase from reassorting at the chain level is 28 percent; maximum localization can give another 13 percent.

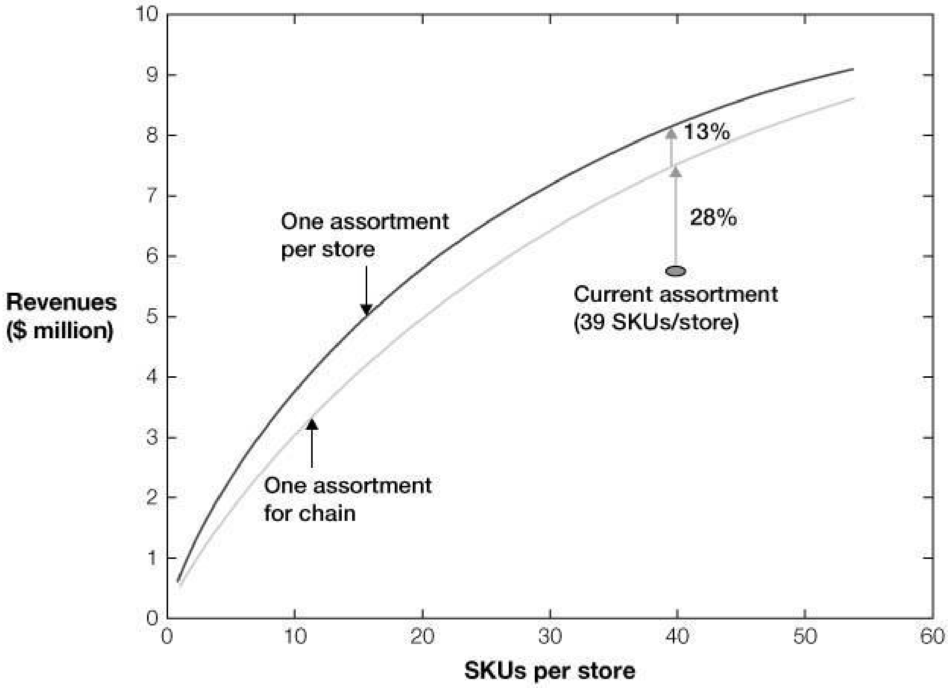


FIGURE 2-3: Reassorting is estimated to add 41% to revenue

This retailer, like many, liked the revenue increase from localization but was reluctant to have a unique assortment for each store because of the high administrative costs. Its buyers asked about having five different assortments for the chain. To do that, you'd begin with the store-specific assortments and cluster these using the following approach, until you'd reduced the number of assortments to five. First, you'd choose two stores to combine. Your criterion for clustering them could be either least loss in revenue or greatest overlap between the two store-specific assortments. You'd then apply the greedy rule to this two-store cluster. You'd continue to pair up stores into clusters until you had exactly five assortments and every store had been assigned to one of these five assortments. The good news is that the localization gain from cutting back to just five assortments only dropped from 13 percent to 12.5 percent, so most of the gain was achieved with just five well-chosen assortments.

Tire Assortments—Where the Rubber Meets the Road

We also applied our approach to planning the assortment for a national tire retailer. When buying tires, people care about brand, mileage warranty, and size. This retailer offered several nationally known brands, including BFGoodrich, Goodyear, and Michelin, which we treated as one category called National. It also offered three house brands of decreasing quality, which we denote as House 1, House 2, and House 3, with House 1 being the best and costliest. Manufacturers provided a couple dozen distinct mileage warranties on their tires. Some of them varied only slightly, so the staff at the retailer believed that consumers viewed them as equivalents. For our analysis, we grouped the mileage warranties into three levels: high, medium, and low.

It doesn't make sense to sell an expensive tire with a low mileage warranty, or vice versa. The retailer therefore offered the following six brand-warranty combinations, which it believed to be logical pairings: National-High (NH), National-Medium (NM), House 1-High (H1H), House 2-High (H2H), House 2-Medium (H2M), and House 3-Low (H3L). The retailer could choose from 64 tire sizes, resulting in 384 (64 × 6) possible SKUs. It offered 122 of the 384 possibilities. That raised an obvious question: might any of the 262 tires *not* offered generate enough demand to warrant selling them?

As with many products, a customer might substitute another tire if she didn't find her first choice. The retailer didn't have sufficient data for us to estimate all possible substitution probabilities. We relied instead on management to tell us the most likely substitution patterns, and focused on those. Substitution across sizes didn't happen. Table 2-8 depicts the likelihood of substitution from a given brand-warranty level listed in a row to another listed over a column, as estimated by the vice president of the tire category. His analysis suggested the need to estimate three substitution frequencies: most likely, likely, and somewhat likely.

When creating a mathematical model of a problem, you face a choice between building a simple, tractable model with a few parameters and a more accurate, but complex, one with many parameters. Here, we could have used a complex model of substitution that allowed for a different substitution frequency from any brand-warranty to any other brand-warranty, which would have led to thirty substitution parameters (six brand-warranties, each of which could substitute to five other brand-warranties). A more complex model often seems more appealing at first; after all, why wouldn't you want as much precision as possible? Unfortunately, that kind of complexity contradicts a statistical principle called *the law of large numbers* (also known as the law of averages), which says that you get a better estimate when you average a large number of values. Imagine, for example, that you wanted to predict the chances a coin would come up heads by flipping it a number of times. If you flipped it ten times, you might see six heads and estimate a 60 percent chance of heads. But this six is likely due to chance. If you flipped it one hundred times, and it was a fair coin, you'd likely see, say, forty-nine or fifty-one heads and estimate a likelihood of about 50 percent. Extend your experiment to a million flips, and you're likely to get a very tired wrist—and almost exactly 50 percent heads.

Table 2-8: Management's estimate of the most likely substitution patterns

From	NH	NM	TO H1H	H2H	H2M
NH			S	S	
NM	L		S	S	
H1H	S			L	S
H2H			S		S
H2M				L	
H3L					M

M = most likely
L = likely
S = somewhat likely
A blank cell indicates no chance of substitution.

Now return to our example of modeling substitution. The more complex model had thirty substitution parameters; the simpler model, three. With a fixed amount of data, that's ten times more data per parameter in the simple model than in the more complex one, which is like flipping the coin one hundred times rather than ten. So the increased accuracy you get with more data per parameter often favors simplicity, especially if, as in this case, the retailer believes that substitution rates are similar between various options.

Table 2-9 shows sales data for a given store for a subset of sizes. We applied the analysis approach described above to this sales data for each store to estimate the six brand-warranty shares, sixty-four size shares, and the three substitution frequencies. Table 2-10 shows the average across all stores of the estimated brand-warranty demand shares and substitution probabilities. Figure 2-4 is based on store-specific estimates and shows that the House 3-Low share in a specific store is correlated with the income level in the store's zip code, which makes sense. (You should always seek confirmation for the conclusions of your analyses of sales history, and store demographic data is a wonderful place to start.)

Table 2-9: Input data for a store is sales during the last six months of 2004 by size-brand-warranty level for SKUs that were offered. A subset of sizes is shown.

Size	National-High	National-Medium	House 1-High	House 2-High	House 2-Medium	House 3-Low
P235/75R15	100				55	40
P215/70R15	282	21		334	203	
P175/80R13					5	20
P205/75R14					10	84
P205/65R15	72	64	20	272	570	
P225/60R16	56		97	285	763	
P215/60R16	10		16	70	76	
P195/70R14		7	33	157	377	
P205/70R15		10		272	524	
P185/65R14		39		225	568	
P225/70R15			8	100	73	

P185/70R14			8	95	223		
P195/65R15				152	298		
P215/65R15				144	221		
P205/75R15	8					200	
P175/70R13						436	
P185/60R14					101		
P195/60R14					115		

Table 2-10: Estimation results

Brand-warranty	Sales share	Estimated demand share
National-High	1%	4%
National-Medium	1%	3%
House 1-High	3%	4%
House 2-High	26%	23%
House 2-Medium	45%	5%
House 3-Low	24%	61%
Substitution probabilities: somewhat likely = 2%, likely = 6%, most likely = 45%		

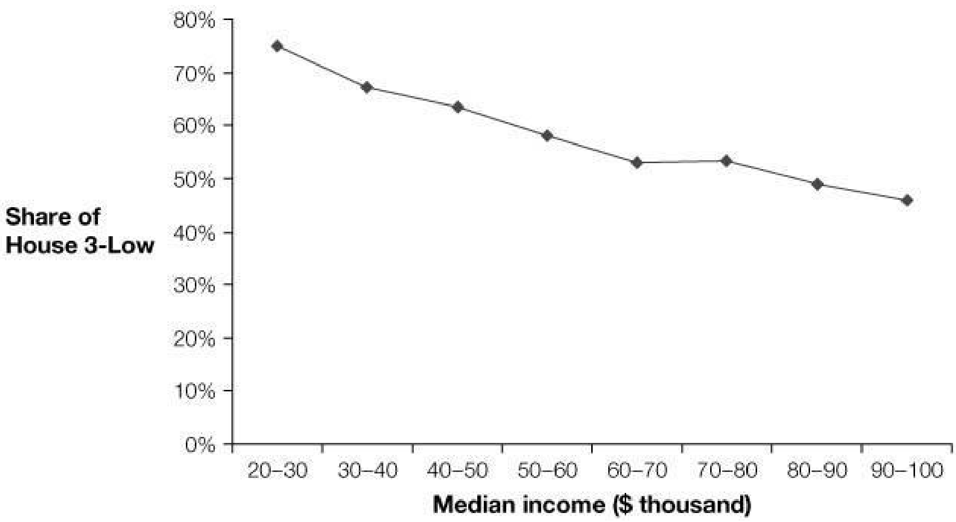


FIGURE 2-4: Share of the low-price tire correlates with income

Table 2-10 also gives the sales shares for comparison with the demand-share estimates. Notice that the demand-share estimate for House 3-Low greatly exceeds the sales share. For House 2-Medium, it falls short of the sales share. This retailer offered House 3-Low in only nine of sixty-four sizes, so customers had few purchase opportunities. But as shown in table 2-11, when the retailer did offer House 3-Low, customers strongly preferred it over the next-highest price selection: House 2-Medium.

The retailer preferred to sell the higher-priced House 2-Medium, believing that its sales staff could persuade customers to trade up. The substitution estimate of 45 percent shows that many customers did trade up, and this explains the high sales share for House 2-Medium relative to its demand share. But the 55 percent of the 61 percent of customers preferring House 3-Low suggests that the retailer lost more than a third of demand due to the meager amount of House 3-Low in its assortment. It could have increased sales by adding House 3-Low in more sizes.

Figure 2-5 shows the results of our analysis. This retailer carried 105 SKUs per store in its current assortment. In the optimized assortment, it would replace 47 of these. The biggest contributor to the 36 percent increase in revenue would be carrying the House 3-Low tire-warranty combination in more sizes.

Table 2-11: In the nine sizes where they competed head-to-head, House 3-Low

significantly outsold House 2-Medium

Size	House 2-Medium	House 3-Low
P205/75R14	2,419	134,183
P195/75R14	1,342	111,339
P235/75R15	1,852	102,749
P205/75R15	1,675	102,580
P185/75R14	1,846	88,348
P215/75R15	1,703	73,255
P225/75R15	2,659	50,664
P155/80R13	2,108	42,432
P175/80R13	2,432	16,486
Total	18,036	722,036

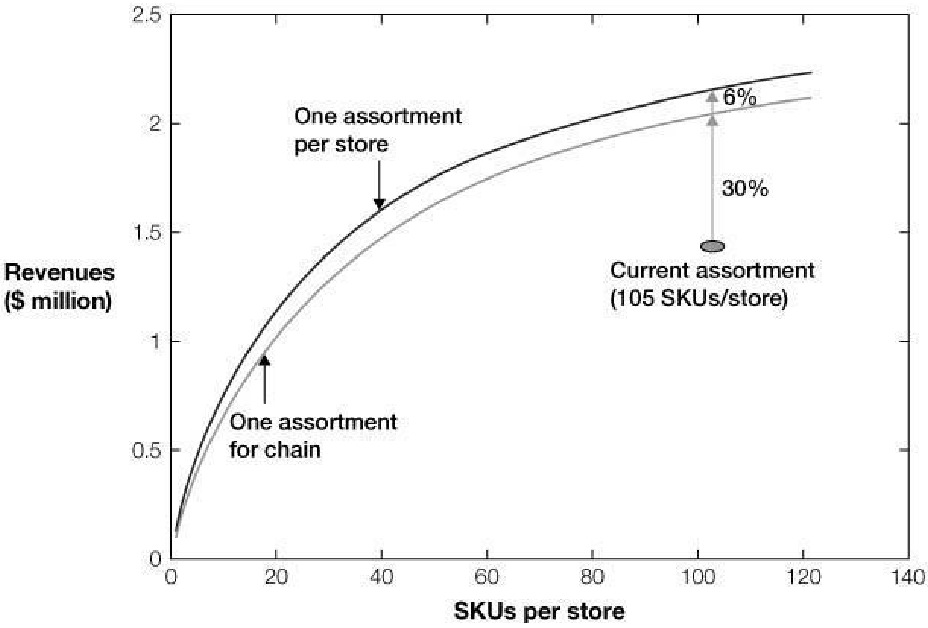


FIGURE 2-5: Reassorting is estimated to add 36 percent to revenue

When Does Localization Pay?

We sought to understand why localization had a significantly lower impact on tires than snack cakes (6 percent versus 13 percent revenue impact). We first thought that the store-to-store variation in demand patterns for snack cakes was greater than for tires, but found that the variation was nearly equal for the two cases, and in fact slightly higher for tires. We then realized that the percentage of maximum demand captured by the single chain optimal assortment would also affect the benefits of localization. If a retailer carried such a broad assortment that the single chain assortment captured nearly all of the potential demand, then there would be very little improvement potential left for localization. The snack cakes assortment offers 40 percent of the potential SKUs, while the tire assortment offers 27 percent of potential SKUs, so it might seem that the snack cakes assortment is broader. However, as shown by the curves in figure 2-6 (which show cumulative percentage of maximum revenue captured by a given percentage of the SKUs in the chain optimal assortment, where the SKUs have been sorted in decreasing order of contribution to revenue), the 27 percent of tire SKUs offered capture 82 percent of maximum revenue, whereas the 40 percent of snack cake SKUs offered capture just 68 percent of maximum potential revenue. Thus for tires, only 18 percent of maximum revenue is left to be captured by localization, whereas 32 percent is left to be captured by localization in the snack cakes case, nearly twice as much.

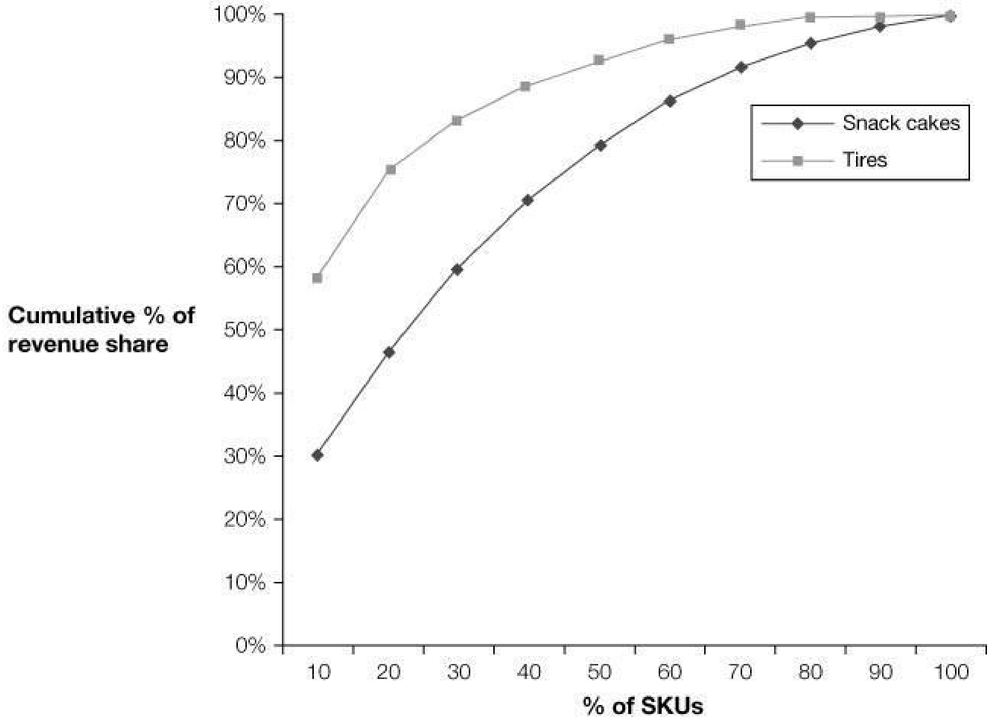


FIGURE 2-6: Cumulative revenue share versus percentage of SKUs

Thus the benefits of localization depend not only on the amount of demand variation between stores but on the percentage of demand captured by the single chain optimal assortment. This is an important principle for retailers to consider in choosing which categories to localize. The natural inclination is for a retailer to localize its most important categories, but we have seen cases where the retailer carried such a broad assortment in its most important categories that there was little to be gained from localization.

While localizing assortments by store added only 6 percent to revenue for the tire assortment, there were meaningful differences between stores. Table 2-12 shows demand estimates for two stores, in Nashville and New Brunswick, and gives median incomes for the zip codes in which these stores are located. New Brunswick customers, with 70 percent higher income than the Nashville customers, buy more of the most expensive national brand and less of the least expensive House 3 brand, and this is reflected in a higher demand share for National-High and a lower demand share for House 3-Low in the New Brunswick store.

These differences in demand estimates influence the store specific assortments for the two stores. The Nashville assortment contains twenty-one SKUs that are not carried in the New Brunswick store and, correspondingly, the New Brunswick store has twenty-one SKUs not carried in Nashville. Ten of the Nashville unique SKUs are the lowest-priced House 3-Low tires and another five are the next lowest-priced House 2-Medium. Conversely, twelve of the New Brunswick unique SKUs are the highest-priced National-High.

These SKU differences didn't arise because we explicitly considered customers' income levels. Our results stemmed purely from the demand data. Higher-priced tires ended up being carried in the wealthier zip code because higher incomes led to their purchase. And that, in turn, led to higher demand estimates for the costlier tires, which caused our revenue-maximizing greedy rule to choose more of those tires. Even so, the apparent causal relationship that emerged comports with common sense. It's a real-world check on the reasonableness of our results.

Table 2-12: Demand shares and income for two stores

		ESTIMATED SHARES	
Brand	**Warranty**	**Nashville**	**New Brunswick**
National	High	2%	6%
National	Medium	1%	4%
House 1	High	3%	4%
House 2	High	28%	29%

House 2	Medium	6%	6%
House 3	Low	61%	51%
Median income		$45,377	$77,194

Implementation Produced a 6 Percent Revenue Increase

The retailer implemented a portion of these recommendations by adding eleven of the SKUs on our list of forty-seven and deleting eleven of the SKUs that we recommended dropping. We estimated these changes would increase revenue by 13 percent. In fact, the retailer got a revenue increase of 6 percent. The lower result stemmed from changes in demand patterns from the sales-history period to the implementation. Even so, a 6 percent improvement is large relative to what retailers typically achieve through enhancements to existing stores. In its annual report, for example, Canadian Tire reports achieving a 3 percent to 4 percent annual revenue increase in existing stores during 2005 through 2007 and is targeting the same increase through 2012. [9]

[6]The material on operational assortment optimization is based on Marshall Fisher and Ramnath Vaidyanathan, "Retail Assortment Optimization: An Attribute Based Approach" (white paper, Wharton School Operations and Information Management, Philadelphia, PA, September 2008; revised May 2009).

[7]The total demand estimate column of table 2-6 is an estimate calculated as total sales divided by percent share of demand captured, as described above. The total demand column gives the total of the four brand-size estimates. The two differ for any flavor for which demand estimates were replaced by actual sales.

[8]This estimation approach, while relatively simple, has some weaknesses. For one thing, the chain offered all four brand-sizes for two flavors, which made the calculations easier. In most cases, you can't count on this happening. Also, by using only two flavors to estimate shares, you're throwing away lots of data that could be used to improve the accuracy of the estimates. In the butter, cheese, raspberry, vanilla, and honey flavors, this retailer offered both Yummy Cakes and Tiny Tina in the single-serving size, so these sales are undistorted by substitution and could be used with sales in the chocolate and cinnamon categories to more accurately estimate the relative demand shares of Yummy Cakes and Tiny Tina in the single-serving size. All sales data is somewhat influenced by random events (weather, the ever-fluctuating economic news, etc.), so the more data you can bring to bear on estimating a value, the more accurate your estimate is likely to be.*For these reasons, in practice, you'll employ a statistical method called maximum likelihood estimation , which uses all of the sales data to find brand-size shares and substitution frequency estimates. You'll apply this technique to sales data for each store to capture store-specific differences in customer preferences. To estimate price on SKUs not currently carried by a retailer, you regress the prices of existing SKUs against their attributes to obtain an attribute-based pricing formula. For additional details, see Fisher and Vaidyanathan, "Retail Assortment Optimization."*

[9]Canadian Tire Corporation Ltd., Annual Report 2007.

Conclusions

The process for assortment planning that we have presented comprises three steps: modeling, estimation, and optimization.

Modeling consists of choosing attributes, attribute values, and possible substitution paths. You'll typically encounter one of three types of attributes in your assortment planning; all three were represented in the examples considered in this chapter.

1. *Functional attributes address whether and how a given product satisfies a consumer need. Examples include the sizes of tires, batteries, shoes, apparel, and sheets. There is no substitution across these attributes. Someone who needs a twin sheet won't buy a queen.*

2. *Price and value are typically seen in the good-better-best segmentation used by many retailers. Many consumers regard a higher-thread-count sheet as a better product, and so it carries a higher price. In general, the closer the price of a product is to a customer's preferred price/value point, the more likely she is to accept it as a substitute.*

3. *Taste attributes include such things as flavor, color, and fabric type.*

In defining attribute values, you should group values that differ only slightly and may be indistinguishable to the *customer. We did this with the tires, grouping many distinct warranty levels into low, medium, and high. The same challenge arose with the snack cake package sizes. In reality, the manufacturers offered a large number of package sizes that varied only slightly. These thus could be grouped into single-serving and family sizes. A reason to group attribute values is that limited data undermines accurate estimation. Thus modeling requires some judgment, especially in choosing the right level of aggregation of attribute values. We have found a trial-and-error approach works well: make an initial choice and then revise, as needed, after seeing the results of your estimate.*

The most important point about estimation is that the assortment currently offered affects sales, and you need to control for this in estimating demand shares. This was especially apparent in the tire example, where the House 3-Low tire had much higher potential demand than was reflected in the sales, because not much of it had been offered.

Typical ways of estimating demand for a new product assume that its sales will resemble the sales of a similar existing product. This works if a new product varies only negligibly from an existing offering, such as when this year's model replaces last year's. But in most cases, if a new product resembles an existing product that closely, you should question the value that the new offering brings to the assortment.

Our approach, in contrast, uses sales of the large number of existing products that have at least one attribute in common with the new product to estimate demand for the new product.

Thinking of a product as a collection of attributes is a familiar idea in marketing and is often used by manufacturers in estimating demand for potential new products. A variant of this approach is called conjoint analysis and consists of asking a panel of potential customers for the new product to make a series of pairwise comparisons of various product concepts. These comparisons enable the manufacturer to assess the utility of different attribute levels and then select an optimal basket of attributes. Conjoint analysis requires a considerable effort but makes sense for a retailer introducing a major new product intended to last for a long time, such as an electric car or a Blu-ray high-definition TV. It's probably too time consuming for evaluating the large number of new products that need to be considered in assortment planning. Even so, you can think of our process as "conjoint analysis on the cheap." When a customer shops in a store, he is making comparisons of products and expressing preferences, just as in conjoint analysis, and the approach described in this chapter mines those purchase decisions to find preferences for attributes.

In the two examples that we provided, the retailers had high in-stock rates. If instead a retailer had a high level of stockouts, you would need to account for this in analyzing the sales data. Understand that stock-outs are both a blessing and a curse. If customers can't find their favorite products and frequently must substitute, then this distorts sales data and obscures true demand. But you can correct for this by calculating a sales rate during periods when a particular item is in stock and basing your analysis on sales rates rather than total sales.

If stockouts are high, then every day in every store, customers see a different assortment. In effect, the retailer is conducting a kind of ad hoc assortment planning experiment. Remember in the snack cake example where we were able to calculate the substitution rate by looking at "holes" in the assortment—that is, flavors where one or more brand-sizes were missing? Frequent stockouts create more holes and thus opportunities to estimate substitution frequencies. [10]

In our optimization analysis, we sought to maximize revenue—which was what the two retailers we helped cared about. But you could apply the same process to maximizing gross margin, unit sales, percentage margin, or really any metric of strategic importance. Also, sometimes the key decision isn't which products to carry but also how much of each one. In a grocery, for example, products can have multiple facings. You can modify the greedy rule to handle this case. When you are choosing the next SKU to add to the assortment, just expand the choices to also include adding another facing or product unit of a SKU already in the assortment. The revenue increase from adding another facing would come from a reduction in stockouts. This can be measured and used in comparison to the revenue increase in adding new SKUs.

The assortment that a retailer offers has an enormous impact on revenue. The revenue increases that we saw were 41 percent in the snack cake sales and 36 percent in the tire sales.

These increases sprang from a variety of factors, but the biggest in the cake example was recognizing, as is shown in table 2-6, that customers of Yummy Cakes in the family size were not loyal; 86 percent of them were willing to switch to Tiny Tina. Thus dropping Yummy Cakes in family size resulted in less than 1 percent in lost revenue and freed space for products that added much more revenue.

In the tire example, the biggest source of gain was discovering a product—the House 3 brand with a low mileage warranty—for which there was enormous latent demand. This is a common pitfall. A retailer assumes a particular product *won't sell, and doesn't offer much of it. For that reason, the retailer then doesn't sell much of it, which seems to confirm the original assumption. When we have presented our findings to groups of retailers, many of them have told us of their own "sales surprise stories"—products that they thought had low sales potential but turned out to be blockbusters. Many of you are also sitting on hidden blockbusters: your current sales numbers can tell you what they are, but you have to take the time to tease them out. The aggressive application of the methods described here will help you to do that.*

[10] *The idea of using stockouts as an opportunity to estimate substitution was suggested to us by Kevin Freeland.*