Paper 1583-2014

Leveraging Advanced Analytics to Create Customer-Centric Assortments

Christopher J. Matz and Wanda Shive, SAS Institute Inc.

ABSTRACT

Traditional merchandise planning processes have been primarily product and location focused, with decisions about assortment selection, breadth and depth, and distribution based on the historical performance of merchandise in stores. However, retailers are recognizing that in order to compete and succeed in an increasingly complex marketplace, assortments must become customer-centric. Advanced analytics can be leveraged to generate actionable insights into the relevance of merchandise to a retailer's various customer segments and purchase channel preferences. These insights enrich the merchandise and assortment planning process. This paper describes techniques for using advanced analytics to impact customer-centric assortments. Topics covered include approaches for scoring merchandise based on customer relevance and preferences, techniques for gaining insight into customer relevance without customer data, and an overall approach to a customer-driven merchandise planning process.

INTRODUCTION

A pervasive theme in the retail industry today is customer-centricity. But what does this mean? The National Retail Federation (NRF) defines customer-centricity as "**an enterprise-wide strategy to fully leverage consumer insights to drive integrated strategies—across marketing, merchandising and operations**." According to a 2013 Retail Systems Research survey of retailers, 45% of leading retailers indicated that "understanding customer preferences" was among their top three business challenges. Retailers recognize that to survive in an increasingly competitive and fragmented marketplace, they must become even more focused on their customers' specific preferences and expectations.

In the area of marketing, retailers have made significant strides in moving toward more personalized communications based on customers' preferences versus a mass-marketing approach. In terms of operations, retailers have begun to build customer-focused supply-chain organizations that address customers' expectations for a seamless experience across channels. But what about merchandising? According to the same Retail Systems Research survey, 46% of retailers indicated that better incorporation of customer segmentation and preferences into the planning process was among the top three opportunities to improve the merchandising process. According to research conducted by McKinsey & Company, retailers and consumer-packaged goods companies that have begun to incorporate customer preferences into their merchandising and assortment decision-making processes have seen significant improvements in sales growth. Conversely, most retailers are familiar with the implications of not accounting for customer preferences in any SKU rationalization strategy based on Walmart's experience with Project Impact in 2008.

However, deployment of approaches to incorporate customer preferences into the merchandising process is still in the early stages for many retailers. According to Retail Systems Research, approximately 30% of retailers surveyed have no ability to target merchandise plans to distinct customer groups, with just over half surveyed indicating that they have some limited ability to do the same. Some of the reasons cited for this include challenges involved with integrating disparate data sources and data management protocols, as well as organizational issues related to greater integration between marketing and merchandising within the retail organization. Assuming diverse data sources containing customer, product, and transactions data can be accessed and eventually integrated, how can insights into customer preferences be extracted in such a way as to make sense within the context of the merchandising/assortment planning process?

The goal of this paper is to provide a perspective on how insights into customer preferences can be extracted from diverse data sources (product, customer, transactions) so that they can be made actionable within the context of an assortment planning process. First, the data that is required to extract insights into customer preferences and techniques using SAS tools such as SAS Enterprise Guide to transform this data into insights and customer relevance "scores" for use in the assortment planning process are described. Next, a case study provides an approach for leveraging some of these same techniques to inform the assortment planning process with transaction data in the absence of customer data. Finally, additional considerations related to the use of customer preferences in the overall merchandising process are introduced.

CUSTOMER PREFERENCE SCORE: DATA REQUIREMENTS AND APPROACH

The assortment planning process can vary significantly across different retail segments (grocery, fashion apparel, specialty retail) and even across retailers within those segments. However, in general, the assortment planning process is focused on ensuring that the **right merchandise** is ordered in the **right quantities** to arrive at the **right locations** at the **right time**. For retailers carrying a larger percentage of replenished merchandise, the primary focus of assortment planning usually includes managing the assortment over time through periodic assortment reviews, the goal of which is to "rationalize" the current assortment of SKUs by removing poor performers, adding new products, and ensuring that the overall assortment will fit into the space available in stores while meeting supply-chain and replenishment constraints (i.e., target days of supply, case-pack requirements). Output of the assortment planning process, in this case, is used in downstream systems such as space planning, store/item authorization for ordering, and replenishment. For retailers carrying more seasonal assortments, the focus might be more on ensuring the right mix and breadth of styles and colors for stores or store clusters, along with the right depth of each style or color for that particular store or store cluster. In the case of sized merchandise, size profiles might then be applied to style and colors (either at the total chain or store group) with the final output informing the purchase order process.

The common factor across these disparate assortment planning processes is that traditionally, decisions around which items to keep, add, or remove from the assortment are based on product and location data coming from merchandising systems. Retailers might look at financial metrics such as historical or forecasted sales, margins, GMROII, sell-through, etc., at different levels of the product and location hierarchies, as well as product and location attributes in order to make assortment decisions. Whereas traditional assortment planning process have tended to be manual, spreadsheet-driven processes, some retailers have begun to take advantage of advanced analytics capabilities to optimize assortments; according to Retail Systems Research, 64% of retailers surveyed had implemented some form of assortment optimization in their business. Assortment optimization capabilities are focused on delivering recommendations for the best possible assortment given a set of maximization objectives (i.e., maximize sales, profitability, or some combination of the two) and a set of constraints (available space, vendor minimums, shelf case-pack requirements, etc.).

However, even when advanced capabilities such as optimization are used, an opportunity still exists to enhance the assortment planning process through the incorporation of customer preferences. In the same Retail Systems Research survey, although 63% of respondents acknowledged the importance of optimizing the assortment against key customer segments, only 44% had implemented some form of this capability. Walmart's Project Impact experience in 2008 is a perfect example of the potentially disastrous results of taking a SKU rationalization approach without accounting for customer preferences. The products that are most important to your best customers might not necessarily be the highest selling or most profitable. Furthermore, customer preferences might vary significantly across locations or channels. A product that is highly relevant to your best customers in one store might not be so relevant to your best customers at a different store, and an item might be extremely relevant to your best online customers, but not to in-store shoppers.

Therefore, a method is needed to quantitatively measure the relevance of a particular product or group of products to customers shopping across all locations and channels. The goal is to define a *customer preference score,* which can be used as an input into the assortment planning process. The intent of this score is not to replace or render irrelevant traditional assortment metrics or decision-making processes, but rather to supplement them so that a more holistic, customer-focused assortment decision can be made. For example, as a Category Manager is evaluating two products with comparably low sales or profitability to decide whether they should be removed from the assortment, she can assess the customer preference score of each of the items to determine whether there is a risk of removing an item that is important to the retailer's best customers. In the case of an apparel retailer who changes the assortment each season, the buyer can assess the importance of key product groups (i.e., based on attributes such as silhouette, fabric, price point, trendy or basic, etc.) to the brand's best customers in order to make a decision about how to define the best mix of styles and colors.

CUSTOMER PREFERENCE SCORE: DATA REQUIREMENTS

The customer preference score attempts to quantify the level of importance of a particular item or group of items to a set of customers (i.e., a customer segment). The score can be calculated at any level of the product hierarchy or for any group of products (i.e., a node of the consumer decision tree or a defined set of attributes) and applied to all items within that group, or it can be calculated for the individual item. To compute the score, the first step is to gather the required data, which includes:

- **Transaction-level data**
    - Key data elements include transaction ID, store ID, item(s) sold in the transaction, number of units, sales amount, and customer or household ID for retailers who can track specific customers.

        - The ability to identify discounts or promotions within each transaction is preferred.
    - **Purpose**: The transaction-level data is the basis for the customer preference score. This score is based on tying historical transactions, including an item or group of items, to a particular customer segment.
- **Customer data (preferred, optional)**
    - Customer data provides associated information about the customer or household IDs found in the transaction data.
    - Each customer should be assigned to at least one customer segment that categorizes each customer based on its economic value to the retailer (i.e., Primary, Premium, Gold, etc.).
    - **Purpose**: Transactions must be able to be tied to a customer record, which, in turn, must be assigned to a customer segment. Scores can be generated based on the relevance of the item or group of items to the "top" segment of customers.
- **Product master data**
    - Key data elements include basic product information (SKU number, UPC), hierarchy information, and product attributes.
    - **Purpose**: Product hierarchy data and attributes are required for circumstances where the customer preference score will be defined at a level higher than SKU or style. Scores can be calculated for certain levels of the hierarchy (i.e., Category, Brand, Classification, etc.), for specific attributes (i.e., relevance of private label products in a particular category) or groups of attributes.
- **Store master data**
    - Store ID and characteristics (store attributes, demographic information, if available).
    - **Purpose**: Store characteristics will be helpful for profiling stores or groups of stores after customer preference scores have been determined for customers by those locations.

This paper focuses on methodologies for generating customer preference scores and not on the sourcing of required data. However, because data will often come from disparate sources, there might be a significant amount of effort involved in sourcing and preparing the data that will be needed to compute the score. Furthermore, this paper does not address best practices in customer segmentation. It is assumed that the retailer has implemented a segmentation scheme that characterizes customers based on their value to the retailer. Segments can be general (across the entire brand) or specific to an individual category.

CUSTOMER PREFERENCE SCORE PROCESS

Figure 1 illustrates the major steps in a customer preference scoring process:

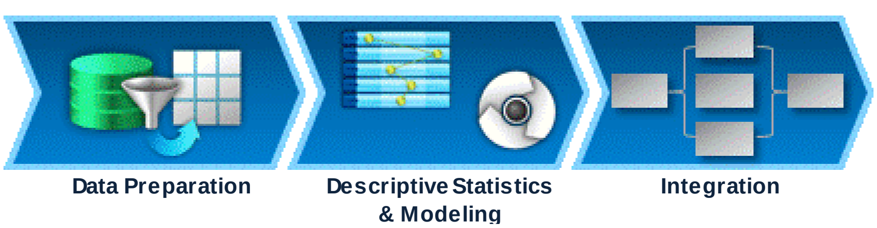


Figure 1. The Customer Preference Scoring Process

In the **Data Preparation** step, data is sourced and transformed in order to compute the customer preference score. For example, in many cases, joining source data sets is required in order to create a combined analytical base table that is used to generate descriptive statistics and perform any follow-on modeling. Data sets might also need to be

restructured to optimally support the generation of descriptive statistics. In the **Descriptive Statistics & Modeling** step, relationships in the data between products or product groups and key segments are analyzed through the use of charts, graphs, and tables. At this point, frequency tables that test for statistically significant association between products or product groups and customer segments are created. Finally, predictive models can be created and run. During the **Integration** step, scoring output is exported so that it can be integrated into downstream systems and processes such as assortment planning. This final step might involve reformatting statistical output into a more "business-friendly" format. For example, items in the upper percentile of frequencies might be designated as "A" or "Highly Relevant" items to make the output easier to interpret for business users.

Customer Preference Score Process Example

In the following example, sample retailer data is used to explain how a customer preference score can be created. The sample data includes three years of transaction data containing customer IDs and product IDs, which can be joined to customer segments and product master data (product hierarchies and attributes) for the scoring process. The goal of this example is to prepare the data and perform some descriptive statistics to assess the relationship between certain products or product groups and the top customer segment. Once those relationships have been identified, customer preference scores can be generated and utilized in downstream processes.

Step I: Data Preparation

Figure 2 shows a Process Flow in SAS Enterprise Guide in which the combined data needed to calculate a customer preference score is prepared. First, a sample of transactions for a group of four stores is extracted. Then, customer segments and product data (labeled "item master" in Figure 2) are joined with the transactions data to create the analytical base table needed for the generation of customer preference scores. The item master data set shares the UPC code with the transactions data set, and the customer segments data set shares the household ID with the transactions data set.

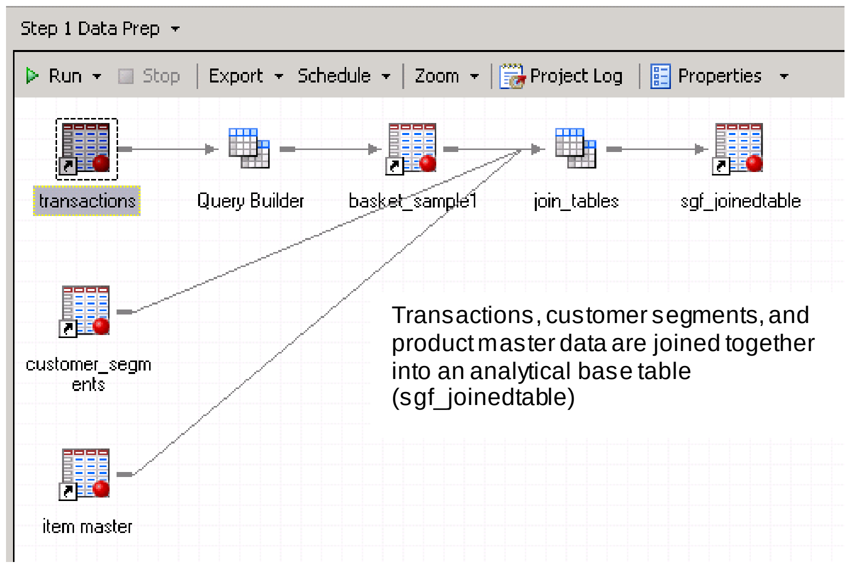


Figure 2. Data Preparation Step in SAS Enterprise Guide

Step II: Descriptive Statistics & Modeling

Next, the relevance of products or product groups to top customers is assessed by generating descriptive statistics and graphical output. In this example, frequency tables and charts are created to identify penetration of top segment baskets by merchandise group (two levels above SKU in the product hierarchy). From these tables and charts, product groups that are more frequently represented in top customer baskets by location can be analyzed. For example, the frequency table shown in Figure 3 highlights the top five product groups found in transactions of best customers for store 6505. The top five are: Meal Solutions, Snacks, Soft Drinks, Fresh Milk, and Frozen Meat Entrées.

	STORENUMBER	GRP	COUNT	PERCENT
2	6505	GRP-MEAL SOLUTIONS-1011	34349	5.3603810273
3	6505	GRP-SNACKS-1033	26713	4.1687344139
4	6505	GRP-SOFT DRINKS-1036	22531	3.5161065803
5	6505	GRP-MILK FRESH-1062	22098	3.4485341623
6	6505	GRP-FROZEN MEAT ENTREES-1094	19832	3.0949103768
7	6505	GRP-CEREALS-1005	18313	2.8578607165
8	6505	GRP-BAKING-1002	18159	2.8338280321
9	6505	GRP-FRESH BREAD & CAKE-1058	17988	2.807142389
10	6505	GRP-DELI-1086	17405	2.7161615121

Figure 3. Frequency Table for Store 6505

Whereas in Store 6509, while Meal Solutions is still the top penetrating group, Natural Products is in the top five:

	STORENUMBER	GRP	COUNT	PERCENT
151	6509	GRP-MEAL SOLUTIONS-1011	18363	4.2579289812
152	6509	GRP-SNACKS-1033	17030	3.9488389996
153	6509	GRP-MILK FRESH-1062	15104	3.5022468732
154	6509	GRP-SOFT DRINKS-1036	14598	3.3849178929
155	6509	GRP-NATURAL PRODUCTS-1048	13870	3.2161125616
156	6509	GRP-DELI-1086	12043	2.7924761052
157	6509	GRP-FRESH BREAD & CAKE-1058	11445	2.6538145831

Figure 4. Frequency Table for Store 6509

Figure 4 highlights the most common product groups found in the baskets of the best customers for Store 6509. By comparing results by store, variations across locations can be identified. For this example, only four stores are examined. However, the same process can be easily applied across large numbers of stores as well as store clusters for the purpose of informing the assortment planning process.

Figure 5 below provides similar descriptive statistics, but at a lower level of granularity, by looking at penetration by subgroup. As seen below, questions about the variation between the top penetrating groups and the top penetrating subgroups can be answered (i.e., is there a top penetrating subgroup that does not belong to one of the top penetrating groups?). By looking at penetration by subgroup, it is highlighted that Yogurt Cups has the highest representation in the best customers' baskets in both comparison stores.

	STORENUMBER	SGRP	COUNT	PERCENT
1422	6509	SGRP-YOGURT CUPS-4401	8275	1.9187693906
1423	6509	SGRP-VEGETABLES-9830	8070	1.8712349223
1424	6509	SGRP-BANANAS-9811		
1425	6509	SGRP-GALLONS-6204		
1426	6509	SGRP-BERRIES-9826		
1427	6509	SGRP-DEF FOR MISC TRAN CO...		
1428	6509	SGRP-DIET COLAS-3602		
1429	6509	SGRP-PACKAGED SALADS-9858		
1430	6509	SGRP-SHREDDED CHEESE-6118		

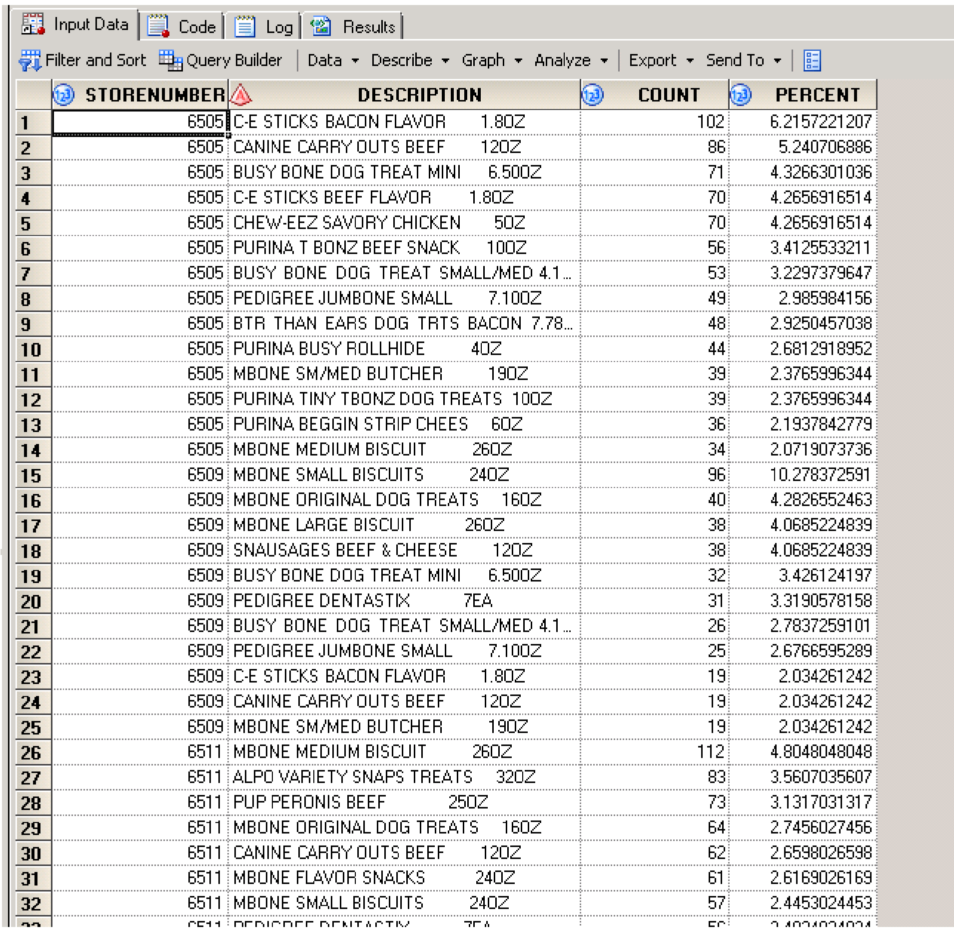
	STORENUMBER	SGRP	COUNT	PERCENT
2	6505	SGRP-YOGURT CUPS-4401	12232	1.9088817935
3	6505	SGRP-GALLONS-6204	9510	1.484096293
4	6505	SGRP-DEF FOR MISC TRAN CO...	9393	1.4658376951
5	6505	SGRP-VEGETABLES-9830	9337	1.4570985371
6	6505	SGRP-BANANAS-9811	7751	1.2095930986
7	6505	SGRP-SHREDDED CHEESE-6118	6040	0.9425806109
8	6505	SGRP-PACKAGED SALADS-9858	5755	0.8981045391
9	6505	SGRP-POTATO CHIPS-3304	5370	0.8380228279

Figure 5. Subgroup Frequency Tables

With an idea of which product groups are penetrating our best customers' baskets, the analysis can be expanded down to the SKU level. For example, a merchant might want to understand which dog snacks are most highly represented in the baskets of our top customer segment. Association tables and corresponding graphical analyses can be created to gain a better understanding of specific product occurrences. As seen in Figure 6 below, for the four sample stores< it is clear that while the top penetrating products are consistent across the locations, their rates of penetration within the best customers' baskets vary:

Figure 6. SKU-Level Penetration by Store

As part of the Descriptive Statistics & Modeling step of the process, the relative penetration of product groups and products in the best customers' baskets can be further analyzed. As a very simple output from the analysis process, relative frequencies by SKU and location, like those shown in Figure 7 below, can be exported. This output can be used to enable buyers and category managers to compare products in an assortment in terms of relative importance to top customers. More sophisticated descriptive statistics, such as index to average or results from statistical tests of association and strength of association, can be added to the output. Any of these output options can be used to create a customer preference score.



	STORENUMBER	DESCRIPTION	COUNT	PERCENT
1	6505	C-E STICKS BACON FLAVOR 1.8OZ	102	6.2157221207
2	6505	CANINE CARRY OUTS BEEF 12OZ	86	5.240706886
3	6505	BUSY BONE DOG TREAT MINI 6.5OZ	71	4.3266301036
4	6505	C-E STICKS BEEF FLAVOR 1.8OZ	70	4.2656916514
5	6505	CHEW-EEZ SAVORY CHICKEN 5OZ	70	4.2656916514
6	6505	PURINA T BONZ BEEF SNACK 10OZ	56	3.4125533211
7	6505	BUSY BONE DOG TREAT SMALL/MED 4.1...	53	3.2297379647
8	6505	PEDIGREE JUMBONE SMALL 7.1OZ	49	2.985984156
9	6505	BTR THAN EARS DOG TRTS BACON 7.78...	48	2.9250457038
10	6505	PURINA BUSY ROLLHIDE 4OZ	44	2.6812918952
11	6505	MBONE SM/MED BUTCHER 19OZ	39	2.3765996344
12	6505	PURINA TINY TBONZ DOG TREATS 10OZ	39	2.3765996344
13	6505	PURINA BEGGIN STRIP CHEES 6OZ	36	2.1937842779
14	6505	MBONE MEDIUM BISCUIT 26OZ	34	2.0719073736
15	6509	MBONE SMALL BISCUITS 24OZ	96	10.278372591
16	6509	MBONE ORIGINAL DOG TREATS 16OZ	40	4.2826552463
17	6509	MBONE LARGE BISCUIT 26OZ	38	4.0685224839
18	6509	SNAUSAGES BEEF & CHEESE 12OZ	38	4.0685224839
19	6509	BUSY BONE DOG TREAT MINI 6.5OZ	32	3.426124197
20	6509	PEDIGREE DENTASTIX 7EA	31	3.3190578158
21	6509	BUSY BONE DOG TREAT SMALL/MED 4.1...	26	2.7837259101
22	6509	PEDIGREE JUMBONE SMALL 7.1OZ	25	2.6766595289
23	6509	C-E STICKS BACON FLAVOR 1.8OZ	19	2.034261242
24	6509	CANINE CARRY OUTS BEEF 12OZ	19	2.034261242
25	6509	MBONE SM/MED BUTCHER 19OZ	19	2.034261242
26	6511	MBONE MEDIUM BISCUIT 26OZ	112	4.8048048048
27	6511	ALPO VARIETY SNAPS TREATS 32OZ	83	3.5607035607
28	6511	PUP PERONIS BEEF 25OZ	73	3.1317031317
29	6511	MBONE ORIGINAL DOG TREATS 16OZ	64	2.7456027456
30	6511	CANINE CARRY OUTS BEEF 12OZ	62	2.6598026598
31	6511	MBONE FLAVOR SNACKS 24OZ	61	2.6169026169
32	6511	MBONE SMALL BISCUITS 24OZ	57	2.4453024453

Figure 7. Output Ready To Be Exported

The scoring process can be made even more sophisticated through the use of predictive modeling to determine the likelihood of an item being purchased by a customer in the top segment of customers. This process would involve adding an outcome variable to the data. For example, if the objective is to score products within the Pet Food category based on their likelihood of being purchased by a customer in the top segment, a binary variable can be created in the analytical base table with a value of 1 if a product from the category was purchased in a transaction, and a value of 0 if it was not found in the transaction. A predictive model that scores products in an assortment based on likelihood of being purchased by top customers can then be created. This process can become complex. For example, when an assortment contains many new items, scoring those new products based on historical transaction data at the SKU level is not possible. However, the binary variable could be created at a higher level of the product hierarchy or for a particular attribute or set of attributes so that the new products can be scored based on the higher

level of the product hierarchy. This will involve in-depth assessment of both the transactional data and product attributes, as well as the assortment planning process.

Step III: Integration

Regardless of the method used to create the customer preference score, the final step is to output the scores to a file that can be consumed by downstream systems such as assortment planning. This output data can conform to a standardized format based on the requirements of the downstream system in which the scores will be integrated. For example, for the SAS Merchandise Planning solution, scores by product and location can be loaded into a two-dimensional fact table that will enable them to be viewed within a plan worksheet. The downstream table can then be updated as often as the scores are regenerated. Much thought will need to be given to how scores can be translated in such a way that they can be easily interpreted by business users who might not have a solid grasp of statistical terms. For example, products that have a much higher than average relative frequency of purchases by top segment customers (i.e., twice the mean or greater) could be labeled as "highly relevant." This transformation of the scores can be processed prior to the file being exported.

COMPUTING A CUSTOMER PREFERENCE SCORE WITH TRANSACTION DATA: FAMILY DOLLAR STORES CASE STUDY

In order to determine each item's customer preference score based on the previous process, retailers must be able to tie transactions to customer data. However, not all retailers have loyalty programs or other means to identify their customers.

SAS and Family Dollar Stores are working together on an approach that seeks to incorporate customer preferences into the assortment planning process. Instead of scoring merchandise based on relevance to key customer segments, this approach scores merchandise based on relevance to key **baskets**, based on the assumption that our best customers are purchasing our best baskets.

The first step in the process is to define a segmentation approach for baskets; what qualifies a particular basket as good, better, or best? A variety of basket characteristics can be considered, including:

- Basket profitability
- Number of distinct SKUs in the basket
- Breadth of categories and product groups in the basket

Once a segmentation approach has been defined based on the above characteristics, each transaction can be assigned to an appropriate segment. For example, baskets that meet a certain threshold of number of distinct SKUs, profitability, and category breadth might be assigned to the "A" segment. Defining what these thresholds should be is a process that requires significant input from the category managers and buyers.

After the segmentation approach is in place and transactions are being assigned to specific basket segments, the same approach taken to score merchandise based on relevance to key customer segments can be followed. Using transaction data, product hierarchy and attributes data, and store data, each item in the assortment can be assigned a customer preference score based on the strength of association between a particular item or group of items and Family Dollar's best baskets. It is important to note that this scoring will be generated for each store cluster, so certain items might score high in a particular store cluster but not in another. Access to store attributes and demographic data adds further depth to the customer preference score. For example, answers to questions like the following can be obtained: What are the salient characteristics of the stores in the clusters where the item or item group is highly relevant? Are there any key characteristics of the stores' trading areas that can shed light on the customers shopping the stores?

Once the customer preference scores have been determined for each product or product group, these scores can be output to a file that can be integrated into the assortment planning database. In this manner, users will be able to evaluate the customer preference score in conjunction with other key assortment planning metrics in order to make better product selection decisions.

This approach is relevant for any retailer who collects transaction-level data, but is not able to tie transactions to customer segments. It might also be relevant as a "Phase 1" activity for a retailer who is in the midst of a customer segmentation project or is looking to upgrade or redefine its segmentation approach. Furthermore, this approach is applicable to both online and off-line transactions, as the items that are highly relevant to a retailer's best online baskets might not be the same as the most relevant items in certain store groups.

CUSTOMER PREFERENCE SCORING: ADDITIONAL CONSIDERATIONS

Generating customer preference scores and integrating them into the assortment planning process is a quick way of providing the retailer's merchants with a data-driven customer perspective for their product scope. Scores can be imported into the assortment planning system and evaluated by the buyer and cCategory manager when making decisions about which products to include or remove from an assortment. Customer preference scores can also help planners and buyers better allocate the time spent on planning, with greater scrutiny being placed on highly relevant items versus non-relevant items.

Furthermore, customer preference scores can be provided as input into an assortment optimization process. For example, a constraint in an optimization process might be that products with a customer preference score higher than a certain threshold must be maintained in the assortment for a particular location regardless of their performance in terms of other key metrics. Alternatively, an optimization objective might be to maximize the overall customer preference score for the assortment in addition to other optimization objectives such as sales and profitability.

In addition to assortment planning, the customer preference score can be used to inform other merchandising processes such as:

Store Clustering

Customer preference scores can be used to inform a store-clustering strategy. In this scenario, stores can be clustered based on the relative importance of key products or product groups in the assortment to key customers versus a traditional approach where stores are clustered based on sales for the product group alone. Stores that have similar selling patterns within a particular category or assortment might have products or product groups that penetrate key customer baskets very differently, and therefore should be assorted differently.

Allocation and Replenishment

Fulfillment policies can be adapted based on customer preference scores. This enables retailers to be more targeted in terms of where dollars are being spent in inventory coverage. For example, service levels for specific products or product groups with high customer preference scores might be increased, with changes to allocation and replenishment policy components such as safety stock, shelf minimums, etc. In some cases, this might trigger retailers to adjust the spend for other products that don't have the same penetration with key customers because the impact of an out-of-stock situation in a highly relevant product with a key customer could potentially be more costly than with other customers.

Omni-Channel Strategy

In order to gain a holistic view of customers who shop the retailer's "brand," it is critical to converge offline transactional data with transactional data from the web and mobile channels. Customer preference scores should incorporate how a customer is shopping the brand across all channels, and assortments should reflect those shopping preferences. For example, answers to questions like the following can impact retailers' decisions: Are there specific products or product groups found more in online baskets than in stores? Are there regional trends that can be gleaned (i.e., based on ordering or ship-to addresses) so that the top segment of customers can be further broken down from a channel preference perspective? At a minimum, when the customer preference score incorporates transactional data from all channels, more effective decisions can be made about the in-store versus online assortment.

Monitoring and Reporting

Incorporating customer preferences into the merchandise planning process will help drive new insights from a monitoring and reporting perspective. For example, how are assortments performing in the market in terms of spend by key customers? Have assortment decisions impacted spend by top customers in a positive way? What trends are occurring in how top customers are shopping the retailer's stores and online? As insights into key customers and baskets start to drive both planning and evaluating assortments, organizational and incentive structures might start to evolve toward a more customer-focused approach versus a product- or category-focused approach.

CONCLUSION

Best-in-class retailers are seeking to bring a customer focus to every aspect of their operations. Merchandising is central to a retailer's business, so it is critical to make the merchandising process as customer-focused as possible. This paper has described concepts and approaches that enable a retailer to begin the process of customer-centric merchandising through the use of the customer preference score in the assortment planning process. Descriptions have been provided of the data that is required and some of the statistical techniques that can be leveraged to create basic customer preference scores. More advanced techniques for the generation of customer preference score, such

as predictive modeling, have been introduced. This paper has also described a high-level approach for incorporating customer preferences into the merchandising process in the absence of customer data. The right approach for a retailer will depend on specific business goals and objectives, data availability and quality, and the level of analytical sophistication in the Merchandising organization. Finally, opportunities have been presented for the customer preference score to be leveraged in other areas of the merchandising process such as allocation and replenishment.

Although the benefits of incorporating customer preference scores into the merchandising process are clear, there are challenges facing many retailers seeking to go down this path. The first relates to data and data management. The foundation of a customer-driven merchandising strategy is a data infrastructure enabling transactional, customer, and product data to be accessed and integrated. The ability to understand customer preference across channels requires the integration of data residing in store and e-commerce systems, which for many retailers are completely distinct. In addition to technical complexities associated with integrating disparate data sources, data quality is always a key consideration.

From a people and process perspective, adoption of customer preference scores in the merchandising process usually requires change management as well. Like any actionable insight resulting from analytics, an essential part of the business rollout is ensuring that the business users are fully bought into the process and have the opportunity to validate the output. Although the concepts of assessing customer relevance might be familiar to some merchants, they might be new to others, and time is required for users to become comfortable with the output. Ultimately, greater infusion of customer preferences into assortment decisions can be a key block in the foundation from which to build truly customer-centric merchandising processes.

REFERENCES

- Rosenblum, Paula and Rowen, Steve. September 2013. “Merchandising Today: Benchmark Report 2013.” Retail Systems Research.
- Ross, Brian. 2009. “Winning at Customer Centricity: 10 Tips for Retailers and Manufacturers.” Loyalty One US Inc.
- MacKenzie, Ian, Meyer, Chris and Noble, Steve. October 2013. “How Retailers Can Keep Up with Consumers.” McKinsey & Company
- Fisher, Marshall and Vaidyanathan, Ramnath. November 2012. “Which Products Should You Stock?” Harvard Business Review.
- Skorupa, Joe. November 2012. “The Art of Decisive Merchandising.” RIS News Custom Research.

ACKNOWLEDGMENTS

The authors would like to thank the following for their collaboration and insights into the topics described in this paper:

- Family Dollar Stores
- James Leone, SAS Institute

CONTACT INFORMATION

Christopher J. Matz
Director, Retail Consulting
SAS Institute, Inc.
35 Village Road, Suite 8000
Middleton, MA 01949
978-646-8388
Email: Christopher.Matz@sas.com

Wanda Shive
Retail Solutions Product Manager

SAS Institute, Inc.
SAS Campus Drive
Cary, NC 27513
919-531-531-2564
E-mail: Wanda.Shive@sas.com