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Which Retail Analytics Do You Need?

To increase ROI, match the right analytic techniques to your business objectives

Number 49—March 2011

The most competitive retailers today are increasing response rates and revenues by using predictive models and other analytics to make relevant, personalized, precisely timed offers to customers. Analytics provide a concrete means of realizing the long-standing exhortation to "Know your customer." They enable retailers to treat customers differently, even individually, based on insights into their desires, preferences and future behavior.

Retailers who know their customers analytically are making smarter strategic decisions about online/ brick-and-mortar store design, merchandising and other investments. Analytics also enable them to implement these organizational-level strategies in individual-level offers. They aim for the "sweet spot" where customer behavior unites with what the retailer and its suppliers need to accomplish.

Find out how retailers are using analytics to replace generalized mailings with targeted mailings that achieve up to nine times the ROI

Choosing the right analytics for the job is becoming a job in itself, however. Numerous vendors have crowded into the marketplace offering a jumble of similar-sounding solutions. Beneath the surface, there are actually significant differences in the analytic techniques being employed, the types of insights they provide and the business benefits they deliver. "One-size" definitely does not fit all requirements. To obtain a substantial return from your analytic investment, choose the right technique for what you're trying to accomplish.

This white paper:

- Helps you match analytics solutions to your business needs.
- Explains what each analytic technique can tell you about customers and the kinds of actions you can take informed by such insights.
- Discusses specific benefits, such as increasing ROI with better incentive targeting, improving supply chain throughput and cash flow by accelerating customer purchasing patterns, and building loyalty program membership, usage and retention.
- Shares FICO case studies illustrating the value retailers are seeing from analytics.

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» What Value Does Analytics Bring to Retail?

For retailers, one of the greatest values of analytics is to provide decision points for determining how to treat customers differently. Analytics provide a reliable means, based on statistically valid data analysis instead of hunches or observational judgments, of deciding what actions to take with your customers. "Will it be profitable to offer free delivery?" "Are we offering a discount to customers who would buy this product anyway?"

Consider what happens when consumers visit an online or brick-and-mortar store for the first time. Initially, the retailer knows nothing about these potential customers and thus treats them all the same. At some point, the consumer may click on a product or category, or make a purchase. This consumer behavior is likely to trigger a business rule that initiates an action by the retailer. Coupons might be printed for complementary products. An email might be sent offering a discount on a product in an abandoned online shopping cart.

In such instances, consumers are differentiating themselves by their behavior. The retailer, however, is still treating them the same because everyone who exhibits the same behavior receives the same offers. Inevitably the offers made will be more relevant to some recipients than to others, and responses will vary accordingly. Because the retailer doesn't know anything more about these consumers beyond that they clicked on or purchased a product, there's no reliable basis on which to make a more specific decision on a more relevant offer.

Now let's look at what different types of analytics can tell retailers about their customers, giving them more decision points to consider when determining which actions to take.

» The More You Know, the More Relevant Actions You Can Take

Here's an overview of the analytic techniques that are most valuable in retail and the kinds of targeted actions they're enabling retailers to take. The benefits of analytics can begin with the first visit, but they really come into play as retailers develop customer relationships for longer-term revenues and profits. For this reason, while our discussion starts with a common technique used with first-time customers, we'll focus on more powerful analytics that deliver stronger value.

Collaborative Filtering—Inferring Behavior Based On Similarity

Collaborative filtering enables retailers to take a degree of targeted action even for first-time customers. This type of analytics is often behind the product recommendations offered on e-commerce sites and the printed coupons generated at in-store checkout.

The form of collaborative filtering most often used in retail is sometimes referred to as an "affinity model" or "lookalike model." It infers how an individual will behave based on how other individuals who look similar (share one or more characteristics) have behaved in the past: "People who buy/view product X often buy product Y."

Collaborative filtering doesn't have to be triggered by a current transaction. It can be used to target subsequent outgoing campaigns and other kinds of promotions. Still, this analytic technique is fundamentally transaction-oriented. The algorithms used are best suited to modeling data about items purchased or viewed. They're not effective for modeling purchase and view data with the wide range of other information retailers have in their databases (e.g., attitudinal data, seasonal purchase patterns, natural product adjacencies, basket builders) or can access from external sources (e.g., demographics, public records, third-party marketing information).

For known customers, therefore, other types of analytics provide far more powerful and accurate insights.

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Figure 1: Clustering algorithms segment customers by like behaviors

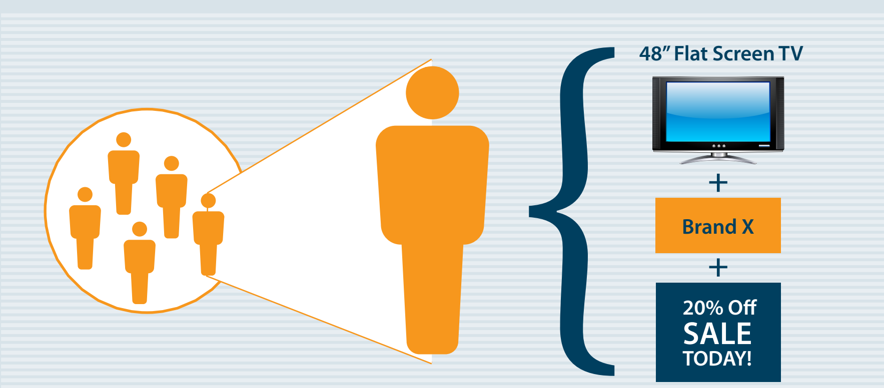
Clustering Algorithms—Segmenting Known Customers by Their Past Behavior

Clustering algorithms enable retailers to differentiate between customers in broad ways such as "Customers who like leading-edge technology" and "Customers who are value conscious." One of the benefits of painting customers with this kind of broad brush is that it can help direct and justify large-scale expenditures on store design, new merchandising schemes and promotional programs.

Using analytics in this way (often called "behavioral segmentation") enables retailers to make far more accurate decisions than can be achieved through traditional methods of database querying on customer attributes such as recency, frequency and monetary value of past purchases. Analytics are more accurate partly because they can handle greater data complexity. While query-based segmentation generally involves no more than three to six customer attributes, analytic-based segmentation can encompass dozens or even hundreds of attributes, greatly expanding the range of possible segmentation schemes.

With many more ways to group customers, and the ability to try lots of alternative groupings quickly, retailers can make better strategic and resource allocation decisions. One large national retailer, for example, has used analytics-driven segmentation to better understand and serve those customers who account for the bulk of the company's revenues. Using their characteristics to define population segments, and using these segments to guide decisions from store layouts to how staff interacts with customers, this retailer increased same-store sales in the first quarter of implementation alone by 8.4%—resulting in a 15% increase in total revenue.

Figure 2: Regression models predict customer behavior at the individual level



Regression Models—Predicting Propensity, Response, Revenue, Attrition and Other Individual Customer Behaviors

Regression models enable retailers to predict how individual customers are likely to behave. With such specific insights, retailers can differentiate between customers to a much greater degree, further increasing the granularity of segmentation and the relevancy of offers. In fact, retailers can go as far as to essentially create segments of one.

Regression analysis delivers this level of specificity and accuracy because while it can encompass a vast range of internal and external data, its power comes from pinpointing the specific customer attributes most predictive of a future behavior.

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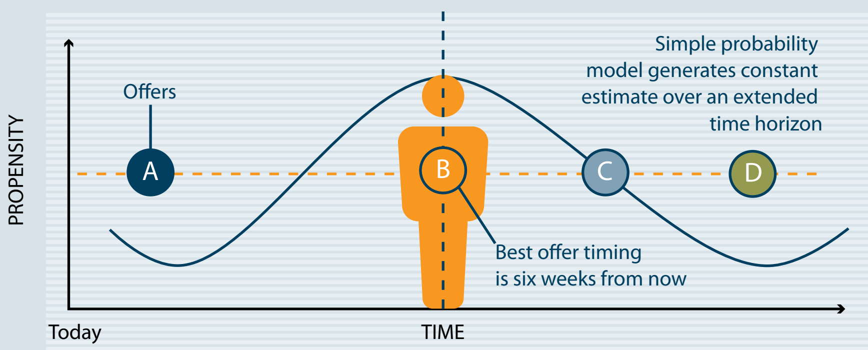
Relationships between numerous attributes and other variables are examined to see how a change in the value of one variable affects the value of another, dependent variable. Attributes that prove to be highly predictive of a behavioral outcome are incorporated into a predictive model. For example, a regression model can be built to predict a customer's propensity to make a purchase in a product category or to discontinue using a service.

Because these models can predict *for each individual customer* the likelihood of such an outcome, they open up the possibility of unique treatment. Moreover, by using multiple regression models, retailers can gain a much clearer picture of the customer. Knowing that Jane is not only likely to buy a 48"TV, but that she tends to like the Sony brand, but doesn't tend to go for cutting-edge products, enables the retailer to greatly increase the relevancy of individualized offers and interactions.

Here are a couple examples of how leading retailers are applying such insights:

- One FICO client, who implemented propensity models for all of its product categories, can dynamically generate individually tailored emails for customers. Every customer is scored for propensity to buy in each product category. Based on where the customer scores the highest, the retailer's automated decision system determines which of several overall mailing themes is most relevant, then adds features or offers in six product categories. No more than 20 customers in a million receive the same set of recommendations. This kind of tailored promotion has enabled the retailer to achieve email open rates of up to 50% and up to 9 times the ROI compared to generalized mailings.
- Another retailer is using predictive analytics to build membership and activity in its fee-based premium loyalty program. The program delivers 12 individually selected relevant offers per month to each member; these are loaded onto the customer's loyalty club card and can also be accessed from the retailer's website or from kiosks in stores. Each offer package includes rewards aimed at increasing buying frequency and customer retention. It also includes an offer encouraging the customer to try a product in a relevant category where they have not purchased before. In the first six months alone, this retailer increased program membership by over 43%.

Figure 3: Time-to-event models pinpoint the best time to make an offer
Purchase probabilities and offer susceptibilities change rapidly



Time-to-Event Models—Predicting When a Specific Customer Behavior Is Likely to Occur

Knowing that a customer is likely to behave in a certain way is useful, but knowing when they are likely to do it is even more powerful.

Retailers are working anywhere from a few days to a few weeks out in their decisions about what to promote to whom. The propensity of a customer to buy a specific product, however, varies over time, as shown in Figure 1. A time-to-event model predicts a window of opportunity when the customer is most likely to act. By timing campaigns and other promotions to these windows, retailers can improve relevancy for their customers, driving higher response rates.

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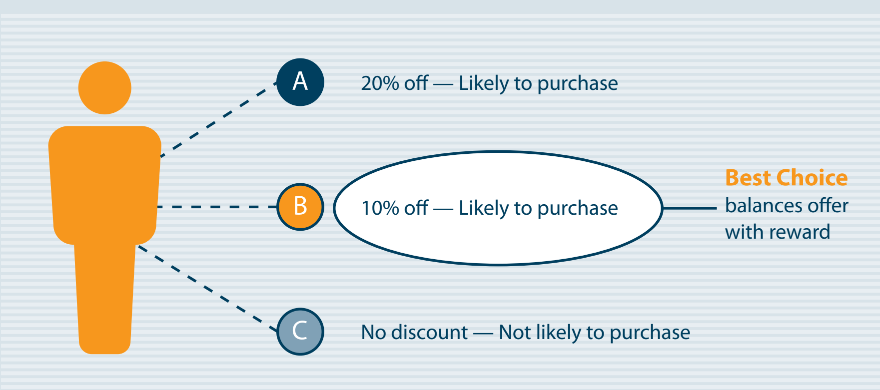
Similarly, the likelihood that a customer will attrite from buyers clubs and premium services varies over time. Some customers fail to renew, and others just stop using the service. Retailers want to prevent this from happening, but if they act too soon to offer retention incentives, they may be spending unnecessarily. Knowing when attrition is most likely to occur enables the retailer to time actions for the highest likelihood of success at the lowest cost.

Here's how some FICO clients are using time-to-event models:

- A large retailer is using this type of analytics to increase the ROI from promotional mailings. When a popular new DVD or videogame comes on the market, for example, the retailer sends offers only to those likely to buy the product within the offer redemption period. Response rates are two-to-three-times higher than when the same offer is sent to everyone. And because the retailer is not wasting customer time with irrelevant offers, future promotions are likely to be received with due attention.
- A home improvement retailer used time-to-event models in an email campaign directing recipients to one of several web landing pages featuring a specific do-it-yourself project, such as painting or replacing flooring. The customers targeted for the emails were those identified by the models as likely to purchase in that product category within a short period of time.
- A large retailer is improving its ability to predict when customers are about to make a big purchase by incorporating customer clickstream data into time-to-event models. Many consumers do extensive online research before making an online purchase or walking into a store to inspect the item. By analyzing clickstream data from its site, along with customer purchasing histories and historical behavior patterns, the retailer can pinpoint the right moment to make an offer. Early results are impressive—and too competitive to be revealed.

Figure 4: Uplift models determine when discounts generate incremental sales



Uplift Models—Predicting How Much a Retailer Action Is Likely to Change a Customer's Behavior

If a propensity model predicts a customer is likely to buy a given product, why should the retailer go to the expense of sending a promotional offer? Uplift models help retailers determine if an investment is likely to be worth the result. Often used in conjunction with time-to-event models, they predict the amount of change likely to occur in a customer behavior as a direct result of a particular retailer action.

Uplift models can save retailers millions by enabling them to avoid offering discounts to customers who will purchase without them. For example, such a model might predict whether or not sending a 20%-off offer is likely to increase a particular customer's propensity to buy a pair of designer jeans within the next two weeks. The retailer can then send the coupon only to customers whose behavior it's likely to change.

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On the other hand, when uplift modeling indicates a customer's behavior is likely to be affected by a promotion, it can also help retailers determine which promotion will have the most impact. Will 20% off be much more effective than 10% off? Than free shipping? Is offering 12 months of interest-free credit necessary, or will 6 months be nearly as enticing? Uplift models provide the analytical insights retailers need to make precise decisions about where to put marketing spend for higher ROI.

Uplift models are based on cutting-edge analytic techniques that can predict individual customer sensitivities to price incentives, redemption terms and even promotional package design. For instance, one FICO retail client that helps to "make markets" for new products by spending heavily on promotion, is using uplift models to increase its return on this investment. The analytics provide insights that are enabling the retailer to accelerate the purchasing behavior of so-called "laggers"—customers who historically haven't been among the first to purchase. By targeting these customers with offers that are likely to change their historical behavior, the retailer is increasing the concentration of sales in the first two months of the product lifecycle—its "critical period" before competitors can draft off of their momentum. Given shrinking product lifecycles, pushing sales forward in this way is becoming ever more critical to this retailer's success.

» Maximizing—and Measuring—the Value of Analytics in Operations

As retailers add better analytics, they increase the number of decision points for differentiating between customers and making more targeted decisions. But just as having lots of data can be overwhelming and of little value in and of itself, so it is with the analytic predictions drawn from this data. Their business value depends on the retailer's ability to operationalize them.

The challenge is to bring all of the relevant analytic insights together into day-to-day decisions. To do that, retailers need a powerful business rules management system (BRMS) and optimization engine. Best-in-class systems incorporating these technologies can take the analytic output of thousands of models and deploy them in decisions across millions of customers.

A BRMS is a fundamental capability since customer behavioral predictions are usually linked with actions through business rules. For example: "If a customer has a high propensity for purchasing new kitchen cabinets in the next 90 days, and is 20% more likely to act within the next 30 days if they receive Coupon A, then include them in this emailing."

Related rules like these make up a decision strategy, that will generally be tested on a small population segment, and the results analyzed. Retailers can make this process faster and more efficient by using technology solutions that allow models to be deployed directly (i.e., without any kind of recoding) into the BRMS powering operational decisions.

Retailers can further compress test-and-learn cycles—accelerating performance gains—by using experimental design. Also called "multivariate testing," this is a methodology with which large numbers of decision strategies are tested simultaneously on smaller population subsets. Because this approach enables testers to infer what the results would have been on untested populations, it yields more learning from fewer tests.

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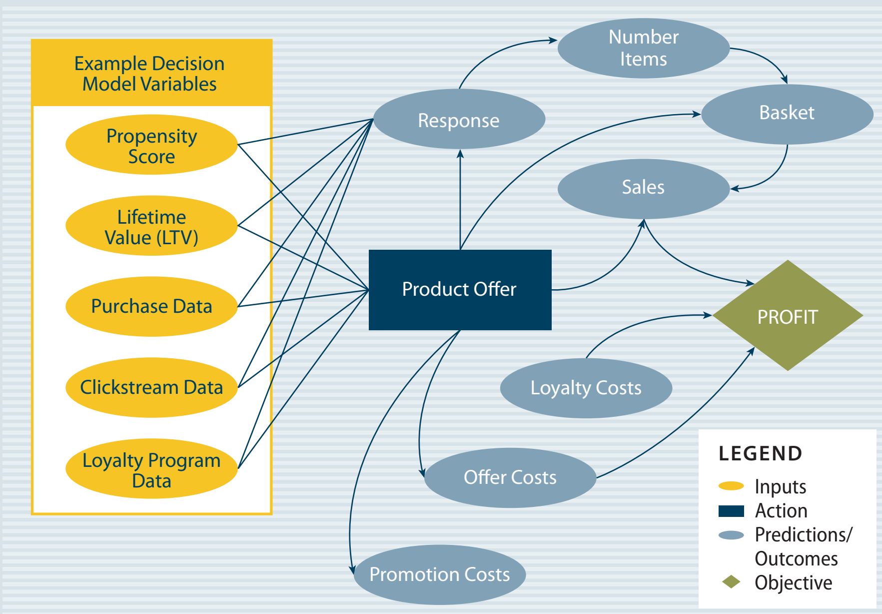
Another way to speed up operational improvements is through "decision modeling," depicted in Figure 5. Every decision, even one based on a single "If …, then …" business rule, could be described as a model, since it is a representation of how a decision is being made. But when large numbers of analytic predictions are used to differentiate and treat customers individually, the number of rules can explode. The decision process can become difficult to manage and even to fully comprehend. A decision model simplifies such complex decisions by mathematically mapping the relationships between all the factors and outputting an actionable result, such as a recommended customer treatment.

Figure 5: Modeling the profit drivers of a product offer decision



Moreover, explicit modeling of customer reactions to a range of retailer actions (often called "action-effect modeling") clarifies complex decisions and exposes key performance drivers. Consider our previous example of a campaign aimed at accelerating purchases by customers with a high propensity to buy kitchen cabinets. An action-effect decision model could determine on a customer-by-customer basis what the net impact would likely be on revenue, costs and profit.

Such a decision model would almost certainly be used with an optimization engine to identify the best treatment for each customer given the real-world constraints (mailing volumes, store locations, program spend limits, etc.) of the retailer and its suppliers. For example, the home improvement retailer, whose experience with time-to-event models was described above, optimized its decision strategy to maximize incremental margin per customer transaction given specified volume constraints.

In this way, retailers can execute portfolio-level business strategies with precision at the level of individual customers. They can find the "sweet spot" where what the customer wants and what the business and its partners want intersect. It's the realization of the very definition of successful marketing—"Find a need and fill it."

Success, of course, must be measurable, and thus retailers need systematic testing practices and rigorous measurement. They must able to determine how much of a result is due to analytics as opposed to other decision elements and operational factors.

For example, a retailer might come to the erroneous conclusion that a discount coupon program produced inadequate ROI because of failing to properly control for selection biases in the coupon targeting. Causal modeling/matching techniques can be used to eliminate or mitigate such biases. These techniques can also empirically tease apart operational outcomes, so that the impact of the analytics on the coupon campaign can be isolated and accurately measured.

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Choose the right analytics technique for your business goals

Analytics Type	Works By	Best Used For	Benefits
Collaborative Filtering	Inferring customer behavior based on similarities (e.g., "People who bought A also bought B")	Treating first-time customers	Enables limited differentiation when no historical behavioral data on a customer is available
Clustering Algorithms	Grouping customers based on similar historical behavior patterns	Creating broad customer segments for promotional programs and strategic planning	Lifts response rates (generally from the traditional 1-2% to 5-6%) over traditional query-based segmentation Performs data-driven customer differentiation at a large enough scale to guide/justify business investments in store design, merchandising, etc.
Regression Models	Identifying customer attributes predictive of future behaviors	Predicting individual customer behavior for 1-to-1 marketing and other personalized treatment	Is generally up to twice as effective as collaborative filtering for targeting known customers Increases response rates (often doubling performance) and boosts conversion rates over clustering algorithms
Time-to-Event Models	Predicting when a specific customer behavior is likely to occur	Timing offers for when a customer is most likely to buy; accelerating customer behavior	Lifts performance by as much as 50% over regression models (2% lift in response rates not uncommon)
Uplift Models	Predicting how much a particular action by a retailer is likely to change a forecasted customer behavior	Determining whether or not a particular action will be worth the expense	Lifts performance by as much as 50% over other analytic techniques Saves millions by enabling retailers to avoid offering incentives for products customers would buy anyway
Decision Models	Mapping the mathematical relationships between numerous predictive model outputs and other decision elements, including a range of possible retailer actions and customer reactions	Managing and improving complex decisions; capturing key results drivers, including constraints, for use with an optimization engine	Pinpoints the best offer, given all retailer/supplier objectives and constraints, for each customer

FICO Retail Solutions

FICO® Retail Action Manager is a marketing decision application that uses predictive analytics combined with integrated optimization to make high volumes of individual customer recommendations. Analyzing vast quantities of customer behavioral data, Retail Action Manager predicts not only which products customers are likely to buy, but when they are likely to buy them. It combines these customer-level predictions with retailer business objectives and constraints to pinpoint the optimal decisions for achieving an overall goal, such as maximizing redemption, revenue or margin. The analytic processes can encompass millions of customers and hundreds of products, stores and e-channels. Flexible outputs (recommended up-sell and cross-sell offers, store planning scenarios, merchandising strategies, etc.) can be delivered through multiple channels via FICO® Precision Marketing Manager, as well as third-party applications that incorporate business rules.

FICO® Precision Marketing Manager is a next-generation precision marketing platform that drives revenues through precise customer targeting, cross-channel campaign integration and dynamic delivery of personalized, relevant offers. Interactive channel management, powered by the industry-leading FICO™ Blaze Advisor® business rules management system, supports personalized consumer engagement on the web or mobile devices, including gathering data, responding to customer choices and pushing promotions in real time. Retailers can easily add promotional incentives, such as sweepstakes and e-coupons, from third-party providers. Precision Marketing Manager also offers dynamically configurable registration and login services, and loyalty tracking solutions that enable consumers to collect and spend points for awards based on their online activities.

» Conclusion

Retailers of all sizes are bringing analytics into their operations. The key to making choices and investments that deliver on your expectations is to understand what various types of analytics do and how they fit (or don't fit) what you're trying to accomplish.

It's also important to think about analytics as an incremental process rather than a packaged solution. No one approach serves all purposes. Wherever you are in the spectrum of analytic benefits, there's a next step you can take for the next level of benefit.

Find out more about what type of analytics you need most:

- Watch the video ***"Achieve Growth Through Smarter Retail Decisions".***
- Download Insights paper #32 ***"Top Retailers Compete With True 1-to-1 Marketing".***

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