

USING ADVANCED ANALYTICS TO MAXIMIZE RETAIL PROFIT

How to Leverage Big Data, Machine Learning, and Optimization in Your Omni Retail Supply Chain



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RETAILERS ARE NOW COLLECTING MORE DATA THAN EVER BEFORE.

They are looking to exploit it to improve profitability using advanced analytics. A lot of attention has been given to predictive analytics, which use statistical and machine learning (ML) techniques to better predict consumer demand. Using these methods, retailers are seeing big improvements in forecast accuracy.

However, most retailers are not taking full advantage of advanced prescriptive analytics, which leverage these improved predictions and promise to deliver a profit improvement equal to or greater than that which they are now seeing from predictive analytics alone.

Advanced Analytics Are Rapidly Changing Retail

Increases in processing power, data storage speed and capacity, and broadband ubiquity have combined to fuel a revolution in retail analytics over the past decade. No longer is it sufficient to use simplistic models based on limited data to make predictions, and then act on them using traditional approaches. The most profitable retailers are now investing in sophisticated techniques that leverage increasingly powerful computing resources to look more deeply into their businesses, find hidden drivers of demand, and make smarter decisions aligned with their ultimate goal: greater profitability.

So what are these new analytical techniques, and how are they being used to change the rules of the game? First, it's important to understand that there are different types of analytics capabilities. A 2014 Gartner press release on advanced analytics identifies four types: descriptive, diagnostic, predictive, and prescriptive. Each type is important for different reasons, and each of them is being reshaped by the availability of more and better data and machines.

Descriptive/Diagnostic Analytics: What Happened and Why?

Descriptive analytics are the most commonly used form of analytics, typified by dashboards and reports that summarize data and perform simple calculations to provide historical insights. In retail inventory management, the focus is on tracking key performance indicators (KPIs) such as in-stock rate, turns, and GMROII (Gross Margin Return on Inventory Investment), which are easily derived from basic data.

Advanced analytics are now providing more sophisticated measurements required to complete the picture and show the true profitability of your decisions. In particular, monetizing the impact of stockouts (i.e., Lost Sales) is a critical measurement capability today. The lost sales calculation must take into account such factors as channel, demand rate, transaction quantity distribution, affinity, and transference, using machine learning techniques to gather needed information. Calculations like lost sales are more than just reporting elements – they are also needed to perform predictive analytics, since they supply critical missing information.

Diagnostic analytics go a step further to explain why something happened. Business Intelligence (BI) tools provide the ability to visualize and compare different streams of data for this purpose; you can use them to lay up a timeline of weather patterns against lost sales on flashlights, for example, to explain why current store orders are so high. But these BI tools are only providing Intelligence Augmentation (IA). You still need an analyst to decide what to compare and then look at the charts and make the connection. That's not a scalable business model. The story now unfolding in retail is how these types of insights are being increasingly discovered, and utilized, by machines. The most profitable retailers are now investing in sophisticated techniques that leverage increasingly powerful computing resources to make smarter decisions aligned with their ultimate goal: greater profitability.



NOT ALL TYPES OF ANALYTICS BRING THE SAME RESULTS GARTNER IDENTIFIED FOUR TYPES: DESCRIPTIVE, DIAGNOSTIC, PREDICTIVE, AND PRESCRIPTIVE.¹

Predictive Analytics: What Will Happen?

Descriptive and diagnostic analytics are concerned with explaining what has already happened. Predictive analytics aim to tell us what will happen.

In retail inventory management, the most important use of predictive analytics is in demand forecasting. Traditional forecasting uses some variation of time-series analysis, in which past demand is used to predict future demand. Advanced forecasting uses machine learning (ML) techniques to mine the available data for additional information. That data is then used to adjust for factors not obvious from the demand data alone. Machine learning eliminates the need for merchants to suggest potential predictors in order to guide the forecasting process; the algorithms let the data speak for itself to find the elements that matter, and how much they matter, at a very granular level.

This capability becomes more important as the number of factors driving demand grows. The improvement in the forecast that can be obtained using these techniques is directly related to how much and what types of data are available. This is where Big Data comes into play: the more data you have, the greater the potential predictive power of your forecasts. Predictive analytics is making inroads in the retail world and starting to produce real results, but a better forecast isn't the endgame: you still have to figure out how to use it to achieve the ultimate goal of higher profits.

A replenishment system using profit optimization doesn't need to be told what the goal is – it already knows that it should maximize profitability.

Prescriptive Analytics: What Should I Do?

While machine learning techniques are revolutionizing predictive analytics, retailers still need systems that can use those results to take action; that's the job of prescriptive analytics.

analytics Prescriptive based are on optimization algorithms, which provide an answer that will minimize or maximize the value of some variable. For retailers, these algorithms optimize the economics of the omni retail supply chain. Such algorithms are being used today by some retailers to set retail prices and maximize revenue on markdowns. Economic optimization solutions exist for other applications, including replenishment, allocation, fashion buying, and assortment optimization, but few retailers are aware of them and fewer are using them.

By way of comparison, consider legacy replenishment systems, which use goal-



seeking rather than optimization. Such systems require a user to specify a target service level (the goal), based strictly on human judgment, to guide the calculation of the level of inventory to be held for each item in each location.





Most retailers do not have the resources for users to set a service level individually for every SKU-Location. Therefore, assignments are done to groups of SKU-Locations using an ad hoc process. The result is inventory levels that meet an arbitrary goal that is not directly related to profitability.

A replenishment system using profit optimization, on the other hand, doesn't need to be told what the goal is – it already knows that it should maximize profitability. In addition to considering the trade off between inventory carrying cost and lost margin, the system can quantify the impact of things like short shelf life (what's the right level of inventory to carry when an item expires after 30-days?); or limited shelf space (how much inventory should I carry for each freezer item if I have limited space for my assortment?). A profit-maximizing solution eliminates some of the labor required by legacy systems, allowing planners to focus on more strategic activities.

All of this requires only a few more pieces of data than a simple goal-seeking solution, and the results can be spectacular. Retailers who have deployed such a system have seen annual profit improvement on the order of hundreds of basis points of revenue – money that drops right to the bottom line.

For other applications, like fashion buying, allocation, or assortment optimization, the value to be optimized may be different – maximizing total revenue, for example – but in all cases the system has a quantifiable economic optimization goal and a method for achieving it. Without this approach, retailers don't have a yardstick to know how much money they may be leaving on the table.

In short, true profit optimization systems understand the relationships among the various variables at play and how they affect profitability, whereas legacy systems focus on easy-to-define KPIs such as service level and lose sight of the true objective. Prescriptive analytics deliver the most profitable results for retailers.

Conclusion

Retailers have historically focused on the accuracy of their forecasting, for good reason: perfect knowledge of what is going to happen would make inventory management decisions far simpler. Big Data and machine learning are now helping them to improve their forecasts. But that improved forecast could be squandered if used to take action that is not driven by economic optimization.

In <u>The Art of War</u>, Sun Tzu wrote that all competitive advantage is based on effective execution of plans: poor execution can ruin superior plans, but superior execution can save mediocre plans. The situation faced by most retailers today is that they are focused on generating better plans in the form of predictions, but in a number of critical applications they have done little to improve execution based on those predictions. Advanced analytics offers the possibility to take that last transformative step and help them win the day.

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ANSWERS TO YOUR QUESTIONS

Q: What advice would you give to retailers looking to employ more advanced analytics?

- A: If I was a retailer looking to up my game, I would first want to make sure I had clear profit-oriented metrics and goals. Then I would look for solutions that 1) provide best-of-breed predictive and prescriptive analytics; 2) work within my existing infrastructure as much as possible, rather than forcing me to rip-and-replace; 3) can be quickly and convincingly evaluated with little or no risk; and 4) demonstrate a compelling, measurable ROI.
- Things are moving far too fast in today's retail environment to allow for protracted selection and evaluation Cycles. You need to be able to "fail fast" and figure out what works for your business without breaking your budget.

Q: What is Machine Learning, and how is it used in Retail Inventory Management?

A: The idea behind machine learning (ML) is to write software in such a way that it can learn from its environment to improve performance. In retail inventory management, ML is primarily used to provide predictive analytics, which in turn form the input to the prescriptive analytics. For example, ML techniques are used to detect and filter anomalous data, estimate the cost of stock-outs, predict the performance of the supply chain, and to figure out how factors such as seasonality patterns, product signage and placement, advertising, and pricing incentives impact consumer demand. As a result, you get far more accurate predictions, which translate into lower inventory costs, fewer stock-outs, and higher profits.

Q: Do I need to have "Big Data" to use ML?

A: ML techniques are designed to take advantage of very granular data, so their use will naturally lead to holding very large data repositories. Nonetheless, for a small retailer the amount of data you need to sift through with machine learning algorithms is well within the scope of conventional database technologies. For larger retailers, especially those with multiple channels, high SKU-Store counts, and a variety of promotional vehicles, the computing demands can be more challenging. Nonetheless, ML techniques for retail inventory management are readily scalable with the right system architecture. In addition to having a scalable architecture, advanced retail solution providers that use ML (including 4R) employ cloud-based computing environments to enable flexible scaling of hardware resources.

Q: What is the difference between Machine Learning and Optimization?

A: Optimization algorithms try find the "best" answer for a problem, given a set of input values and a value to be minimized or maximized. Machine learning algorithms try to improve future performance based on observations about past events. Many machine learning algorithms rely on optimization algorithms to create the model that describes what they have learned. So you can think of an optimization algorithm as a more general tool that can be used as part of an ML algorithm.



Q: How is Machine Learning different from Artificial Intelligence (AI)?

A: There is a lot of overlap between the two; AI has historically been associated with autonomous machines that can mimic the types of decisions considered to be uniquely human. To achieve that behavior, ML techniques are often used. On the other hand, a machine can use ML techniques and still not be autonomous; it might, for example, stop short of decision-making, and instead simply provide predictions that are used by humans to make the final decision. In retail, for example, machine learning can be used to predict the likelihood that a store is stocked out of an item, even though it is reporting that inventory is on hand. So in that situation, the machine is not fully replacing human intelligence; it's providing Intelligence Augmentation, or IA, rather than AI. Many retailers opt for this type of solution as it essentially allows them to add art to science, or vice versa.

Q: If ML is used mostly for predictive analytics in retail, what techniques are used to provide prescriptive analytics?

A: Prescriptive analytics generally involve optimization or simulations, or both. In retail replenishment, for example, 4R uses optimization algorithms that find the level of inventory that maximizes profitability. There aren't any other commercially-available solutions out there today that do that; in fact, what the best of those other solutions do is ask you to tell the machine what percentage of the time you want to be in-stock, and it figures out what inventory level will do it. There's no optimization involved, you have to manually set millions of service level settings, and you aren't guaranteed to get a profit-optimal answer. All of 4R's prescriptive analytics are based on economic optimization, whether you are talking about replenishment, allocation, markdowns, assortment optimization, or anything else we do - it is one of our guiding principles.

4R runs simulations for clients and uses those to illustrate the impact of different business decisions. For example, what if I moved to daily delivery for my urban locations? What would happen to inventory carrying costs? How would lost margin be affected? Simulations can answer those questions and help guide your decisions.

Q: It looks like prescriptive analytics can be used for decision support or decision automation. What's the difference?

A: If prescriptive analytics recommendations are delivered to a human, the analytics are being applied in decision support mode; if they feed directly into a production system for implementation, the analytics are being applied in decision automation mode.

In retail inventory management, the setting of replenishment inventory levels or the generation of allocation quantities are typically used in decision automation mode; there are just too many decisions being made to allow for meaningful human intervention, so these systems have to be very robust and self-healing. Fashion buy quantities and assortment optimization decisions, on the other hand, are more likely to be delivered in decision support mode. Pricing and markdown decisions can be used either way, depending on the philosophy and rules of the particular business.

Q: Advanced analytics take into account factors that I have never even considered. Given that fact, how can I validate the results I am getting?

A: Here we need to distinguish between the predictive and the prescriptive part. From a prediction standpoint, the results of machine learning algorithms can be validated once the process we are forecasting materializes and the "true signal" becomes available. That allows us to determine the accuracy of the prediction. However, prediction itself is just an intermediate step to the value creation equation; any assessment of the overall solution must therefore involve the actual recommendation (the output of prescriptive analytics). The accuracy of those recommendations can be retrospectively measured via simulation, which allows us to evaluate if that particular use of resources was indeed more beneficial, compared to alternative decisions.



ABOUT 4R

4R Systems provides retailers breakthrough technologies that profit optimize inventory decisions throughout an item's life including:

- Initial buy
- Replenishment and allocation for stores and distribution centers
- Assortment Optimization
- End-of-life strategies including markdowns

4R clients have increased profits by 100s of basis points. In fact, for a \$1 billion retailer the profit improvements could be in the \$10's of millions. How? By profit optimizing decisions, such as how much and when to buy, how much inventory to put in each store or DC for replenishment items, when and how much to allocate for seasonal and fashion items, and how much and when to markdown at end-of-season.

Founded by supply chain experts Dr. Marshall Fisher of Wharton Business School and Dr. Ananth Raman of Harvard Business School—whose groundbreaking research on product lifecycles with over 30 world-class retailers pioneered retail supply chain analytics—4R provides retailers with services designed to maximize their profitability by the application of sophisticated retail and supply chain analytics. Some of Dr. Fisher and Dr. Raman's research can be found in their book <u>he New Science of Retailing: How Analytics are Transforming the Supply Chain and Improving Performance</u>, which was released in 2010 by Harvard Business Press.

1 http://www.gartner.com/newsroom/id/2881218





4R's *inventory as an investment* approach is designed to maximize the profit opportunity of your number one asset: inventory!

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