Four key factors in advanced market tracking

The process of tracking item sales used to be fairly straightforward. Add up the total sales in each location, factor in price changes, subtract any discounts and promotions, and you'd end up with a reasonably clear view of which items were selling in which stores, at which prices.

Today, on the other hand, an ever-growing array of sales platforms, price points, product categories and customer behaviors demand a far more robust approach to market tracking. To accurately forecast the right stock levels, price points and product assortments for the coming months, it's necessary to model the effects of many different factors.

By understanding the ways in which each of those factors impacts the sales of each product at each location, it's possible to discover the optimal product assortment for each location, and discover new opportunities for increasing revenue. Let's take a closer look at four factors that play into an advanced market tracking model.

Changes in product mix

Since demand for every product shifts over time, every store needs to change its product mix in anticipation of the appearance of new products, seasonality, marketing campaigns, changes in fashion, and many other demand drivers. In addition, product mixes at individual stores change as some items are reprovisioned from warehouses, or from other locations.

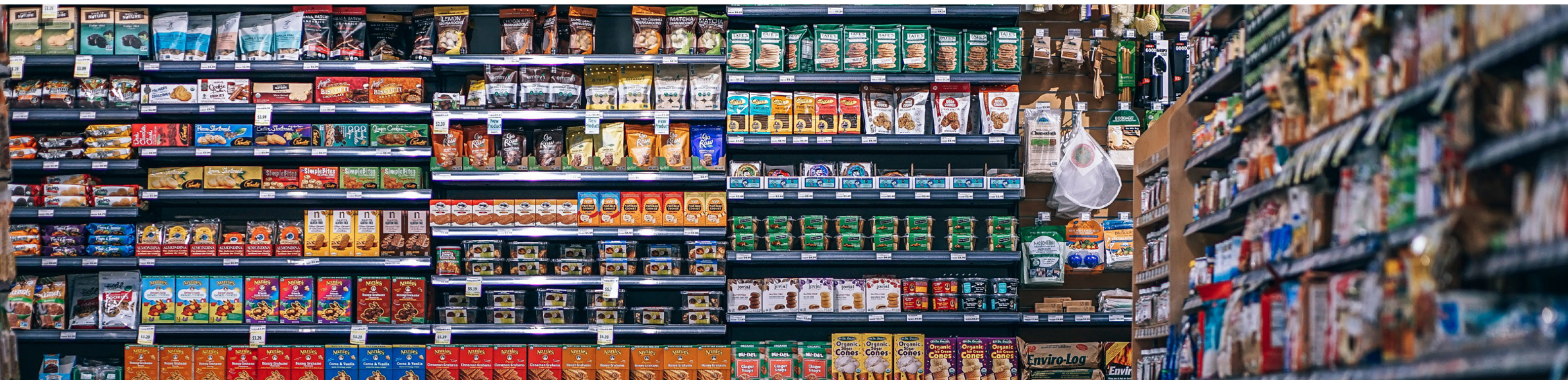
While it's impossible to boil the ideal product mix down to any single factor, it's extremely helpful to model the relationship between changes in product mix and changes in sales. For example, a stock-out of a high-demand item, such as a popular video game, may actually drive demand up – while running out of stock on a low-demand item, such as frozen pizza, may result in increased sales of alternative products.

Changes in like-for-like pricing

When a competitor raises or lowers the price for a given item, it's often necessary to make a similar price adjustment for items that directly compete with that product. In cases like this, a standard elasticity calculation – which models a simple relationship between price changes and sales volume – fails to take the effects of competitors' price changes into account. As a result, traditional elasticity models will fail to predict the true effects of a like-for-like price change.

#Market tracking isn't as simple as it used to be. To accurately forecast the right #retail strategy, it's necessary to model the effects of many different factors. https://bit.ly/2KzJ5Vn Tweet This

When a prices changes due to like-for-like competition, the only way to accurately model the correlation between price changes and sales is to use a model that factors in competitors' prices. A model that incorporates this data can produce a much clearer picture of the relationship between like-for-like price changes and item sales – and what's more, it can generate much more accurate forecasts of the results of future price changes.



Changes in discounting

Although discounting remains one of the most popular tactics for increasing sales in the immediate term, it comes with significant risks. A retailer who simply discounts lower-selling items may end up cutting into their own profits – and even worse, they may create discount-dependent customers who only shop at that location when a sale is on.

A more robust calculation looks beyond a simple relationship between discounts and sales, and examines the overall sales generated when certain percentages of items are discounted, as well as the sales volume resulting from different discount levels. Advanced machine learning tools (like ours) can even generate recommendations for ideal discount levels and percentages at each location.

Tagging and comparability

Similar items sometimes sell at very dissimilar volumes. This is particularly true in industries like fashion, where a specific fabric or stitch type is often in high demand for a season, only to be supplanted by a different variation a few months later. For this reason, a surface-level similarity between two items may not be the best predictor of their demand or price elasticity.

This is where human insight comes into the equation. In order for a model to generate an accurate market forecast, retailers need to be able to tag and categorize items according to their contextual knowledge of intangible factors, such as seasonally trendy fabrics, relevance to local events, upcoming holidays, and so on. The more human feedback the model receives, the more it'll be able to factor these tags into its analyses – and into forecasts of future market behavior.

As crucial as these four factors are, they're only the beginning of a truly robust market analysis. To generate an ideal balance of product mix, inventory level, pricing and discounts, a model needs to take a wide range of additional factors into account – from weather and foot traffic to competitor promotions and social media attention.

Many of those factors require human input – which is why, to generate optimally accurate predictions, humans and machines need to work together in an ongoing feedback loop, continually learning and providing information that enhances one anothers' performance.