FORECAST FOR SUCCESS:

THE IMPACT OF MACHINE LEARNING ON DEMAND PLANNING PRECISION

A state of the industry report from Path to Purchase Institute,
in collaboration with SAS

EXECUTIVE SUMMARY

- The traditional approach to demand forecasting is unable to capture many of today's complex market dynamics and is plagued with bias, human error, waste and inefficiency. Advanced analytics blended with intelligent automation are laying the foundation for a powerful new model that can improve demand planning processes and increase forecast accuracy, leading to significant cost savings.
- A convergence of industry trends has accelerated the need for change: SKU proliferation and a shortened product lifecycle have introduced greater complexity into the sales forecast; Increased promotional activity and omnichannel shopping are rapidly expanding the points of contact between internal demand planners and sales and marketing teams; Consumer packaged goods companies are under pressure to generate more savings within the supply chain and increasingly view forecast accuracy as a critical KPI.
- With the introduction of machine learning, CPGs now can guide demand planning activities with almost surgical precision, enable a nimbler response to complex situations, and ensure that changes to the forecast will result in better outcomes, thus improving Forecast Value Added (FVA).
- Recent research finds major potential from new automation methods. In one comprehensive test, an assisted demand planning model using an intelligent automation process enabled a major CPG to reduce the number of manual overrides by 47%, which in turn allowed demand planners to focus only on the products and periods that would add the most value. As a result, the model run improved the FVA by 6.3%.

Over the past 20 years, the approach to demand planning at most CPGs has remained largely stagnant, despite the increasing availability of advanced data analytics tools and techniques. Today, many organizations continue to rely on the traditional practice of using historical shipment volume data, statistical models (e.g., the time series models deployed in many legacy ERP systems) and Excel spreadsheets to develop a sales forecast and demand plan. It is a labor-intensive, consensus-driven planning process in which hundreds of manual overrides may be made to the forecasts before the numbers reach supply planning for execution in manufacturing and distribution.

But this approach is now problematic, since it's unable to capture many of today's complex market dynamics, including the impact of price changes and promotions, as well as external factors such as fluctuations in weather. "Legacy systems that create historical forecasts were not designed for the new digital economy," says Charlie Chase, Executive Industry Consultant for Demand Planning at SAS. "They can only model patterns associated with broad trends and seasonality. They do not account for the effects of promotions and they cannot correct outliers in the data."

Moreover, bias and human error are often introduced into the forecast by sales and marketing teams who don't necessarily have access to the full spectrum of analytics needed to guide decisions about when to adjust a forecast, or by how much to take it up or down. Instead, manual overrides are typically made based on anecdotal information about a promotion's success or expectations for hitting a particular sales target. Consider:

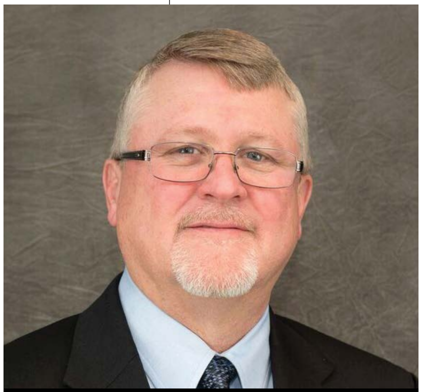
According to research by Fildes and Goodwin, 75% of demand forecasts are adjusted using human judgment in each cycle — far too many. In addition, the research found that:

- over-optimism is at play when planners raise forecasts. This human bias results in positively adjusted forecasts that ultimately are less accurate.
- when forecasts are lowered, they tend to reduce MAPEs (Mean Absolute Percentage Error) more than positive adjustments, yielding greater accuracy.

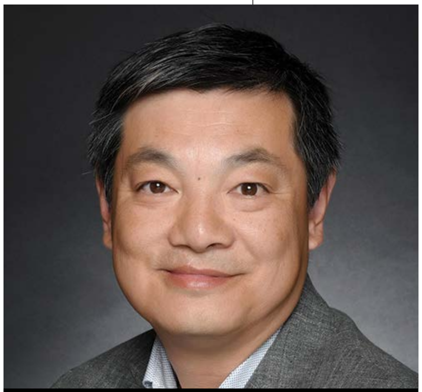
Overall, Fildes and Goodwin found that small adjustments were most common and that, on average, they slightly lowered forecast accuracy. Moreover, between 25% and 50% of adjustments have little impact.

Rick Davis, an industry consultant who spent 27 years at Kellogg in various roles related to demand planning and data analytics, says these trends jibe with common experience. "The bias could come from a sales executive who calls a retailer and says, 'Last time we ran this promotion we did 10,000 cases, but I think we'll do 15,000 this time,'" he explains. "It could also be tied to the velocity in the marketplace. Let's say product sales are growing at 4% right now, and you decide to keep that 4% in the forecast for the next 52 weeks. That's a big assumption because it may tail off."

Machine learning can go a long way toward removing these kinds of biases and human errors from the system. It can also free up valuable resources. "It lets the demand planner focus on things that require human judgment, such as new POS data entering the market," says Davis. "Over time, all of these things will be integrated into the forecast engine. It allows demand planners to be far more efficient and add value to the things they're working on."



Rick Davis, Davis Development Group



Dr. Davis Wu, Nestlé

Intelligent Automation: The Next Mile

A convergence of industry trends is driving the need for change in the demand-planning processes of major consumer goods companies. SKU proliferation arising from consumer desire for more unique products and pack sizes, along with changes at retail (such as localized assortments) has created a shorter, less stable product cycle, which in turn has increased the burden on companies to account for all the complex factors that go into creating a demand plan.

At the same time, CPGs are under greater pressure to produce revenue growth and are looking to squeeze higher margins out of the supply chain. Thus, they increasingly view forecast accuracy as a critical KPI for the entire business. "There's an even greater emphasis on revenue growth for the industry as a whole," says Roger Baldridge, Advisory Consulting Business Development Manager at SAS. "There's a higher degree of focus on how companies can reduce inventories and they're looking at old ERP systems — which are not getting it done. That's a big part of what's driving this."

Dan Woo, Principal Industry Consultant for CPG at SAS, says that many CPG companies have made huge investments in ERP technology and are understandably trying to leverage those systems as much as possible. But as more advanced analytics capabilities enter the market, they face the difficult choice of either making new investments or getting left behind by the competition.

"They've pushed the limits in capabilities of those ERP systems in terms of demand planning," says Woo. "That's where advanced analytics first came into play. They use actual events, not just sales history, which is more accurate than trend forecasting. Now, machine learning is laying down the next mile in using advanced analytics to improve the demand planning process and, ultimately, the forecast."

Developing an accurate forecast for a new product is especially complicated, adds Dr. Davis Wu, Global Lead of Demand Planning & Analytics at Nestlé S.A.

"The impact of a poor forecast is multi-fold," Wu says. "It can lead to stock being overproduced and turn into bad goods being destroyed. It can also potentially lead to customer requirements not being fulfilled due to a low forecast. Machine learning-enabled forecasting capability in new product launches has helped Nestlé achieve step-change improvement in forecast accuracy, which brings immediate benefits in ensuring high order fulfillment with optimal stocks produced."

Food and beverage manufacturers in particular stand to benefit from a reduction in slow-moving or obsolete inventory (SLOB) levels. "A lot of that inventory tends to get written off or remarketed and runs through liquidation channels. It's a huge issue," notes Rick Davis. Machine learning, meanwhile, can help improve the process in a number of ways. For example, it could allow the planner to match product attributes (such as flavors, pack sizes, gluten status) to other products with similar characteristics and volume, and use that information to develop a surrogate product forecast. "Instead of it taking weeks to comb through all product forecasts, you could do it in a matter of hours," he says.

A Multitude of Potential Benefits

There are a number of potential benefits to using machine learning to guide demand planners in developing a more accurate sales forecast. A 2018 SAS test of assisted demand planning using an intelligent automation process (see "Putting Machine Learning to the Test") reduced the number of manual overrides by 47%, allowing the demand planners

Putting Machine Learning to the Test

In fall 2018, SAS embarked on a comprehensive test of a new patented intelligent automation technique with a large global CPG. The research was set up to allow the machine learning system to learn from past manual overrides of demand planners in order to boost the forecast value added (FVA).

There were two main objectives: (1) Identify forecast entities that needed overrides; and (2) Provide demand planners with the direction and range of overrides at various levels of the business hierarchy, which are typically divided into planner, customer and product.

"The idea is that machine learning becomes a digital assistant to the demand planner," explains SAS's Charlie Chase, Executive Industry Consultant for Demand Planning at SAS. "It says to the planner: Don't just make mass aggregation overrides anymore. I'm going to tell you, based on the accuracy of the forecast and your performance in making prior adjustments, where and by how much and in what direction to make manual overrides. So that now, every time you touch the forecast, you're always going to add value."

A minimum of two and a half years of historical overrides based on an 18-month rolling forecast were collected for five product categories in two geographic areas for more than 700 items. A 60-day future forecast was employed for FVA purposes. In-sample and out-of-sample training and validation periods were used in comparison to the FVA analysis to choose the appropriate machine learning model in a three-step approach:

1: Enrich the process by identifying value-added and non-value-added overrides made by several demand planners, and add any other attributes that are available.

2: Build machine learning models using neural networks, gradient boosting and ensemble random forest training models in a competition to determine the champion model.

3: Assess models using the out-of-sample validation data and report levels of accuracy.

The user interface in the patented SAS platform guides demand planners in making manual overrides, identifying which specific forecasts to adjust, the direction of the adjustment needed and the recommended override quantity, along with a lower/upper range should the demand planner want to make an adjustment to the recommendation.

to focus only on those products and periods that would benefit the most from overrides. As a result, it improved the value added to the forecast by 6.3%.

Those are significant improvements with far-reaching impact. Previous research has determined that, for every 1% of forecast accuracy improvement, companies on average realize a 7% reduction in finished goods inventory, a 2% reduction in transportation costs and a 9% reduction in inventory obsolescence. Such reduction or elimination of back orders lowers the need for safety stock and therefore would cut down on shrink and waste in the supply chain.

"That could mean tens of millions or, in some cases, hundreds of millions of dollars in savings," says Chase. "We've done assessments for various CPGs and have often found there was more money left on the table from back orders than it costs to carry finished goods inventory. Plus, a lost sale means you may have lost the consumer [for good], so this all accrues to improved customer service, loyalty and retention."

The lure of such benefits is drawing more interest from CPGs. Kellogg Co., for example, has begun testing the impact of machine learning on its sales forecast and demand-planning functions, and the results so far have been "very promising," says Benjamin Pineda, Senior Data Scientist at Kellogg.

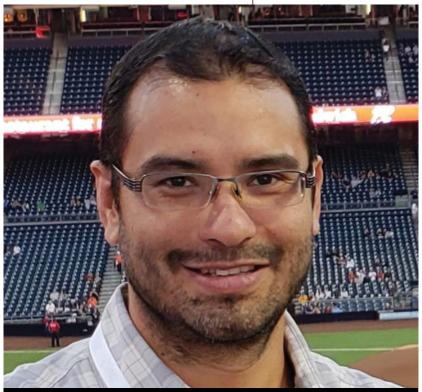
"Some parts of the project are going to be used to better understand a 'touch/no touch' plan for sales planners," says Pineda. "The idea is to understand where they add more value and recommend which pairs [or combinations of customer/promoted item, and promoted product group] not to touch based on the probability they will not improve the forecast. We are also going to use it to create new merchandising profiles and suggest merchandising support for promotions."

Challenges to Adoption, Implementation

As with any digital transformation, the adoption and implementation of intelligent automation processes for demand planning involves a number of organizational challenges. Some are logistical in nature. Large corporations that have grown through mergers and acquisitions must be able to synchronize disconnected legacy systems. And companies of all sizes may require a shift in mindset, such as embracing the need to test and learn with new technologies and platforms.

There's also the question of training needs and finding the right talent. Some CPGs might discover that newly created efficiencies could allow for a dramatic reduction in the number of required demand planners. But at the same time, they may need to add to their stable of experienced data scientists.

Justin Honaman, Georgia-Pacific



Benjamin Pineda, Kellogg Co.

"A good demand plan requires external data in the form of market intelligence, such as customer behavior, supply/trade disruptions, price changes and sell-through data from a retailer," says Justin Honaman, Vice President of Analytics, Data and Digital Transformation at Georgia-Pacific. "Demand planning involves lots of number crunching and data analytics, and that's repeated cycle after cycle. Given the nature of the activity, similar skill sets may be leveraged here, as in other parts of the business where automation, advanced analytics and data engineering are priorities."

Support from key stakeholders and leadership from the C-suite is also critical, adds SAS's Baldridge. "There's an aspect of organizational change to every new forecast project," he says. "You have to keep communicating and show users why this is a more accurate forecast. That's how trust in the system gets built over time."

Nestlé's Wu agrees. "Developing and embedding analytics at scale, including machine learning and automation, requires a significant commitment and efforts from all stakeholders and user communities," he says. "Nestle has been successful [recently] making analytics the [standard] way of working in demand planning across all geographies globally. The company has achieved this with laser focus on a few key areas of functional needs, and deploying widely. This is how maximum benefits can be reached quickly, [without] getting distracted by endless new possibilities."

Or, by allowing the fear of change to impede progress. Intelligent automation allows demand planners to work smarter — but not be replaced by the machine. It can assist demand planners by analyzing vast amounts of information to boost the FVA process, guiding them with surgical precision. They're then able to ingest and analyze massive amounts of forecast information, respond quickly to complex inquiries, and make overrides with precision across the entire business hierarchy.

Based on those inputs, the forecast for success is looking strong. ●