WHITE PAPER

The Future of Forecasting

How machine learning is transforming the demand planning process

Excess inventory is a growing problem for companies across all industries. Since 2011, the ratio of inventory to sales, as reported by the U.S. Census Bureau, has been on the rise. New sales channels have ushered in a new level of demand volatility, and many companies have responded to this uncertainty by increasing their inventory levels to ensure that product is always available, whenever and wherever the customer needs it.

While this approach can help to ensure that there is enough product to meet customer demand, carrying excess inventory is not a profitable or sustainable long-term solution. Not only does it drive capital costs higher, but it increases the risk of inventory waste and obsolescence, especially in industries with perishables or fast-moving consumer goods. In fact, the associated costs of insufficient forecasting accuracy are staggering. According to IHL Group, a research firm, in 2015 the cost to companies of overstocking was around $470 billion and of understocking $630 billion worldwide.[1]

Faced with growing supply chain complexity and demand volatility, improving forecast accuracy has become a top priority for many companies. While the availability of real-time digital signals has the potential to provide demand planners with new information about demand drivers and customer behavior, many companies have not had the technology or processing power they need to analyze hundreds of real-time data signals and derive insights from it.

Thanks to new cognitive demand planning capabilities, this is now possible.

The power of cognitive demand planning

Historically, sales history has been the primary input into time-series forecast models to produce sales projections. However, advances in machine learning, availability of big data and cloud computing have enabled a new era of cognitive demand planning capabilities. This cutting-edge approach incorporates deep-learning capabilities – a subset of machine learning in artificial intelligence (AI) where machines “learn” from data without being explicitly programmed – that enable demand planners to get a better view of the data and derive better insights about what is driving customer behavior.

With cognitive demand planning capabilities, companies now have a systematic way to gather and analyze hundreds of internal and external data signals and incorporate those that matter – while also ignoring those signals that represent noise – into the forecasting process in real time. The types of digital signals include:

- **Global data.** This is data that’s generally available such as demographic data, social sentiment, news, events and weather (SNEW) data, macroeconomic data around consumer spending, publicly available Internet of Things (IoT) data, etc.
- **Enterprise data.** This is proprietary data that the enterprise owns such as information on pricing, promotions, store assortments, data from in-store IoT sensors, etc.
- **Industry-specific data.** This is data that would be of interest to companies operating in specific industries such as data from the Centers for Disease Control and Prevention (CDC) or the Department of Motor Vehicles (DMV). For instance, a pharmacy could leverage flu data from the CDC to track areas with the most diagnoses and adjust the forecast for its flu medications accordingly, and automotive aftermarket companies could leverage DMV data to learn the types of cars being registered, as well as what types of tires they have, to forecast future demand.

To analyze very large data sets and optimize every possible outcome, companies need the processing scale and precision that only machine learning can provide. To take advantage of AI-based cognitive solutions, companies need extensible cloud capacity that can be increased or decreased based on the processing power needed to compute massive petabytes of big data.

By incorporating hundreds of internal and external signals in a highly automated way, companies can achieve significant step-function improvements in forecast accuracy. Machine learning and cognitive computing make sense of these data signals by determining which to include, and how much to adjust demand, using a probabilistic forecasting approach.

The advantage of probabilistic forecasting

One of the primary advantages of cognitive demand planning is that it uses a probabilistic forecasting approach, where the forecast is calculated in the form of a probability density function. Consider that traditional forecasting techniques produce a single number such as 6. However, the actual sales may be 6, or they could just as easily be 7 or 8 … or 4 or 5. Probability-based forecasts show this range of outcomes, each associated with a probability. When compared to traditional forecasting methods, probabilistic forecasting delivers a more accurate picture of the probable outcomes, thus enabling further forecast optimizations.

Because probabilistic forecasting applies machine learning to prediction models, hundreds of different data sources can be analyzed to evaluate the influence of all input data – such as events like promotions, weather, Facebook posts and more – on customer demand, down to the stock keeping unit, location or time. Each calculated prediction quantifies the likelihood of different demand outcomes. This information then enables demand planners and advanced demand-supply matching algorithms to make informed decisions and ensure KPI alignment, optimally weighing the risks associated with different demand outcomes.

This new level of detail takes probability distributions with the same mean prediction – which would have resulted in the same forecast using a deterministic forecasting method – and shows how different the risk values are for factors such as stock-outs and waste. Figure 1 shows two probability distributions with the same mean prediction of seven but different risk values. The example on the left-hand side shows there is a higher probability for high demand (e.g., above 18) than on the right-hand side example, and thus the risk of a stock-out is higher.

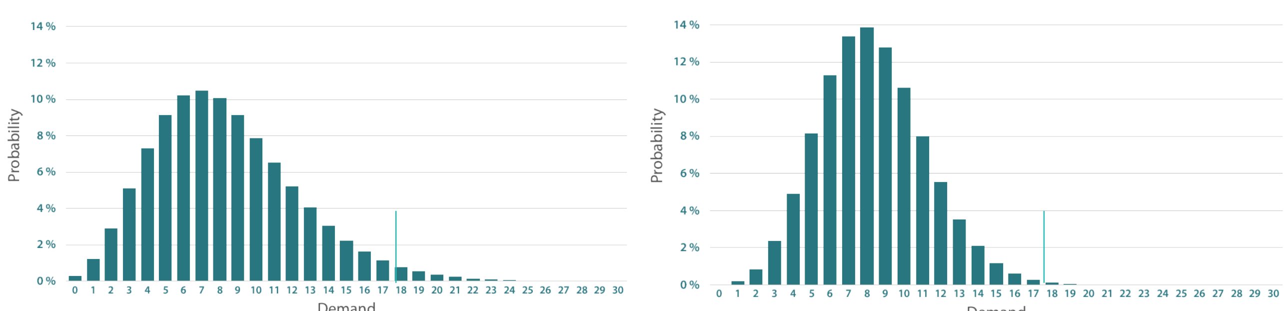

Figure 1

The value of increasing forecasting precision

Cognitive demand planning capabilities offer significant operational improvements in forecasting accuracy and planner productivity when compared to traditional forecasting methods. These operational improvements further drive enhancements in business value, increasing revenue due to fewer lost sales while also reducing inventory investment and waste, resulting in higher gross margins.

Best-in-class cognitive demand planning capabilities should include the following features:

- Deploys as a cloud-based, Software-as-a-Service application
- Leverages machine learning to produce highly accurate forecasts
- Incorporates hundreds of real-time demand signals and data points
- Uses a probabilistic forecasting approach to calculate business impact and risk

By leveraging the combined power of machine learning, cloud computing and big data in cognitive demand planning, companies no longer need to boost their inventory levels to counter demand volatility. Instead, they can use this cutting-edge approach to develop more risk-aware, probability-driven forecasts, leading to improved forecast accuracy, improved business decisions and ultimately, superior customer experiences.

1 The Economist, "How AI is spreading throughout the supply chain," March 31, 2018.

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