White Paper

2022 Planning Tip: Eight Methods to Improve Forecast Accuracy

Forecasting best practices
for varying supply chain scenarios

Executive Summary

Most companies recognize the importance of a repeatable and accurate forecasting process. Accurate forecasts help minimize inventory, maximize production efficiency, streamline purchasing, optimize distribution, maximize customer service and ensure confidence in company projections. However, developing accurate product forecasts at all stages of a product's life cycle can be very challenging. Gartner places demand forecasts at the top of their Hierarchy of Supply Chain Metrics to highlight its impact back through the supply chain.[1] After all, a forecast is not simply a projection of future business; it is a request for product and resources that ultimately impacts almost every business decision the company makes across sales, finance, production management, logistics and marketing.

Typically, a variety of forecasting methods are applicable to any particular type of supply chain scenario. Smart supply chain planners use multiple methods tuned to perform well at different phases of the product life cycle, chosen to best exploit the available historical data and degree of market knowledge. The key is to pick the most effective and flexible methods and models, blend their best features, and shift between them as needed to keep forecast accuracy at its peak.

In this paper we take a brief look at the three categories of forecasting models and the eight methods that have produced superior results for Logility's many clients in a variety of industries and market conditions around the world. We also discuss how causal forecasting can help you incorporate internal and external demand data to improve forecast quality and uncover insights to make better and faster decisions.

1 "Retire the Functional KPIs: End-to-End Supply Chain Planning Requires End-to-End KPIs"
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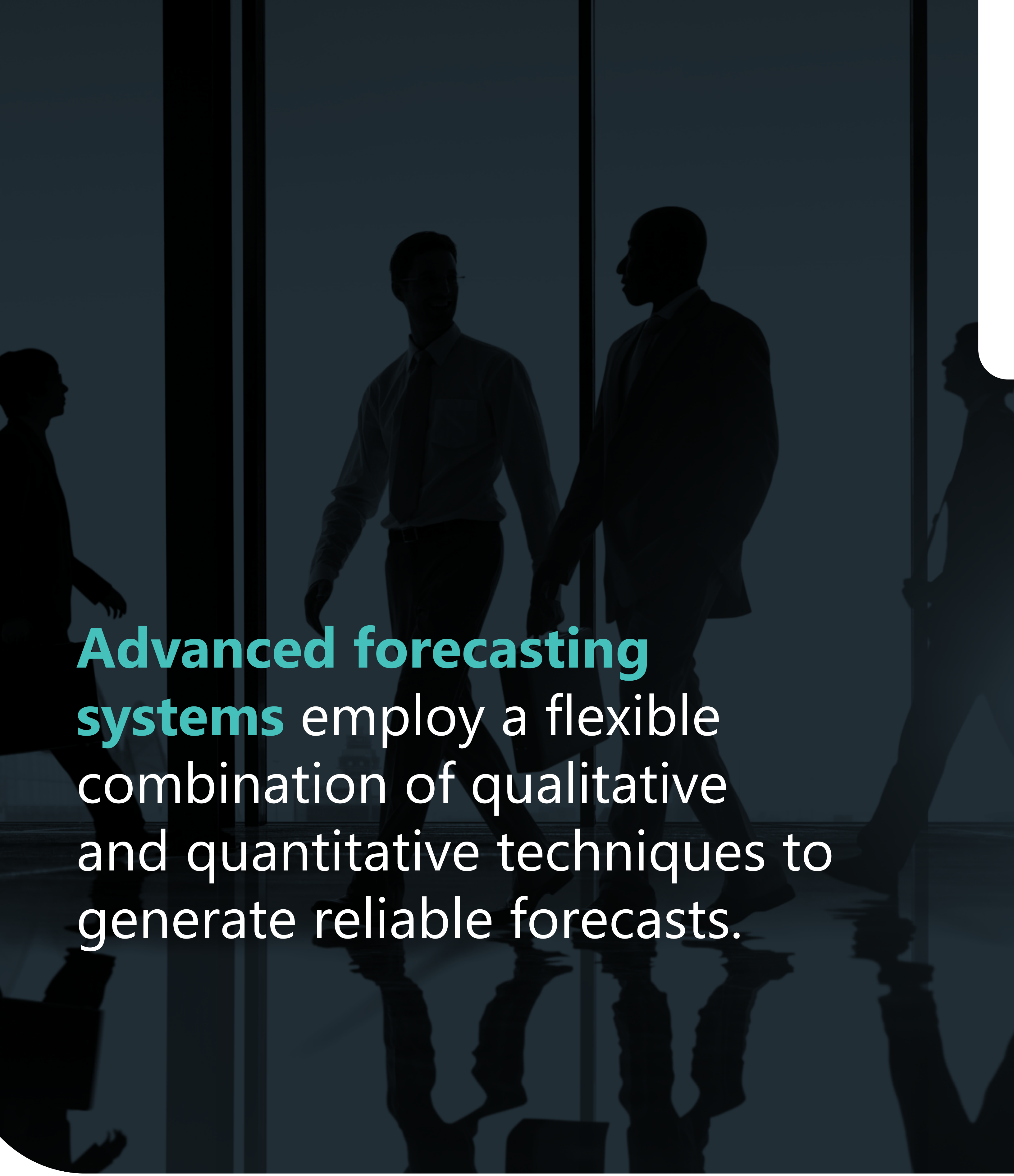

Advanced forecasting systems employ a flexible combination of qualitative and quantitative techniques to generate reliable forecasts.

Three Categories of Forecasting Models

Forecasting models classically fall into three categories: qualitative, quantitative and hybrid. The primary differences between them include the type of input data and the mathematical and statistical methods employed to generate forecasts.

1. **Qualitative models** are experience-driven, relying on subjective inputs from knowledgeable personnel, such as salespeople, account managers, and the like. This approach typically sets up formal procedures for data review, and requires a consensus to determine the value of various forms of information. Consensus among forecasters may be obtained by aggregating individual estimates or through structured polling methods. Qualitative models are generally the most time-consuming models to generate, and the most prone to human bias.

2. **Quantitative models** are statistically driven, drawing heavily on historical performance data as the basic data input and relying on future demand being similar to historical demand. The calculating logic is defined and operations are purely mathematical.

   Time series models employ a time-ordered sequence of observations of a particular variable, and use only the history of that variable to determine future values. For example, if monthly sales volumes of lawnmowers sold in the Southeast United States display a linear pattern, a linear trend model would provide the best basis for the forecast.

   Derived models create new forecasts based on existing forecasts. When a new item's forecast is thought to be fundamentally the same as an existing item, characteristics can be used in creating the new forecast, which may be factored up or down by a percentage. This preserves the overall trend and seasonal characteristics of the item, providing a good starting point for the new item.

3. **Hybrid models** typically draw on historical demand information as a starting point, then use empirical data to further refine the forecast.

   Attribute-based models employ user-defined attributes to model new product introductions, seasonal or fashion driven products, and product end-of-life retirement based on a demand profile.

   Causal models use a causal relationship between a particular time series variable and other time series factors to calculate the forecast. Causal techniques are useful in forecasting 'lift' during promotional campaigns, where demand caused by promotional factors has an established relationship to base demand. Additional factors can be used, such as end-cap displays, seasonality of the product, etc. Factors are not additive but are used together to calculate the expected lift for your product.

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Eight Forecasting Methods that Improve Supply Chain Performance

For many supply chain scenarios, it's typically best to employ a variety of methods to obtain optimal forecasts. Ideally, managers should take advantage of several different methods and build them into the foundation of the forecast. The best practice is to use automated method switching to accommodate selection and deployment of the most appropriate forecast method for optimal results.

Advanced demand planning and forecasting systems automate many of the functions required to select, model and generate multi-echelon forecasts, lifting the burden of manually intensive approaches and accelerating sensitivity to model changes as market conditions evolve. A best practices approach also must include the ability to incorporate personal expertise and weight the various factors in generating forecasts.

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In Logility's experience working with more than 1,200 organizations ranging across dozens of industries, eight specific forecasting methods stand out. Their unique strengths combine to deliver powerful, flexible and accurate results.

1. **Modified Holt** is a best-fit statistical technique used when demand is trended, but does not vary by the time of the year. A Holt-Winters variant is often used when demand is seasonal.
2. **Moving Average** is used for products whose demand histories have random variations, including no seasonality or trend, or a fairly flat demand.
3. **Inhibited** is a type of derived model used to produce a zero forecast.
4. **Modified Parent-Child** is a derived model technique used to forecast products as a percent of the forecast for another product [dependent demand].
5. **Modified Croston** is an intermittent demand technique used for products such as slow-moving parts that have low demand or some zero demand periods.
6. **The Demand Profile** technique is attribute based. It employs user-defined attributes to model new product introductions and product end-of-life retirement.
7. **Proportional Profiling** is another attribute-based technique used to disaggregate higher-level forecasts into lower-level forecasts using user-defined attributes.
8. **Demand Sensing** techniques provide real-time visibility and insights into short-term demand, and are enabled through downstream data sources such as point-of-sale (POS) and syndicated scanner data and by advanced technologies such as machine learning driven pattern recognition and natural language processing algorithms, simulation, and optimization.

Best-fit Statistical Modeling

For most levels of management within an organization, aggregated demand history for product family, brand category, country and/or selling region are good predictors of future performance. Such demand history also serves as a baseline for effectively forecasting stock keeping units (SKUs). When there are more than four to six periods of sales history, SKUs can be effectively forecast with moving average and basic trend methods. SKUs with at least one year of sales history offer sufficient information to incorporate a seasonal profile into the projected trend.

A modified Holt-Winters decomposition model with best-fit analysis can generate forecasts based on demand history that incorporate trends and seasonal information. The method “senses” the amount of history available for each time series or segment to create a basic model that best fits the history. Then it uses the best combination of smoothing factors to enable the model to react to changing conditions going forward without overreacting to anomalies in demand (such as unplanned seasonal events, transportation disruptions, and so on).

For factors relating to seasonality, planners need the ability to weight the historical demand. Under the assumption that the previous year is the best indicator of what will happen next year, most forecast systems apply a higher weighting factor to the previous year’s demand, less to the year before and even less to the years before that. But if the previous year was unusual in any significant way, the planner must have the capability to change the historical weighting factors so as not to under- or over-forecast the business. For instance, the planner should be able to change the historical weighting factors so that the history two years ago has more impact on the current forecast than last year.

Seasonal methods can be effective with less than 24 months of history; the minimum required is twelve months. An effective approach for expected seasonal items with less than twelve months of history is to assign a seasonal curve that has been captured from a similar item or item group.

A powerful best-fit statistical method should include flexible features such as trend, seasonal-with-trend, moving average and low-level pattern fitting, as well as trend models for products with sporadic, low-volume demand. The method should provide limiting and damping, as well as seasonal smoothing, demand filtering, reasonability tests, tracking signals and tests for erratic nature that evaluate the validity of each element, determining which are anomalous and should be filtered. These parameters give the planner the flexibility to tune the process to best fit conditions at any element of the organization.

“Best fit” refers to the ability to change forecast methods as a product evolves. The process may start out as a demand profile method, evolve to a modified Holt-Winters method as the product becomes stable, and ultimately transition to a demand profile method again as the product life cycle comes to an end.

Parameter	Description
Limiting	Confidence limits describe the spread of the distribution above and below the point forecast.
Smoothing	Removes random variation (noise) from the historical demand, enabling better identification of demand patterns (primarily trend and seasonality patterns) and demand levels. Results in a closer estimate of future demand.
Damping	Applies various “weights” to each period to achieve the desired results. These weights are expressed as percentages, and the total of all weights for all periods must add up to 100%.
Filtering	Forecast error, viewed as the difference between forecast value and actual value, is usually normally distributed. A demand filter is usually set to ±4 mean absolute deviation against the forecast value. Whenever the deviation is more than that, the adequateness of the forecast model should be reviewed by analyzing the actual data.
Forecast Error	The difference between actual demand and forecast demand. Error can occur in two ways: bias and random variation. Bias is a systematic error that occurs when cumulative actual demand is consistently above or below the cumulative forecast demand. Type 1 Bias is subjective and occurs due to human intervention. Type 2 Bias is a manifestation of a business process that is specific to the product. For instance, persistent demand trend and forecast adjustments don’t correct fast enough for items specific to a few customers.
Reasonability Tests	An important type of reasonability measure is the tracking signal, which can be used to monitor the quality of the forecast. There are several procedures used, but one of the simpler is based on a comparison of the cumulative sum of the forecast errors to the mean absolute deviation.

Derived Modeling

One method of generating new product forecasts is to use demand variations or extensions from existing products, families or brands. Consequently, they draw on the historical data of existing products or families. When combined with causal effects or management-selected overrides to accommodate introductory promotions, derived modeling can provide a realistic and dynamic forecast for new products.

Using this approach, new products are assigned a percentage of the parent, family and/or brand, enabling them to proportionately inherit a forecast that contains the base, trend and seasonal elements of the associated category. As the forecast for the associated category is adjusted to reflect changing conditions over time, so too is the derived product's forecast. If the derived product's POS or demand levels deviate from the forecast and exceed a user-defined tolerance, the system can generate a performance management alert to notify forecast analysts to take corrective action.

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Once the product has accumulated sufficient demand history of its own, the link to the derived model's source model is severed and the product is then forecasted on its own using multiple best-fit statistical methods.

Modeling for Intermittent Demand

Slow-moving parts typically exhibit irregular demand that may include periods of zero or excessively lumpy demand. A modified Croston method handles low and lumpy demand that exhibits either a patterned variation or no pattern.

The patterned variation looks at available history and classifies each demand element relative to those around it. It classifies the periods into peaks, valleys, plains, plateaus, up-slopes and down-slopes. It measures the duration of plateaus and plains, as well as the severity of peaks and valleys. It then conducts pattern-fitting analysis to find regularity over time, attempting to fit the pattern to the history and averaging for low and high points. The patterned forecast is put in context of future periods with the average trend, and the pattern is reevaluated using demand history of subsequent periods.

If no pattern is present, the unpatterned variation method attempts to use averaged highs and lows to create a step-change forecast for future demand.

Both techniques permit zero demand to reside in the history, and will acknowledge such in the future demand forecast. In forecasting for spare parts, for example, the demand is frequently low-level and spotty, containing many periods of zero demand interspersed with low-level demand. This forecasting technique allows patterns of zero demand to be forecast into the future.

Attribute-based Modeling

What if lack of data, short-life cycle or other mitigating factors make it difficult to forecast using time series or qualitative techniques? Forecast creation for new product introductions, short-life or seasonal products, and end-of-life products calls for attribute-based modeling techniques.

The attribute-based model provides a wide variety of demand profiles by which to characterize the product, and can adjust the product's plan dynamically in response to early demand signals. The method will analyze historical sell-in and/or sell-through data to develop a wide variety of demand and seasonal profiles. These profiles are assigned to individual planning records. Then, as actual demand information is captured, the current profile is validated or alternate profiles identified to dynamically adjust the product's plan.

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Attribute-based modeling consists of four unique processes.

1 **Creation of Demand Profiles.**
Demand profile creation is based on mathematical concepts known as Chi-squared analysis. The demand planner selects products to be included based on attributes such as color, fabric type, region of the country, etc., and multiple attributes can be used at once. Planners can efficiently realign history for events like various religious holidays, which do not occur during the same period each year.

2 **Assigning Demand Profiles.**
New, seasonal and end-of-life products can now be assigned to demand profiles. Advanced attribute-based models offer 'user-defined attribute' matching capabilities, allowing the planner to set criteria for how a new product's attributes must match the attributes of a demand profile.

3 **Automatic Revision of the Forecast Based on Demand Signals.**
Forecast accuracy must be monitored continually using data such as POS to accurately monitor customer buying patterns. Other demand signals such as syndicated data is used to check the accuracy of the forecast. Correctness-of-fit modeling adjusts the forecast to reflect and quickly react to real-world changes.

4 **Assess Accuracy of Demand Profile Based on Demand Signals.**
New products never sell exactly the same way as other products with similar attributes. But by using point-of-sale or other demand signals, the accuracy of the assigned curve can be checked against other demand profiles that have similar attributes. Relative error index (REI) calculations quickly show planners which demand profile has the most accurate fit based on current demand trends. The current demand profile can be switched to the profile that has the lowest REI.

Demand Sensing

Demand sensing is the translation of market-based demand information to detect short-term buying patterns. Demand sensing leverages new mathematical techniques and near real-time big data to improve a supply chain organization's capability to respond to unplanned demand changes.

Demand sensing involves the import of short-term demand data such as POS scan-based data, point-of-use (POU) device data, weather data, or social media data on an hourly/daily basis to immediately sense demand signal changes. Through advanced algorithms the statistical significance of demand changes are evaluated and short-term forecast adjustments made to drive short-term supply chain responses.

Internal Downstream	• POS • Price/promotion moves	• Warehouse depletions • Customer/channel
Environmental	• Weather • Seasonality	• Precipitation by month • Temperatures
Economic	• Consumer Price Index (CPI)	• Commodities pricing
Competitor	• Promotion actions • Store openings • New product introductions	• Pricing adjustments • Store closings
Synthetic	Shipments, depletions, lags	• New metrics derived by combining your array into new ratios and indices
Regional Factors	• Trade areas • Housing starts	• Demographics • Car registrations
Syndicated Sources[IRI/ Nielsen/VIP]	• POS by brand • Distributor depletions	• Store-level dynamics • Consumer preference

The typical performance of demand sensing can reduce near-term forecast error by 30% or more compared to traditional time-series forecasting techniques. However, since demand sensing usually takes place inside of the supply planning time fence, the greatest value gained from demand sensing is the ability to optimize inventory and resource deployment. Demand sensing can lead to a 5%—10% improvement in customer service.

Demand sensing is most successful when the following capabilities are already in place:

- Prior experience using customer POS data in ad-hoc ways
- Strong collaborative relationship between commercial and supply chain groups
- Strong supply chain visibility capabilities
- Statistical-based demand, inventory, and replenishment planning
- Workflow and exception-based alerts
- Constrained/profit-based “what-if” scenario analysis
- Agile manufacturing capabilities (short change overs)
- Agile distribution capabilities (inventory visibility and agility to reroute shipments)
- An integrated platform to collect and analyze demand signals and to enable optimized response

An evolving demand sensing trend is the use of artificial intelligence (AI) to automate the process of analyzing big data to recognize complex patterns and to separate actionable demand signals. Used together, machine learning (ML) and natural language processing (NLP) algorithms can be used to analyze information like social media text to determine the “sentiment” of the text and to predict the impact of that sentiment on demand. Today’s natural language processing algorithms have the ability to correctly categorize the sentiment of most social media content. Machine learning algorithms can quickly learn the differences between humor, sarcasm, irony and so on to improve categorization capabilities.

Companies are using social media insights today to make significant operational impacts:

- Evaluate the Health of a Brand—An understanding of how your target market feels about your company, product and services through analysis of overall sentiment can provide valuable insight into the health of your brand.
- Address a Crisis—Analysis of social sentiment might reveal a spike in negative posts and provide an early warning to a potential product or service issue. Through alerts and analysis, the root cause of the issue can be uncovered and corrected.
- Research the Competition—Social sentiment analysis can help you understand how to position against the competition.
- Improve Demand Prediction—Companies can now use the ‘Voice of the Consumer’ to drive improvements in forecasting and inventory positioning.

An evolving demand sensing trend is the use of artificial intelligence (AI) to automate the process of analyzing big data

Causal Forecasting

Leading companies are turning to causal forecasting to capture data from multiple demand streams and translate it into demand data insights used to provide input for future planning activities, identify and pre-empt service disruptions, and generate measurable sales and profit growth. Causal forecasting integrates all relevant demand signals into a single source of truth and enables predictive analytics to uncover insights to make decisions ahead of the demand curve.

Causal forecasting is a more proactive approach than basing inventory and replenishment on only shipment or order data—it gives better access to downstream data, analysis and insights to make more accurate decisions, faster. More than forecasting trends and seasonality, it is about identifying and measuring market signals, then using those signals to shape future demand. Causal forecasting augments demand forecasting, enables demand sensing and answers the question of how to react to external factors that drive demand for buy decisions.

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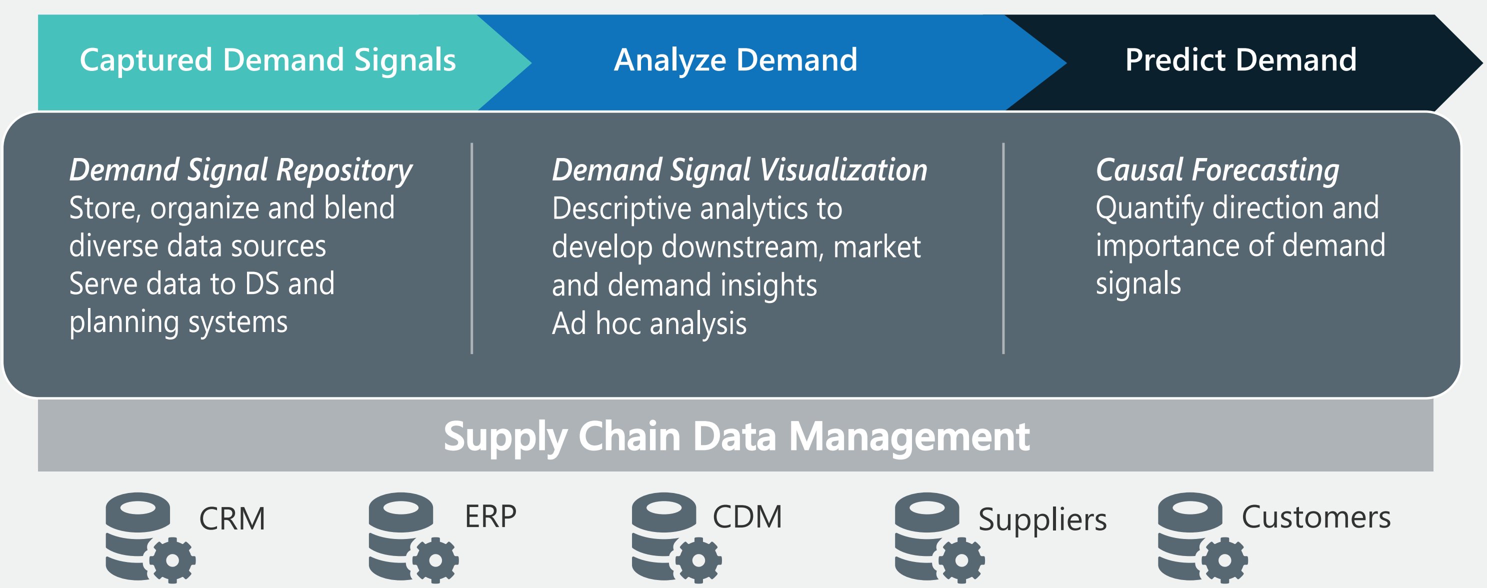
Typical demand signals to boost demand sensing

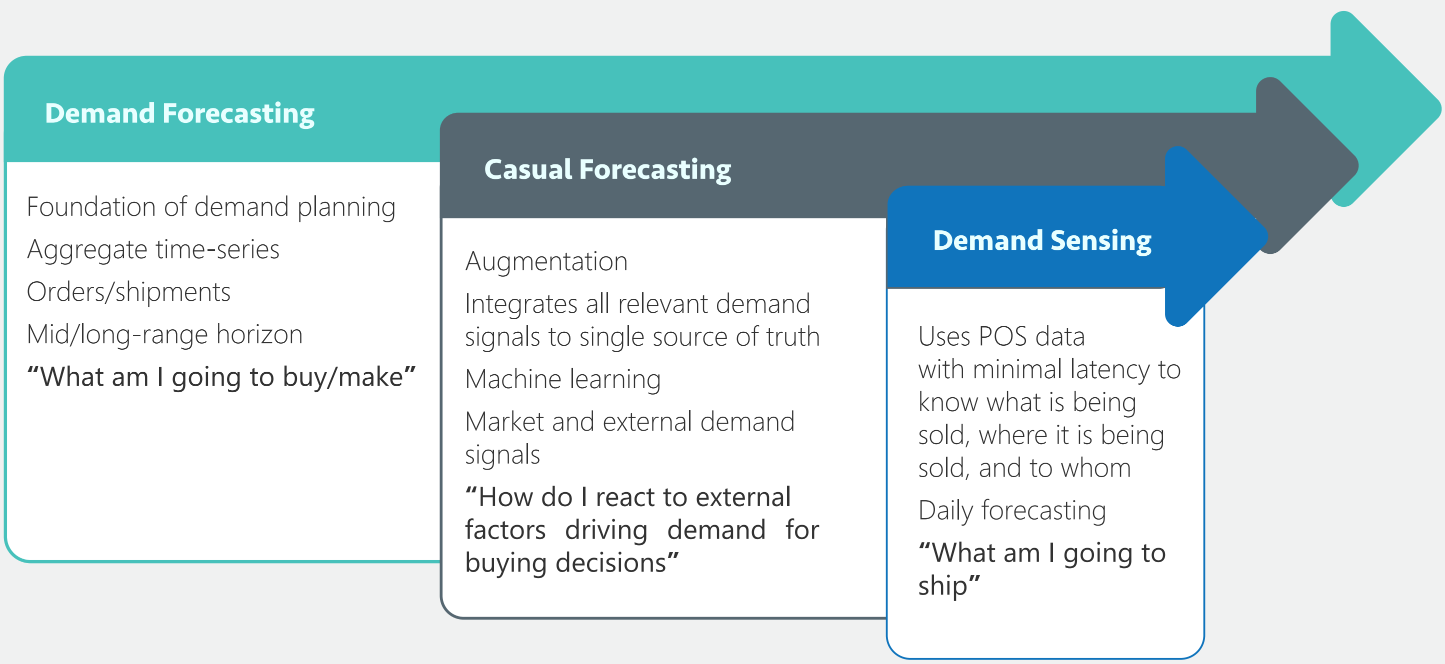


Causal forecasting includes the tools and services to aggregate, cleanse and harmonize disparate downstream data streams. It also drives a stronger link between sales, marketing and brand teams with their supply chain counterparts. Leading users of causal forecasting incorporate short-term fast response planning technologies like demand sensing to improve their ability to optimize a supply response to short-term demand. Causal forecasting works best when organizations have a technology structure in place that supports a quick supply planning response and can use demand signals updated daily or weekly.

Typical causal forecasting benefits include:

- Demand planners are better prepared to quantify variability in demand through increased visibility downstream by capturing and analyzing external demand signals
- Planners can improve forecast accuracy by incorporating information from external demand signals and predicting mid-term demand patterns
- Operations improve lead time because of the improved use of real-time forecasts to drive enhanced scheduling and procurement
- Sales teams can boost sales by predicting and reducing stock outs with demand pattern recognition
- Sales can improve new product introduction through better customer insight at POS
- Operations can lower expediting and inventory costs
- Logistics build transport and deployment scheduling efficiency because of improved visibility of customer requirements

Where does causal forecasting fit in?



Conclusion

Supply chain organizations routinely rank demand planning immaturity as a major obstacle in meeting their supply chain goals. Accurate forecasts are the foundation for profitable business growth. Optimal demand planning and forecasting requires comprehensive modeling capabilities plus the flexibility and ease-of-use to shift methods as life cycles progress and market conditions change. The Logility Digital Supply Chain Platform provides a combination of qualitative, quantitative and hybrid techniques to generate reliable forecasts.

Attribute-based methods that use demand profiles are often suited to new product introduction and end-of-product life cycles, at times when reliable historical demand data is lacking or the available data is less relevant.

At the more mature stages of the product life cycle, five different time-series statistical models come into play, including modified Holt, Holt-Winters, moving average, and intermittent or low demand, whether patterned or unpatterned. These models are used to create retrospective forecasts that cover prior periods of documented demand, typically three years.

Derived models can be used to create a parent-child relationship in which forecasts for closely related products are driven as a percentage of the forecast for a 'leader' product. This ensures that when the forecast is modified for the 'parent' all the 'child' forecasts would be updated accordingly.

The ability to sense and quickly react to demand changes has become a critical capability to meet ever increasing customer service requirements. Through the use of machine learning and natural language processing algorithms, big data can be systematically mined to gain new insights to improve operational capabilities.

Logility's powerful software solutions help planners leverage the best methods, spot trends and forecast demand signal changes more quickly, and sense and respond to market changes and inventory investments and deployments.

To prevail in a business economy shaped by uncertain demand and rapid market changes, all of these forecasting methods must be harnessed within one practical, comprehensive solution suite. Causal forecasting sorts out the flood of data in a structured way to recognize complex patterns and to separate actionable demand signals from a sea of "noise". A best-in-class forecasting system is one that provides flexibility for users to weight elements and override key parameters in the forecast calculation based on their intuitive knowledge and market expertise.

Logility's powerful platform helps planners leverage the best methods, spot trends and forecast demand signal changes more quickly, and sense and respond to market changes and inventory investments and deployments.

About Logility

Accelerating the sustainable digital supply chain, Logility helps companies seize new opportunities, sense and respond to changing market dynamics and more profitably manage their complex global businesses.

The Logility® Digital Supply Chain Platform leverages an innovative blend of artificial intelligence [AI] and advanced analytics to automate planning, accelerate cycle times, increase precision, improve operating performance, break down business silos and deliver greater visibility. Logility is a wholly owned subsidiary of American Software, Inc. (NASDAQ: AMSWA).

To learn how Logility can help you make smarter decisions faster, visit www.logility.com.

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