

Demand Forecasting Primer

10 Things We Wish Someone Had Told Us Earlier



EBOOK



Introduction

Some people say that AI has changed everything and renders much of what we know about demand forecasting obsolete. AI is certainly a breakthrough technology that is advancing the state of the art. One of the reasons we started New Horizon was to take advantage of advances in AI. But certain basic forecasting principles are timeless, regardless of the technology used.

Based on our experience with over 100 supply chain implementations, we've put together a list of 10 such principles our clients have found valuable to review at the outset of projects. We wish we knew these things when we started out in forecasting many years ago! We hope they are enlightening to those new to the field, and also serve as a valuable refresher course for seasoned pros.



Don't Confuse Demand Forecasting with Demand Planning

The two terms are often used interchangeably, and this is often a source of confusion. Forecasting is a subset – a very important subset – of demand planning. Demand planning refers to the broader process of not just creating forecasts but turning them into enterprise plans and includes things like sharing forecasts with dozens or hundreds of users; collaborating and reaching consensus among different departments and with customers; reviewing, editing, and approving forecasts; and allocating demand for products in short supply. This eBook focuses on the narrower topic of demand forecasting.

2

Demand Forecasting Is Not Just a Supply Chain Process

The supply chain department of every organization can have a big impact on other functions, affecting whether sales and marketing can hit their revenue targets and whether finance can hit their revenue, cost, and profit goals. This is particularly true for demand forecasting. Forecasting is the key link between the supply chain group and other functional areas. Forecasting is where expectations of market demand are translated to operations so that they can meet this demand and generate revenue. Accordingly, forecasting must be a collaborative process among different functional areas. In fact, demand planning sometimes sits within the sales or marketing organizations or is even a freestanding group in some companies.

3

Forecast Accuracy Is Not a Good Way to Measure Forecasting Effectiveness

Let's say you sell two different types of products, and both have an average forecast error of 20%. Many people would





say the demand forecasting team did an equal job of forecasting the two products. But it may be that one of the products is fundamentally more difficult to forecast because of the nature of the product or the go-to-market strategy. For instance, a staple category like paper towels, with a limited set of competitors, is far easier to forecast than a discretionary category such as ice cream, with lots of competitors, new products, and demand highly dependent on promotions and warm weather.

Thus, to evaluate the effectiveness of your forecasting process, instead of looking at forecast accuracy, you should look at the extent to which you've improved it over a relevant baseline. This improvement is known as forecast value added (FVA) and is a measure of the value your forecasting process is providing above and beyond the baseline. The baseline is the so-called naïve forecast, the forecast resulting from a simple forecasting method (such as moving average of prior demand) one would use in the absence of a more sophisticated forecasting technique. In the chart below for a hypothetical company that makes paper towels and ice cream, we see that the forecasting process was much more effective for ice cream because it decreased forecast error by 60%, whereas for paper towels, it decreased error by only 20%.





Forecast Bias Is a Measure of Organizational Dysfunction

We often talk about forecast error and bias as the two primary measures of forecast accuracy. For those unfamiliar with these measures, the most common forecast error metric is mean absolute percent error (MAPE), typically defined as the absolute value of (Forecast-Actual) / Actual. MAPE measures how far off your forecast is from the actual value, but does not distinguish between forecasting too high or too low.





Bias, on the other hand, aims to capture whether your forecasts tend to be too high or too low and is calculated by dividing the difference between total forecasts and actuals by total actuals. Ideally your bias will be zero, meaning your forecast error is random and you are as likely to forecast too high as too low. A non-zero bias means you are systematically over or under-forecasting. This is generally not the result of a problem with your forecasting techniques. It is more likely some type of dysfunctional organizational behavior, such as increasing the sales forecast to "game the system" and avoid stockouts — a noble goal, but one that should be achieved through inventory policies, not by doctoring the forecast. So bias is best thought of as a measure of the quality of your organizational consensus forecasting process.

5

There's No Right Forecasting Level

When you forecast, you will need to choose at which level to forecast, e.g., item vs. product family, DC vs. store, day vs. week. If the logistics group needs to deliver specific items to specific stores daily, they need a forecast at that level. Likewise, if the sales and operations planning team wants to plan long-term capacity needs, a forecast by product family, month, and factory is more appropriate. Forecasts need to be available at different levels for different business needs. There shouldn't be a single level for everyone. Note, the more aggregate the level, the more accurate the forecast, because positive and negative errors at a more granular level cancel each other out. That's good news if you just need an aggregate forecast, but beware the temptation to set too aggregate a level of forecasting to make your accuracy look better. Some forecasting groups take that approach for reasons of company politics, but it's a recipe for poor supply chain performance.

6

Beware Forecast Comparisons

This is a corollary to the previous item. Forecasts exist at different levels for different use cases, but since forecast accuracy improves with the level of aggregation, you can't compare forecasts at different levels, whether within a company or between companies. Nevertheless, some people talk about how good their 5% forecast error is at the product family, national, and quarterly level compared to someone else's 30% forecast error at the item, DC, and week level. This is an apples to oranges comparison.



Time Series and Causal Forecasting and AI, Oh My!

There are two general classes of statistical forecasting techniques traditionally used in enterprise demand plan-





ning applications: time-series forecasting and causal forecasting. New AI approaches have emerged in the last decade. As with any technical subject, these terms can be confusing and are often misused for marketing purposes. Here's an attempt to set the record straight:

Time-series forecasting refers to projecting the value of a variable such as sales, solely based on the historic values of that variable. So if you have a few years of sales data, various time-series algorithms can detect some combination of overall trend, seasonality, and irregular cyclical patterns and use that to project future values. Such techniques do not take into account external factors such as weather or marketing promotions. Example time-series algorithms include Holt-Winters and ARIMA (Autoregressive Integrated Moving Average), to name just a couple.

Causal forecasting, on the other hand, looks at how other factors, such as weather and promotions, affect the forecast variable. To do causal forecasting, you need additional data streams besides the variable you are forecasting. Various types of regression analysis are commonly used for causal forecasting. Many casual forecasting algorithms include an element of time-series forecasting, so they are in fact a hybrid of the pure time series and causal approaches.

Some vendors of AI-based forecasting technologies claim that traditional forecasting applications use time-series forecasting exclusively and that AI is required to take into account causal factors. This is not true; causal forecasting algorithms have been commercially available for decades.

But AI allows you to do a better job of causal forecasting. The most common form of AI applied to forecasting is machine learning (and is what New Horizon uses). Machine learning generally considers a larger set of data than traditional techniques and can discover correlations that a human forecaster might not even consider with a traditional algorithm. It also "learns" by examining data, making predictions, comparing those predictions with actual results, and then automatically tweaking the algorithms to continuously improve predictive accuracy.



You Need to Learn How to Deal with Bad Data

Many discussions of forecasting techniques assume you have perfect data. This assumption is not reflective of reality. In practice, demand data is messy. Outliers are common — data that doesn't fit the predominant pattern and can't be explained, either because of an error or some factor not captured by the existing data. Outliers must be removed to avoid distorting forecast results. In addition, data is often missing for various reasons, and this can further confuse forecasting models. Special algorithms are needed to take into account such missing data.





Then there is the issue of hidden demand. This occurs when demand (as measured by orders, shipments, or retail sales) is depressed or zero because a product is out of stock. Such hidden demand does not represent an error in the data like the above two cases, but rather an inability to measure what demand would have been had the product been available to purchase. Again, special algorithms are required to account for such hidden demand if you want to be able to meet this demand in the future and maximize sales.



Don't Confuse Turn and Promoted Volume with Base and Promotion Lift

These last two items relate to promotions, which are most relevant to the consumer products and retail industries. They are included in this list because promotions account for a huge portion of volume in these industries, and forecasting promotion effects is a major focus of forecasting teams.

Companies use two different frameworks for talking about promotion volume, and this can cause some confusion. Consider a product that is being promoted in weeks 5–7 and again in weeks 12–14. In the following chart on the left, we show Base in orange, the volume that would have sold in the absence of any promotion. Promotion Lift, in yellow, is the incremental volume attributed to the promotion. This decomposition of volume into base and lift reflects the use of a causal forecasting model which statistically infers what portion of the total volume was caused by the promotion vs. what amount would have been sold in the absence of the promotion.

On the right, we show the same total volume, but using a different framework this time. Turn (green) is the volume in non-promoted weeks, while Promoted Volume (blue) is the volume during promoted weeks. The Promoted Volume does not make a distinction between what you would have normally sold and the incremental amount caused by the promotion. We are simply showing how much volume was sold during the promoted and non-promoted periods.







Both these frameworks are valid but are used for different purposes. The base/lift framework is useful for attributing incremental volume to promotions (and thus measuring promotion impact and ROI). The turn/promoted framework is useful for understanding what portion of your volume is sold during promotions, a measure of the promotion intensity of your business.



Promotions Are Going to Cause More Trouble Than You Think

While we're on the topic of promotions, it should be pointed out how promotions have effects beyond the intended effect. When a company promotes a product, the intent is to increase sales of that product in a specific location for a specific period. However, such a promotion has effects on other products, locations, and periods. Consider the example of Utz Brands, marketer of Utz[®] snack foods and On the Border[®] dips and salsas. If Utz promotes their tortilla chips at the Kroger supermarkets in a certain region in week 10, such a promotion could have the following indirect effects:

- **Cannibalization:** The Utz tortilla chip promotion could cannibalize sales of Utz potato chips and other snack products.
- Halo Effects: The Utz tortilla chip promotion could have a halo effect (increased sales) on On the Border salsa and other dips.

- Cherry-Picking: The Utz tortilla chip promotion at Kroger could decrease Utz and other tortilla chip sales at other supermarkets in the area, as some consumers forego tortilla chip purchases at their regular store and buy them at Kroger instead.
- Pantry Loading: The tortilla chip promotion in Week 10 could depress tortilla chip sales in the weeks before and after week 10, as some consumers stock up during the promotion week.
- Forward Buying and Diverting: A similar dynamic to the above could happen at the wholesale level. Kroger could reduce purchases before and after the promotion and engage in forward buying, that is, stocking up on tortilla chips on deal to supply their future retail demand beyond what they need to meet consumer demand during the promotion period. They could buy even more on deal to divert the product to sell at a profit to other retailers in other parts of the country where Kroger doesn't compete.

These indirect effects can have a sizable impact on your supply chain, one that may catch you by surprise if you don't plan for them.





Conclusion

There you have it – our top ten list. We often review some or all of these items with client teams at the outset of projects, depending on their experience level, their industry, and the specifics of their business. We hope you've found it useful and thought-provoking.

About New Horizon

New Horizon Soft is a rapidly growing provider of AI-powered supply chain planning software that enables manufacturers, wholesalers, and retailers to achieve breakthrough improvements in performance. We leverage the latest machine learning and cloud technologies to help planners make better decisions with applications that are faster to implement and easier to use than traditional software. Our suite of SaaS applications includes Demand Planning, Multi-Echelon Inventory Optimization, Supply Planning, Buyers Workbench, Replenishment Planning, Production Planning, Sales and Operations Planning, and Strategic Planning. New Horizon is headquartered outside of Boston and has customers in North America, Europe, and Asia.

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