Forecasting Optimization
White Paper

Quickborn Consulting LLC

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Background

In this webinar we will explain how a retailer can **measure, control and improve demand forecasting** in his/her business. **The accuracy of demand forecasting in retail has a major impact on business performance.** Important operational decisions are based on forecast results. Measuring, improving and controlling those results must be a top priority for any retailer who relies on data driven insights for support in the decision making process. Accurate forecasts are used to make decisions in pricing, ordering, replenishment, stock balancing and overall movement of goods in the enterprise.

Intended audience for this webinar is any retail professional with merchandising, controlling, finance, planning or supply chain role in a retail organization.

The **following questions will be answered** with relevant retail examples to demonstrate their role and impact on forecast accuracy:

1. **What is forecasting** and how is it used in retail?
2. **What data is needed** for forecasts?
3. **How is data quality checked** for forecast generation?
4. **What methods are most widely used** to generate forecasts, what are their advantages and disadvantages?
5. **What are the options for adjusting generated forecast?**
6. **How can accuracy of forecast be measured** for fine tuning forecasting?

This webinar was held on Wednesday, May 27th at 10 am Eastern US Time, which is 4 pm Central European Time.
Download recording: https://qbcs.com/demand-forecasting-webinar/

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A native speaker of English, German and Hungarian.

About Quickborn

We are a diverse team of experts, passionate about solving problems in the retail industry.

We introduce next practice business processes that enable retailers to achieve high level of customer satisfaction.

- Established in 2003
- 100+ Global Consultants
- 12 offices in 9 countries worldwide
- 100% Retail focused

- Business and technology consultancy
- Implementation services provider
- For Fashion, Grocery, Specialty retailers
- In all geographies

What is forecasting?

Forecasting is **the process of estimating future demand** within a defined time frame. It is usually based on past sales history, market research and trend analysis. A good quality forecast enables companies to make informed strategic decisions and provides reference for business performance evaluation. It is a critical success factor in achieving operational excellency. To understand the importance of forecasting, let us take a look at the challenges most retailers are facing nowadays.

Retail challenges

Top three **consumer expectations** are price, product, and convenience:

- **Price** – as a consumer, I expect to pay a competitively low price. If price is too high then consumer spending slows down.
- **Product** – as a consumer, is the retailer selling the product I need? If the assortment does not contain items sought by the consumer, the consumer will switch to a different retailer and sales will decrease.
- **Convenience** – as a consumer, is the product I seek available in the store or online, whichever channel I prefer? If the product is out of stock, the consumer will be disappointed and again will switch to an other retailer.

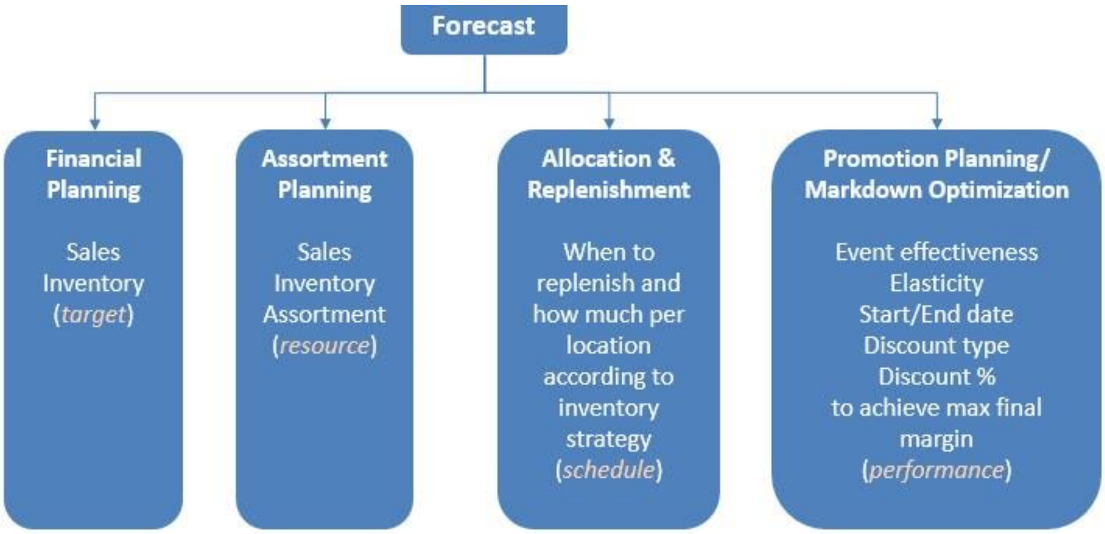
The **ultimate goal of successful supply chain management** is the following: "Get the right product to the right place at the right time" is actually not that easy to achieve.

In addition to these consumer expectations, the overall situation of the business environment can also provide a challenge. Retailers have been struggling with exponential technological disruptions, increasing market share volatility and currently, on top of all these, a great deal of uncertainty caused by the COVID pandemic.

More than ever, as retailers, we need a game plan that supports us in making informed business decisions and to promptly adapt to the constantly evolving consumer demand and eco-system.

To be able to build this game plan, an accurate demand forecast is the first step.

In the following paragraphs we will explain **how forecast supports various strategic decisions** within a retail organization:



In the above diagram, we see how demand forecast results feed into various retail operational steps. At the highest level, forecast can be used as a reference point in **financial planning** to define the overall sales target and corresponding inventory investment budget.

Under this framework, as part of the **assortment planning** activity, the business decides the combination and ratio of products that will bring the most profit. These are the products where the resources will be invested in.

Once the product offer has been concluded, it is time to schedule the logistics as part of the **allocation and replenishment** activity. Based on the demand forecast and inventory strategy, the allocation and replenishment system can calculate when to deliver which product in what quantity to which location. An accurate forecast combined with an intelligent supply chain solution can efficiently reduce the need for safety stock and avoid stock-out situations.

Later, during and after the season, forecast can be compared with actual sales to define **promotion and markdown** efficiency. The conclusions can then be used to adjust forecast methods and parameters in order to improve accuracy for the future.

In summary, an accurate forecast provides the essential visibility and capability to build an optimal sales and inventory strategy. It also improves the sell-through rate and increases the overall margin. When quantity and timing of inventory are perfectly aligned with sales and production capacity, retailers won't have to deal with massive unsold inventory anymore.

In the above diagram, we provide an example to illustrate how demand **forecast** results drive retail business decisions, as described in the previous paragraphs: I am planning to buy a "silk scarf" for the 2020 fall-winter season. My total forecasted sales are one hundred thousand units, so I set my total **sales target** to the same number.

From the possible items, I pick two for my assortment **resourcing**: One is black and one is leopard. I distribute the total sales unit in a 6:4 ratio. The reason is, that according to the forecast, my margin will be maximized when the assortment is constructed this way. The sixty thousand and forty thousand units are further distributed to the stores according to the forecasted demand of each location.

To **schedule** my buying and assortment distribution, my replenishment system recommends me to order twenty thousand units of black scarves and ten thousand units of leopard on August 6 for preparing the season launch on October 1. The system takes into account the demand forecast for all stores combined, lead time, pack size, minimum order quantity and store receiving days. In-season order suggestions will be made by the system later on.

To measure **performance** at the end of the season, I check how many of my items have sold. I realize that there is a lot of leftover stock of the leopard scarf. After analysis, I find out that it is because consumers are less sensitive to price cuts on this item than I originally assumed. Therefore, I adjust the estimated sales uplift in my forecast parameter for the next season.

Necessary data input

Forecasting requires data input for the accurate observation of trends in consumer demand. The only **mandatory** data is historical sales of at least 2-3 years (if available, segmented into sale types of regular, promotional, and clearance sales).

Optional data are:

- Past price change (promotion, markdown etc.)
- Special events (VIP access, roadshow etc.)
- Seasonal profile
- Item/location attributes
- Store open and close dates
- Exceptions (stock-out, natural disasters etc.)
- Customer segment/behavior analysis

The more information we can load into the forecasting system, the better. For example, if the system knows past price change details, such as start and end dates, discount percentage or special events, it will be able to estimate the corresponding sales uplift and apply it to future price change and events. It is also helpful to provide item life cycle and seasonal profile data so that the forecasting system can employ best-fitting strategies during forecasting.

If we want to bring in even more information, we can look at customer segments and spending behavior analysis to forecast based on customer characteristics, decision tree and purchasing patterns. **Basket analysis** enables understanding of halo and cannibalization effects and demand transference. Market and trend analysis provides the system with an additional insight of the future.

Data quality

Data quality is the cornerstone of reliable forecasts. When the historical data quality used for forecasting has high quality, that means half of the work is already done. Below we take a closer look at what defines data quality.

Data smoothness

Smooth data is essential to detect seasonality. Smooth data means when data points are connected into a curve, the shape of the curve is "smooth", does not contain sharp angles.

Data density

To help achieve forming smooth curves, data points ideally should be close together in a curve. Too few data points will lead to inaccurate forecasts.

Data congruency within hierarchies

In case data is not dense enough, there are not enough data points to form a smooth curve. One technique that can help is analyzing historical data on an aggregated, or higher level, where more data points are available to form a smooth curve.

When we aggregate multiple items' history together, we need to be careful that the items grouped together in the aggregation have similar curves individually. This is to ensure that curves detected on an aggregated level are relevant on the lower, contributing levels. If the sales profiles of lower level items are quite different, we could get two possible results:

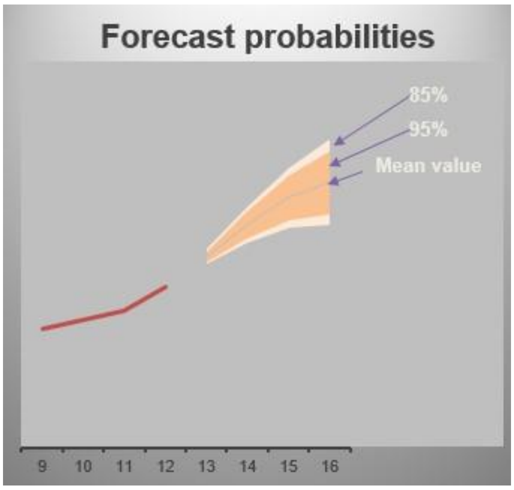
1. In case of a normalized addition, the result will be irrelevant for any of the lower level items.

2. In case of a simple addition, the result will be relatively good for one of the items (swimsuits in this example) but absolutely wrong for the other (black socks).

FORECASTING METHODS

There are plenty of forecasting methods available for data scientists. We will list and discuss the most frequently used data-driven methods.

Traditional judgmental methods could also be useful when no historical data is available, such as Delphi method, Analogy method, or Scenario based forecasting.

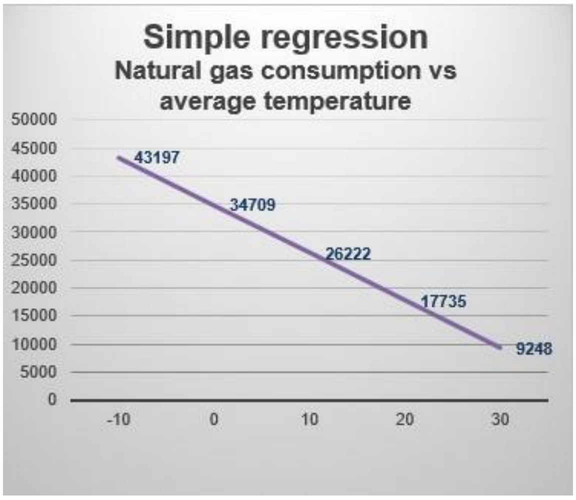


Keep in mind that forecasts are just mean values of an area where the actual demand is expected to be.

Regression method

Simple or Dynamic Regression: captures a parameterized relationship between external variable(s) and forecast value

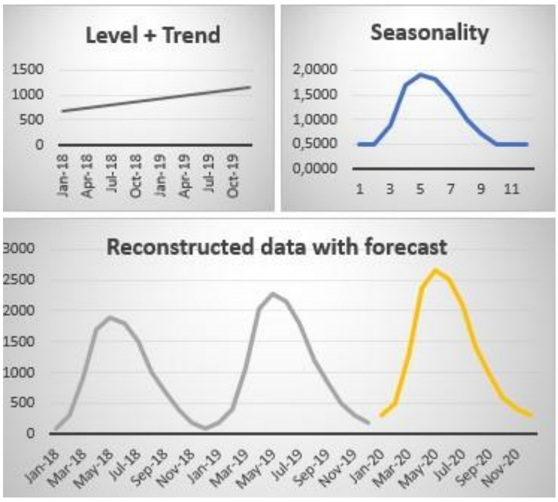
- Pro:
  Various external variables can be used.
  In case of an external shock (such as an economic crisis), these methods generate more reliable forecasts because they leverage the correlation between external variables and the dependent variable (which is the forecast).



- Con:
  It can be impractical to generate longer forecasts, since the explanatory variables need to be modeled longer as well, therefore the accuracy decreases because of the more complex modelling that is required. Very sensitive to correlation between variables - leads to less accurate forecast due to volatility.

Decomposition of time series method

This method consists of two steps: **Identification step:** separate Level, Trend and Seasonality is identified then the model is fitted to the historical data as precisely as possible (calibration). **Prediction step:** Various statistical methods can be used on the identified components to improve their quality and produce a forecast.



- **Pro:**
  Flexibility in choosing the best method to identify components.

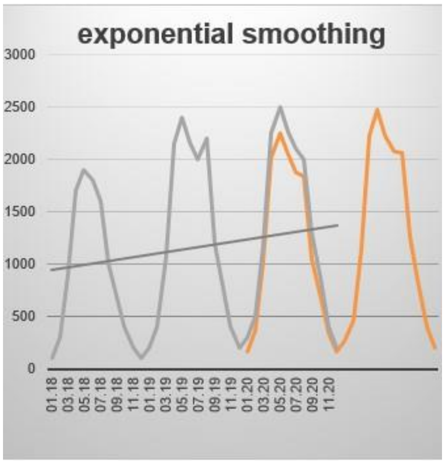
- **Con:**
  Overfitting and robustness significantly dependent on modelling choices.

Auto-regression method

Auto-regressive methods use the same series to forecast and to regress. Exponential smoothing (weighted moving average) is also applied in the generation of the forecast.

- **Pro:**
  Robust and easy
  It is reasonably easy to fit multiple complicated patterns.

- **Con:**
  Lags behind trend and seasonality changes.
  Extension: Holt-Winters which tracks Level, Trend and Seasonality
  Seasonality can be additive or multiplicative
  Bad parameter choices, especially for seasonality, can lead to very unstable results, intermittent demand is not handled properly.



MA and ARIMA method

Moving Average methods

This method is based on calculating the average values in historical data in a moving timeline, adjusting for trends reflected in data.

- Pro:
  Better fit in cases when no or minimal trend can be identified.
- Con:
  Model-fitting is more complicated.

ARIMA (Auto-Regressive Integrated Moving Average)

This method focuses on identifying trends and seasonalities, then separating them. It then performs a fit with moving average and auto-regressive terms to produce a forecast.

- Pro:
  Flexible (can be mathematically equivalent to other popular forecasting models in special cases - based on parameter selection).

- Con:
  Model type selection is very hard and needs a lot of analysis.

AI-based method

Artificial intelligence is a hot topic in forecasting that leverages improvements in AI technology which allows computer systems to autonomously observe and predict correlations. Such approach is relevant for forecasting demand, and is an area developing rapidly today.

- Pro:
  Very flexible (i.e. can fit any kind of process based on structure).
  Better results with appropriate setup.
  Can learn autonomously.

- Con:
  Selection of model setup is a very hard question with no ideal answer.
  Hard to maintain.
  Huge number of parameters can lead to overfitting.
  Robustness can be questionable.
  May be less deterministic than statistical methods.

Options for adjustments

What should happen when a generated forecast is wrong? To answer this question, we need to define a "wrong forecast". Typically, a wrong forecast means that forecasted data is different from actual data by a **deviation** that is greater than our tolerance.

Tolerance needs to be defined based on the business impact of a deviation between forecast versus actual results. If a small deviation makes a big business impact, the tolerance should be low. If the impact of a deviation is negligible, the tolerance can be set to a higher value. Tolerance is defined at the forecasting level.

To understand what steps need to be taken, it is crucial that we understand why actual results are different from our forecast. Only then can we identify and take the necessary corrective action – if needed.

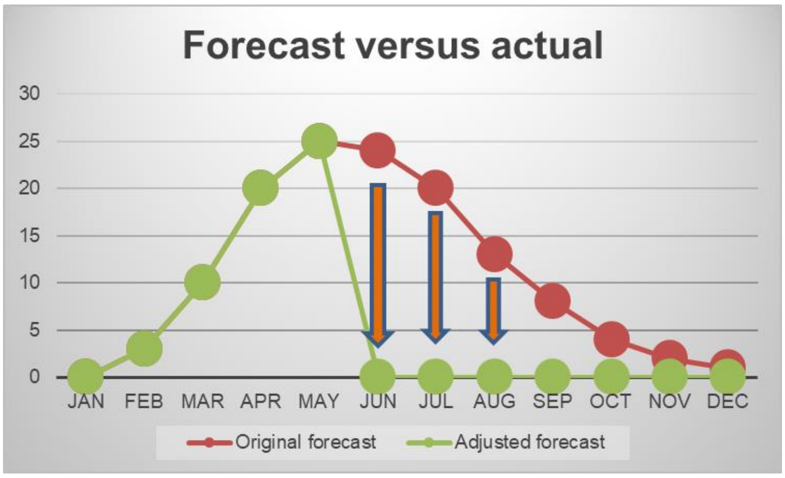
Do nothing

It is important to point out that a demand curve could be different from actual results in season for a number of reasons, some of which have nothing to do with the forecast and do not necessarily mean the forecast is inaccurate.

This is simply because forecasts aim to predict unconstrained demand, while in reality supply chain capacities, human error and random unexpected events can all alter actual results, such as a missed supply run causing a stock-out in a store, resulting in decreased sales. The demand forecast is still accurate, however, fulfilled demand is lower.

Manual override

Manual override in a forecast is needed when an event is unforeseen based on past data, but known to merchandisers, is about to happen, such as store closing for renovations.



In the example the store is closing from June 1, making demand 0 for June and on. The forecast is not aware of this based on historical data and produces the red forecast curve.

The merchandiser adjusts the forecast for June and on in the green curve to reflect store closure.

Time shift

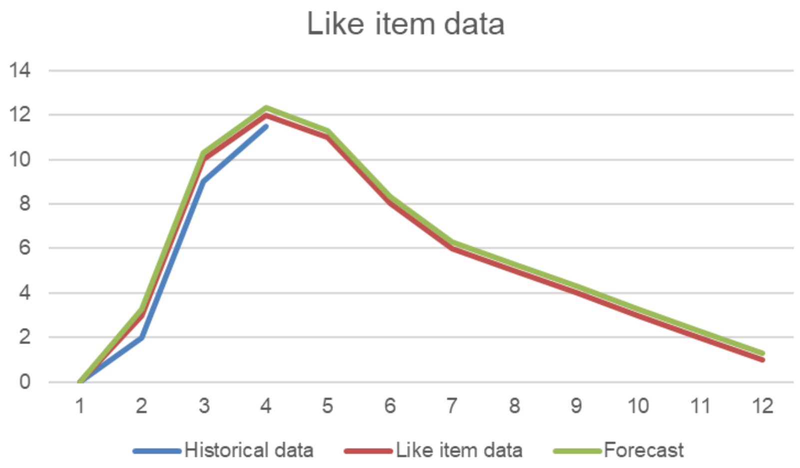
Time shift in a forecast is needed when an event falls in different times from year to year, such as Easter may be in April one year and in March the next year.

In the example to the right, an item that sells seasonally well at Easter is forecasted to peak demand in April (red curve) since in historical data, Easter was in April.

This year, Easter is in March, the forecast is adjusted to peak in March instead, by shifting forecasted demand one month earlier (green curve).

Incomplete historical data

Incomplete historical data in a forecast means there are not enough data points in the history of an item to form a demand curve. For example, an item is new and has little or no history.

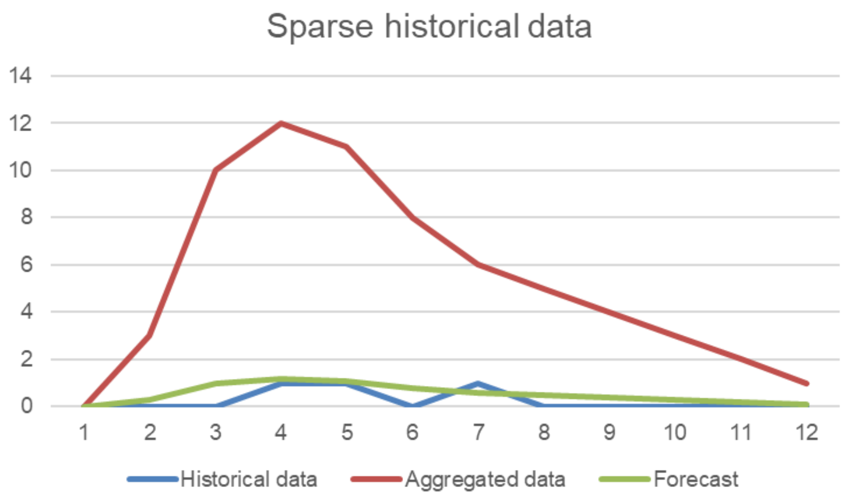


To solve this problem, a like item can be chosen manually to copy its historical data to the item that has missing data to support a forecast.

Like items can also be chosen by item and/or store attributes or based on customer segmentation information of the item.

Sparse historical data

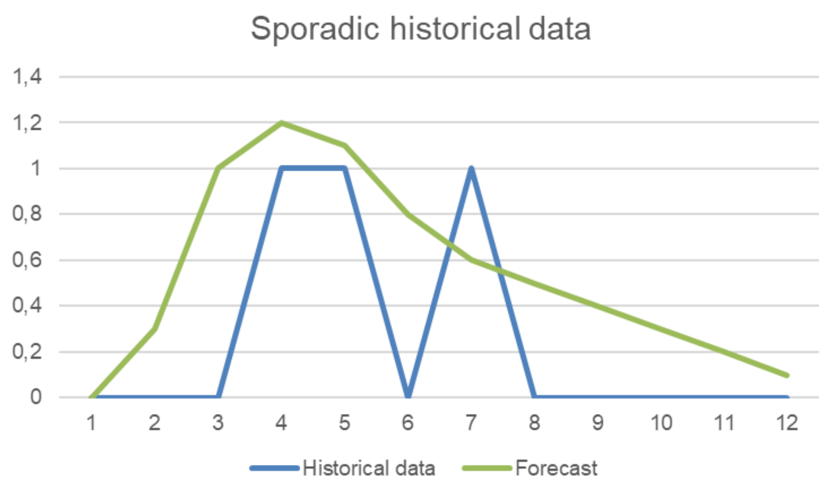
An automated solution to a **sparse data** scenario is aggregation.



Items with sparse historical data (blue curve) need to be forecasted based on aggregated historical data above the item level in the merchandise hierarchy. The resulting forecast curve (red curve) is then copied back down to the item level with values transformed down to the demand history of the item (green curve).

Sporadic historical data

When **historical data is sporadic**, it may or may not make sense to forecast the items in question. Such items sell rarely and in low volume.

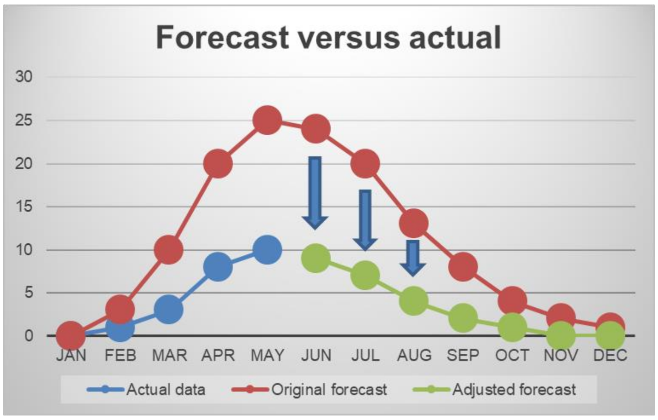


Since very low volume sales have little coherence with demand curves, managing them as non-forecasted low volume items often makes more business sense than forecasting them, since the forecast would provide little additional insight into their demand.

Adjusting a forecast level

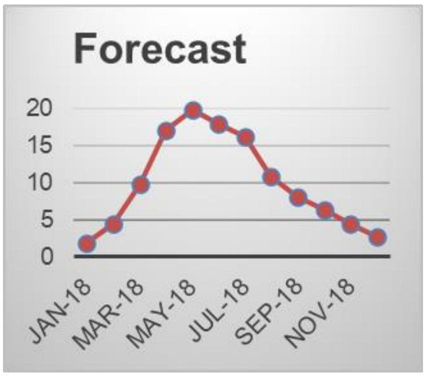
Adjusting an existing forecast means transforming its results to a different level, but retaining its curve.

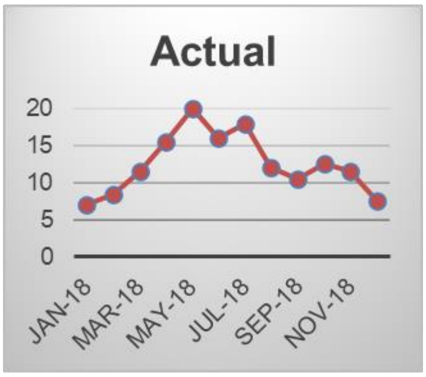
In the example to the right, a forecast was made (red curve) that was measured to be higher than actual demand (blue curve). To adjust the demand forecast to match closer to the actual demand, the original forecast was adjusted down to match the actual demand curve.



Re-running a forecast

Re-running forecast calculations means choosing a different forecasting method to produce a better fitting curve. This is necessary when an actual demand curve turns out to be radically different from its forecast.

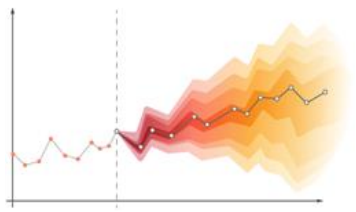




In the above example, a forecast was made (Forecast) that produced a demand curve with a different shape than what the actual demand curve (Actual) is turning out to be. In this case adjusting the existing forecast is not enough to fall within tolerance.

Measuring results

Measuring accuracy of forecast results is a critically important step towards success in the business because of the high number of decisions supported by forecasting results.



Forecast results **must be measured against actual data** on an ongoing basis to continuously check if forecasting is producing accurate figures.

Continuously measure **deviation of forecast versus actual data** and take action immediately when deviation is greater than tolerance.

Fine tune forecasting by identifying the reasons for deviations and making required adjustments to the forecast to produce results with deviation within tolerance.

Next steps

Options to leverage forecasting in retail

- Build a data scientist team to build forecasts. Scientists are rare and expensive.
- Implement a solution that provides accurate forecasts, process automation and support. Covers daily needs, but still needs expertise to operate and maintain.
- **Use a forecasting service** that delivers value and insight for future demand without having to implement and run complex systems or dedicated teams. **Call Quickborn**!

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