Key Concepts: Week 2 Lesson 1: Introduction to Demand Forecasting

Learning Objectives
- Forecasting is part of the entire Demand Planning and Management process
- There are both subjective and objective methods for forecasting – all serve a purpose
- Range forecasts are better than point forecasts, aggregated forecasts are better than dis-aggregated, and shorter time horizons are better than longer.
- Forecasting metrics need to capture bias and accuracy

Summary of Lesson
This lesson is the first of six that focus on demand forecasting. It is important to remember that forecasting is just one of three components of an organization’s Demand Planning, Forecasting, and Management process. Demand Planning answers the question “What should we do to shape and create demand for our product?” and concerns things like promotions, pricing, packaging etc. Demand Forecasting then answers “What should we expect demand for our product to be given the demand plan in place?” This will be our focus in these next six lessons. The final component, Demand Management, answers the question, “How do we prepare for and act on demand when it materializes?”. This concerns things like Sales & Operations Planning (S&OP) and balancing supply and demand. We will cover these topics in SC2x.

Within the Demand Forecasting component, you can think of three levels; each with its own time, horizon and purpose. Strategic forecasts (years) are used for capacity planning, investment strategies, etc. Tactical forecasts (weeks to months to quarters) are used for sales plans, short-term budgets, inventory planning, labor planning, etc. Finally, Operations forecasts (hours to days) are used for production, transportation, and inventory replenishment decisions. The time frame of the action dictates the time horizon of the forecast.

Forecasting is both an art and a science. There are many “truisms” concerning forecasting. We covered three in the lectures along with proposed solutions:

1. Forecasts are always wrong – Yes, point forecasts will never be completely perfect. The solution is to not rely totally on point forecasts. Incorporate ranges into your forecasts. Also you should try to capture and track the forecast errors so that you can sense and measure any drift or changes.
2. Aggregated Forecasts are more accurate than dis-aggregated forecasts –The idea is that combining different items leads to a pooling effect that will in turn lessen the variability. The peaks balance out the valleys. The coefficient of variation (CV) is commonly used to measure
variability and is defined as the standard deviation over the mean. Forecasts are generally aggregated by SKU (a family of products versus an individual one), time (demand over a month versus over a single day), or location (demand for a region versus a single store).

3. Shorter horizon forecasts are more accurate than longer horizon forecasts – Essentially this means that forecasting tomorrow’s temperature (or demand) is easier and probably more accurate than forecasting for a year from tomorrow. This is not the same as aggregating. It is all about the time between making the forecast and the event happening. Shorter is always better. This is where postponement and modularization helps. If we can, somehow, shorten the forecasting time for an end item we will be able to be more accurate.

Forecasting methods can be divided into being subjective (most often used by marketing and sales) or objective (most often used by production and inventory planners). Subjective methods can be further divided into being either Judgmental (someone somewhere knows the truth), such as sales force surveys, Delphi sessions, expert opinions or Experimental (sampling local and then extrapolating) such as, customer surveys, focus groups, test marketing. Objective methods are either Causal (there is an underlying relationship or reason) such as regression, leading indicators, etc. or Time Series (there are patterns in the demand) such as exponential smoothing, moving average, etc. All methods have their place and their role. We will spend a lot of time on the objective methods but will also discuss the subjective ones as well.

Regardless of the forecasting method used, you will want to measure the quality of the forecast. The two major dimensions of quality are bias (a persistent tendency to over or under predict) and accuracy (closeness to the actual observations). No single metric does a good job capturing both dimensions, so it is worth having multiple. The definitions and formulas are shown below. The most common metrics used are MAPE and RMSE for showing accuracy and MPE for bias. But, there are many many different variations used in practice, so just be clear at what is being measured and how the metric is being calculated.

**Key Concepts:**

**Forecasting Truisms**

- Forecasts are always wrong
  - Demand is essentially a continuous variable
  - Every estimate has an “error band”
  - Compensate by using range forecasts and not fixating on a single point
- Aggregated forecasts are more accurate
  - Forecasts aggregated over time, SKU or location are generally more accurate
  - Pooling reduces coefficient of variation (CV), which is a measure of volatility
  - Example aggregating by location: Three locations (n=3) with each normally distributed demand $\sim N(\mu, \sigma)$

$$CV_{ind} = \frac{\sigma}{\mu}$$

$$\mu_{agg} = \mu_1 + \mu_2 + \mu_3$$
\[ \sigma_{agg} = \sqrt{\sigma_1^2 + \sigma_2^2 + \sigma_3^2} \]

\[ CV_{agg} = \frac{\sigma \sqrt{3}}{3\mu \mu \sqrt{3}} = \frac{CV_{ind}}{\sqrt{3}} \]

Lower coefficient of variation (CV) for aggregated forecast shows less volatility

- Shorter time horizon forecasts are more accurate
  - It is easier to measure next month’s forecast rather than the monthly forecast one year from now

**Forecasting Metrics**

There is a cost tradeoff between cost of errors in forecasting and cost of quality forecasts that must be balanced. Forecast metric systems should capture bias and accuracy.

**Notation:**
- \( A_t \): Actual value for observation \( t \)
- \( F_t \): Forecasted value for observation \( t \)
- \( e_t \): Error for observation \( t, e_t = A_t - F_t \)
- \( n \): number of observations
- \( \mu \): mean
- \( \sigma \): standard deviation
- \( CV \): Coefficient of Variation a measure of volatility, \( CV = \frac{\sigma}{\mu} \)

**Formulas:**

Mean Deviation:
\[ MD = \frac{\sum_{t=1}^{n} e_t}{n} \]

Mean Absolute Deviation:
\[ MAD = \frac{\sum_{t=1}^{n} |e_t|}{n} \]

Mean Squared Error:
\[ MSE = \frac{\sum_{t=1}^{n} e_t^2}{n} \]

Root Mean Squared Error:
\[ RMSE = \sqrt{\frac{\sum_{t=1}^{n} e_t^2}{n}} \]

Mean Percent Error:
\[ MPE = \frac{\sum_{t=1}^{n} \frac{e_t}{A_t}}{n} \]

Mean Absolute Percent Error:
\[ MAPE = \frac{\sum_{t=1}^{n} \frac{|e_t|}{A_t}}{n} \]
Statistical Aggregation:
\[ \sigma_{agg}^2 = \sigma_1^2 + \sigma_2^2 + \sigma_3^2 + \cdots + \sigma_n^2 \]
\[ \sigma_{agg} = \sqrt{\sigma_1^2 + \sigma_2^2 + \sigma_3^2 + \cdots + \sigma_n^2} \]
\[ \mu_{agg} = \mu_1 + \mu_2 + \mu_3 + \cdots + \mu_n \]

Statistical Aggregation of n Distributions of Equal Mean and Variance:
\[ \sigma_{agg} = \sqrt{\frac{1}{n} \left( \sigma_1^2 + \sigma_2^2 + \sigma_3^2 + \cdots + \sigma_n^2 \right)} = \sigma_{ind} \sqrt{n} \]
\[ \mu_{agg} = \mu_1 + \mu_2 + \mu_3 + \cdots + \mu_n = n\mu_{ind} \]
\[ CV_{agg} = \frac{\sigma}{\mu} = \frac{\sigma}{\mu \sqrt{n}} = \frac{CV_{ind}}{\sqrt{n}} \]

Additional References:

There are literally thousands of good forecasting references. Here are some that I like and have used include:

- Spyros Makridakis ; Steven C. Wheelwright ; Rob J. Hyndman., 1998, "Forecasting : methods and applications", Wiley, New York. ISBN 9780471532330

Within the texts mentioned earlier: Silver, Pyke, and Peterson Chapter 4.1; Chopra & Meindl Chapter 7.1-7.4; Nahmias Chapter 2.1-2.6.

Also, I recommend checking out the Institute of Business Forecasting & Planning (https://ibf.org/ and their Journal of Business Forecasting.