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Choosing the Right Forecasting Technique

Planning for the future is the essence of any business. Businesses need estimates of future values of business variables. Commodities industry needs forecasts of supply, sales and demand for production planning, sales, marketing and financial decisions. Some businesses need forecasts of monetary variables - costs or price, for example. Financial institutions face the need to forecast volatility in stock prices. There are macro economic factors that have to be predicted for policy-making decisions in Governments. The list is endless and forecasting is a key "decision-making" practice in most organizations.

Managers should always keep themselves abreast of forecasting methods, whether they already have a forecasting package, have built models themselves or plan to invest in one. Most forecasting packages boast of having a variety of models built into them, but then ask the user to choose the model he or she thinks would be most relevant. There are plenty of forecasting models available and "choosing the right one" is not an easy task. A common, erroneous perception is that complex forecasting models always give better results than simple ones.

Different forecasting models work best for different situations- **the nature of the business, the nature of data, forecast granularity, forecast horizon, shelf life of the model and the expected accuracy** of the forecasts. **Forecast granularity** is the unit of time of each forecast. **Forecast horizon** is the number of time units into the future for which forecasts are required. For example, weekly forecasts for the next 2 months have a granularity of a week and a horizon of 8 weeks. **Shelf life** is the time after which a model becomes useless and there is a need to switch to another model.

Broadly, forecasting methods fall under **two** categories -

1. **Judgmental or Subjective methods**
2. **Mathematical or Quantitative methods.**

The rest of the article focuses on **Quantitative forecast methods**, given that they are widely used across a spectrum of industries and organizations. Quantitative methods can be Non Causal or Causal.

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We provide decision-making solutions to improve operational efficiency and business responsiveness. Our consulting services employ our strengths in industry knowledge, conceptual rigor, and information technologies. Developed using concepts from decision theory; our solutions use robust optimization, simulation, and statistical engines adapted to our client's focus areas.

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When to use Non-Causal and Causal methods?

Non-causal methods work best for businesses that are characterized by typical behaviors or patterns (levels, trends and seasonality) in variables and that are not influenced or minimally influenced by causal factors.
Causal models work best for businesses that are characterized by both patterns in variables and the influence of causal factors (such as price, marketing activities and macro economic variables in the commodities industry).

Non Causal methods

These methods are also known as "time-series" methods. They project or extrapolate historical values of the variable being forecasted into the future by identifying past patterns. The table below lists the **most common time series models** that are used in the commodities industry and the set of criteria that are used to evaluate the appropriateness of the model.

Model Type	Most Suited Data Types	Forecast Horizon	Shelf Life of Model
Exponential Smoothing	No Trend, Varying Levels	Short	Short
Holt's Method	Varying Trends, Varying Levels, No Seasonality	Short	Short
Winter's Method	Varying Trends, Varying Levels and Seasonality	Short to Medium	Medium
ARIMA	Varying Trends, Varying Levels, Seasonality	Short to Medium	Long

** Note on time granularity: Short - a day to a quarter, Medium - a quarter to a year, Long - a year to 5 years,*

ARIMA (Auto Regressive Integrated Moving Average) is probably the most powerful of all non-causal forecasting models, but is expensive in terms of the time to build a model. Both ARIMA and Winter's model take into account the **seasonality** but ARIMA needs more data (at least 4 seasons) than the latter. A common practice for an amateur forecaster, who has no idea on data patterns, is to try each of them starting from exponential smoothing and stop with the model that gives the desired accuracy.

Cause and Effect methods

These methods are best suited for businesses that are regularly characterized by ups and downs due to causal factors or drivers

transactional data to identify underlying patterns, unravel hidden relationships and recommend areas for improvement that can improve ROI and reduce costs.

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It is a good idea to consult an expert to identify causal factors and build a complete cause and effect model. Identifying causal factors could be a real challenging task. Domain knowledge, combined with statistical correlation tests is required. The forecast granularity and horizon also determine the causal factors to be included in the model.For example, when forecasting short-term demand for a product in small time granularities, a question that arises is whether to include macro economic factors (such as GDP, Population) or not. Most macro economic factors are available on a quarterly, half yearly or yearly basis and cannot be used for forecasting variables in short time granularities and horizons.A"perfect" cause and effect model here wouldn't include macro economic factors but just the micro drivers whose effects are noticed in small time granularities. Such drivers typically include price increases or decreases and marketing activities. The model does not need to specifically include macro economic factors as the level and trend in the data has already captured the macro economic factors. Also, Macro economic factors don't increase or decrease rapidly and in short time periods. Their effects are noticed over longer periods of time. But for large time granularities and long horizons, such as yearly forecasts for the next 5 years, macro economic factors could be included.

Regression, Econometric models and Artificial Neural Networks (ANN) are the three prominent cause and effect models. ANN is not widely used in the Commodities industry.

It is a good practice to combine numerical forecast output with subjective or judgmental input to refine forecast numbers. Most forecasts are "numbers that give insights" and need refinement through subjective methods. Random events like the tsunami or 9/11 cannot be modeled into the forecast method, as they are unpredictable. But based on prior warnings or just after they occur, subjective estimates of their effect can be combined into forecast numbers.

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