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Predictive Analytics: Selecting Useful Forecasting Techniques

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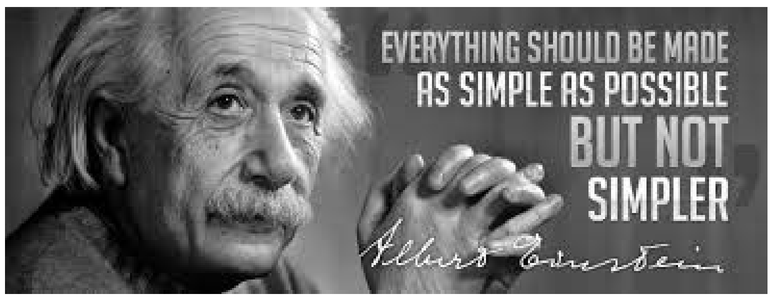


This chapter provides an overview of the most widely used forecasting techniques available for solving demand forecasting problems. One of the first things you will need when you start putting a forecasting model together is a listing of projection techniques. We describe a way of classifying projection techniques into qualitative and quantitative approaches. Whatever the technique, you need to start the selection process with

- a statement of the forecasting problem in terms of the stages of a product/service life cycle
- an economic theory stating what changes will affect demand for a product or service
- a gathering of market intelligence from field sales forecasters, market research studies, and competitive analyses
- a listing of plans for new products and special events or promotions.

The most common application of a projection technique involves some form of smoothing to diminish or highlight an important aspect of the data. Familiarity with the moving average helps to motivate the basic ideas behind a smoothing technique for forecasting.

All Models Are Wrong. Some Are Useful

Many different forecasting techniques are available, ranging from elementary smoothing methods to more complex ARIMA and econometric models. How are we to select the most appropriate one for a particular situation? Firstly, there is no best forecasting model, only appropriate and credible models for the context to which they are being applied. How can we expect to derive accurate forecasts before we have asked the right questions? Delving straight into the methods and models is no substitute for a careful examination of the data first, followed with the listing of the pros and cons of what is available. Attributed to the world-renowned statistician George E. P. Box (1919–2013) is the saying, “All models are wrong. Some are useful”.

In most circumstances, a demand forecaster will be well advised to develop multiple models in a given situation and maintain them as the best selection. For what performs best in one instance may very well rank lower in the next forecasting cycle.

Forecasting techniques can be classified as either **qualitative** or **quantitative**. This distinction may have no bearing on the accuracy of the forecast achievable by a particular approach. What is the difference between a qualitative and quantitative technique? To describe what one of two mutually exclusive things are, we only need to define one. It is easier to define quantitative as something that involves *mostly* numbers and *some* judgment. Then, the concept of qualitative is the opposite–*mostly* judgment and *some* numbers.

Quantitative techniques are characterized by a rigorous data acquisition procedure along with a mechanical application of techniques. Qualitative techniques may lack rigorous data acquisition and involve techniques that are more intuitive and requiring more human judgment.

Qualitative Techniques

Qualitative techniques provide a framework within which running models (including forms of quantitative analyses, such as decision trees and data mining) are brought to bear on a particular forecasting problem. The objective of a qualitative technique is to bring together in a logical, unbiased, and systematic way all information and judgments that relate to the demand variables of interest. These techniques use informed judgment and rating schemes to turn qualitative information into numeric estimates.

Qualitative techniques are most commonly used in forecasting something about which the amount, type, and quality of data are limited.

Familiar qualitative techniques include the panel of consensus, Delphi method, market research (focus groups), surveys, visionary forecasts, and historical analogies. Treatments of these subjects can be found in forecasting textbooks, Wikipedia pages, and other search results available online. A brief description of some of these qualitative techniques follows.

Panel consensus. Perhaps the most widely practiced qualitative technique, a panel consensus can be as simple as having managers sit around a conference table and decide collectively on the forecast for a product or service. Bringing executives from various business disciplines together increases the amount of relevant information available to the decision makers.

A further advantage of the approach is the speed with which forecasts can be obtained, particularly in the absence of complete historical or market data. This advantage may be offset by the lack of accountability for the forecast.

Also, the typical problems of group dynamics become apparent here and are compounded by the relative ranks in management. Unfortunately, the person with the best insight may not have sufficient weight to sway the whole group decision.

Delphi method. This method is used to obtain the consensus of a panel of experts about a problem or issue. The Delphi method attempts to avoid the possible negative aspects associated with group dynamics (e.g., suppression of minority opinions, domination by strong individuals who may be incorrect, unwillingness to change public positions, and bandwagon effects). Therefore, instead of bringing these experts together in a debating forum, the Delphi method relies on the distribution of questionnaires to the experts with an admonishment not to discuss the problem among themselves. They may not know who the other members of the panel are, and they are not provided with individual opinions or estimates.

The initial questionnaire may be used to state the problem and to obtain preliminary estimates and reasons or assumptions behind them. The responses are then summarized and fed back to the panel. Members with widely differing estimates are asked to review the responses and, if appropriate, revise their estimates. Through several iterations it may be possible to refine the differences among experts to a usable range of opinion. However, there is no attempt to force an expert to accept the majority opinion. If an expert feels strongly about another position and can articulate it persuasively, the method provides a range of opinion, which may be desirable in conditions of high uncertainty.

Criticisms of the Delphi method include questions about panel members' true level of expertise, the clarity (or outright vagueness) of questionnaires, and the reliability of forecasts.

Historical analogue. This method uses the history of similar products as a reasonable guide in situations such as the introduction of a new product. For example, the introduction of digital television into households can be related to the earlier introduction of color television; perhaps the type of growth curve is comparable here.

The depletion of natural resources may be viewed similarly. Wood burning was replaced by coal, which was replaced by oil. As oil resources are eventually depleted, and if nuclear power continues to face problems, we find that solar and wind technology will become a serious energy alternative.

Historical analogues may also be useful in the shorter term when a new product replaces and improves on its predecessor. For example, each new generation of computers can be evaluated in terms of price and performance relative to the existing market. Comparing the current improvements in price and performance with previous new product introductions, given their rate of price and performance improvement, can suggest the appropriate introduction or replacement rate.

Surveys. Business surveys have been widely used throughout the world to measure economic movements such as manufacturing production in a country. The variables used in these surveys are typically qualitative in nature with only a few responses possible, such as Larger, Smaller, and Unchanged.

Some examples of variables used in a manufacturing production survey include volume of production, production capacity, prices, orders, purchases, and time of deliveries. The responses are then further calibrated into barometer-type series in which the difference between larger and smaller responses is summarized.

The resulting series are reported by central statistical agencies for use by business economists and managers to get a pulse of the overall economy in relation to their own particular industry sector.

Visionary technological forecasting. This approach offers a variety of techniques that attempt to predict future technological trends. Often, a set of "S" curves are constructed from data representing factors such as speed, efficiency, horsepower, and density to predict the characteristics of the next generation of technological products. For example, the capacity of a memory chip to store a given number of bits of information can be plotted over time (often using semi-logarithmic scales). By extrapolating this growth curve, the forecaster in effect predicts the next breakthrough. Similarly, the constant dollar cost per chip can be plotted and extrapolated. Because there are relatively few data values for most items being forecast, significant judgment is required and assumptions must be developed and evaluated. There are physical and theoretical limits to certain factors such as speed not exceeding the speed of light and efficiency not exceeding a certain value.

Morphological research. This method attempts to identify all possible parameters that may be part of the solution to a problem. A (multidimensional) box is created showing all possible combinations of parameters. Each possibility is then individually evaluated. By determining the number of parameters by which the proposed technology differs from present technology, we can evaluate which breakthroughs are most likely to occur.

Role playing. In a role-playing scenario, several panel members are assigned the role of the competitor. (One of the potential drawbacks of using the Delphi and panel consensus techniques for forecasting demand is that the competitor is typically not represented.) Several panel members are made responsible for developing information about the competitor and for creating competitor strategies and reaction plans. In a simulated forecasting session, assumptions developed by the home team are challenged by the competition. The separation of roles may allow a greater range of possibilities to be explored and more realistic assumptions to be developed than would otherwise occur.

Decision trees. Decision trees are used to help decide upon a course of action from a set of alternative actions that could be taken. Alternative actions are based on selected criteria such as maximization of expected revenues and minimization of expected costs. The method uses probability theory to assess to the odds for the alternatives. In most cases, however, the probability assessments are subjective in nature and cannot be tested for validity. Decision trees are frequently used in making pricing and product-planning decisions and for developing hedging policies to protect against future currency changes in international financing arrangements.

Consider a simple situation in which a firm is deciding how to respond to a published request for bids for 1000 units of a nonstandard product. The firm's managers believe there is a 30% chance of winning the contract with a bid of $1000 per unit and a 70% chance of losing the contract to a competitor. A win would result in $l million in revenue (1000 units x $1000/unit). At a price of $750 per unit, the probability of a win is expected to be 60%. A win of $750 would result in $750000 in revenue.

If the decision is made to go with a bid of $1000/unit, the expected value is equal to the probability of a win (0.3) multiplied by the revenue ($1 million) plus the probability of loss (0.7) multiplied by the revenue ($0), or $300000. Similarly, for the alternative $750 bid the expected value is (0.6) ($750000) + (0.4) ($0), or $450000. If the managers' expected probabilities are correct, a lower bid would yield more revenue.

The profit margin for the alternative bid is smaller but the probability of winning the bid is substantially increased. If a firm has little available capacity, a $1000 bid might be appropriate. If it wins the bid, the job will be very profitable. If they lose the bid, they still have plenty of business. A firm with a smaller backlog of orders on hand may be more interested in keeping the volumes up to help maintain revenues and operating efficiencies.

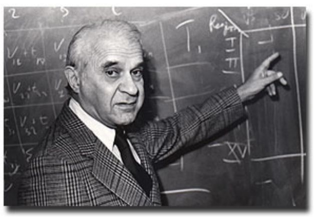
Quantitative Approaches

If appropriate and sufficient data are available, then quantitative techniques can be employed. Quantitative techniques can be classified into two more categories: **stochastic (**statistical**)** and **deterministic**.

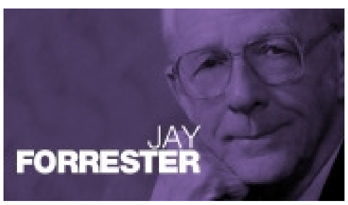
Quantitative approaches are often classified into statistical and deterministic.

Deterministic methods. These methods incorporate the identification and explicit determination of relationships between the variable being forecast and other influencing factors. Deterministic techniques include anticipation surveys, growth curves, leading indicators (Chapter 7), and input-output tables.

Input-output analysis. This method was developed by Nobel laureate Wassily Leontief (1905–1999) as a method for quantifying relationships among various sectors of the economy. This forecasting approach, generally used for long- range forecasts, can be used to answer one or more of the following questions: What is happening in the economy or industry sector? What is important about different aspects of the economy or industry sectors? How should we look at the economy or industry sectors? How should we look at changes in the economy or industry sectors?



Dynamic systems modeling. This branch of modelling involves building evaluation models that replicate how systems operate and how decisions are made. In a business environment, the analyst models the flows of orders, materials, finished goods, and revenues and subsystems are developed for functional areas such as marketing/selling, pricing, installation/maintenance, research, product development, and manufacturing. The information and operational **feedback** systems are also modeled. The objective might be to evaluate alternative policies to determine the combination of policies and strategies that will result in growth in assets employed and profitability.



Pioneered by Jay Forrester (1918-2016), the equations that describe the system are not based on correlation studies; rather, they are descriptive in nature.

For example, the number of salespeople this month equals the number last month plus new hires minus losses. Equations are then developed describing how hires and losses are determined If an individual salesperson can sell a given amount of product, the desired sales force equals the desired total sales divided by the quota per salesperson. Hires are initiated when the actual sales force size falls below the desired level.

In a similar manner, a set of equations is developed that represents the behavior of the system or business. **Assumptions** are established and the model is exercised using an evaluation language incorporated in computer software. A properly developed model should be able to simulate past behavior and provide insights into strategies that can improve the performance of the system.

Self-Driven Forecasting Techniques

Statistical (stochastic) techniques. These techniques focus entirely on patterns, pattern changes, and disturbances caused by random influences. This book extensively treats quantitative techniques as **methods** (moving averages and time series decomposition) and **models** (State Space and regression analysis), with the distinction being that models explicitly include a random error assumption as the *certain* uncertainty component.

Within statistical techniques, there are essentially two approaches. The first approach is best illustrated by a **time series decomposition** method, discussed in Chapter 5. The primary assumption on which this methodology is based is that the historical data can be decomposed into several *unobservable* components, such as trend, seasonality, cycle, and irregularity, and that these components can then be analyzed and projected by component into the future. A *self-driven* forecast is then obtained by combining the projections for the individual components.

A decomposition method is an approach to forecasting that regards a time series in terms of a number of unobservable components, such as trend, cycle, seasonality, and irregularity.

An underlying assumption made in a time series approach is that the factors that caused demand in the past will persist into the future. Time series analysis then helps to identify trends in the data and the growth rates of these trends. For instance, the prime determinant of trend for many consumer products is the growth in the numbers of households.

Time series analysis can also help identify and explain cyclical patterns repeating in the data roughly every two, or three, or more years - commonly referred to as the business cycle. A **business cycle** is usually irregular in depth and duration and tends to correspond to changes in economic expansions and contractions.

Trend, seasonality, and cycle are only abstractions of reality. These concepts help us think about how to structure data and models for them.

In Chapter 7, we show how these concepts can be effectively used to make a qualitative **turning-point analysis** and forecast. Other uses of time series analysis include inventory forecasts dealing with daily or weekly shipments of units over short-term sales cycles or lead times, sales forecasts dealing with dollar-based volumes on a monthly to annual basis (this also includes seasonality, which is related to weather and human customs), and forecasts dealing with quarterly and annual economic time series.

A second approach comprises a set of time series techniques that include the model-based approaches associated with the State-Space (an integrated family of exponential smoothing and ARIMA models) and econometric modeling methodologies, discussed in Chapters 8 and 9.

A model-based approach to forecasting represents the situation usually in terms of mathematical equations with stochastic error terms.

The econometric approach may be viewed as a cause-effect methodology. Its purpose is to identify the drivers responsible for demand. The econometric models of an economy, for example, can be very sophisticated and represent one extreme of econometric modeling. These models are built to depict the essential quantitative relationships that determine output, income, employment, and prices.

It is general practice in econometric modeling to remove only the seasonal influence in the data prior to modeling. The trend and cyclical movements in the data should be explicable by using economic and demographic theory.

The Detroit model, illustrated in Figure 1.13 in Chapter 1, is an example of how an econometric system is used in the telecommunications industry. The growth in revenues might be analyzed, projected, and related to business telephones in service, a measure that is related to the level of employment. It is not necessarily assumed that the drivers that caused demand in the past will persist in the future; rather, the factors believed to cause demand are identified and forecast separately.

There is often a finer distinction made within the model-based approaches: (a) the Box-Jenkins (ARIMA) methodology versus (b) the econometric approaches. Although they share similarities in their mathematical formulations, these two model-based approaches offer significant practical differences in the way relationships among variables are constructed and model parameters are interpreted.

As part of a final selection, each technique must be rated by the demand forecaster in terms of its general reliability and applicability to the problem at hand, relative value in terms of effectiveness as compared to other appropriate techniques, and relative performance (accuracy) level. With selection criteria established, the forecaster can proceed to produce a list of potentially useful extrapolative techniques. An understanding of the data and operating conditions is the forecaster's primary input now. This knowledge must, however, be supplemented by a thorough knowledge of the techniques themselves.

Combining Forecasts is a Useful Method

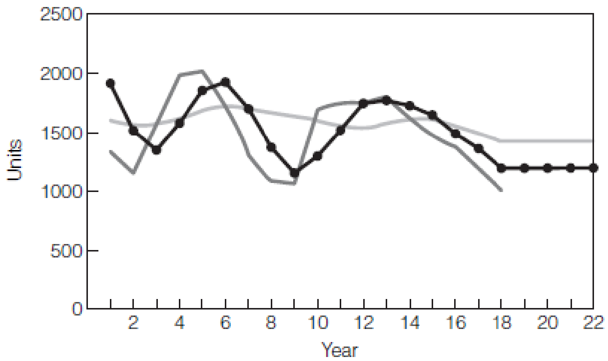
Rule-based forecasting employs dozens of empirical rules to model a time series for forecasting. These rules are distilled from published empirical research, surveys of professional forecasters, and recorded sessions with forecasting experts. The result of a rule-based forecasting procedure is a combining forecasting method.

A number of extrapolative procedures are fit to a time series, such as a random walk, a least-squares trend line, or an exponential smoothing method. At each forecast lead-time, the methods’ projections are averaged by a set of rules that determines how to give weights to the various components of the combined model. For example, a possible rule is that the weight assigned to the random walk component of the combined model is raised, from a base of 20%, if recent trends depart from the global trend, there are shifts detected in the level of the series, or the series is considered suspicious in that it seems to have undergone a recent change in pattern.

Incorporating informed judgment into the extrapolations can further enhance rule-based procedures that an exponential smoothing technique is unable to do directly.

A rule-based forecast is based on empirical rules to model a time series for forecasting.

Informed Judgment and Modeling Expertise



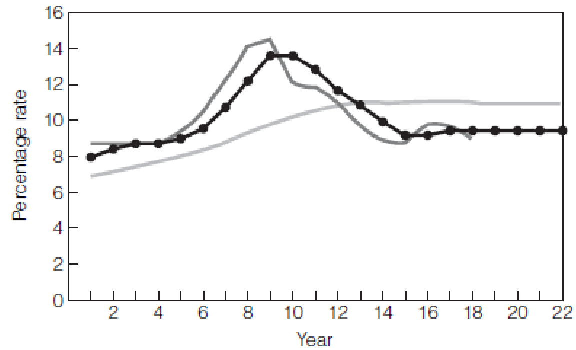


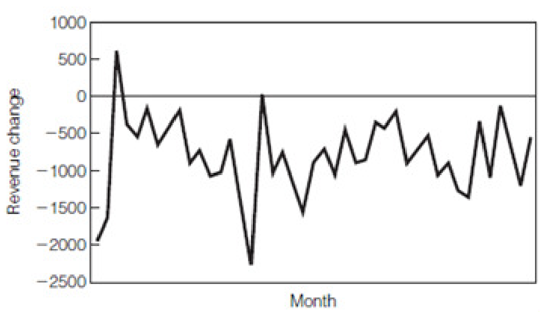
Figure 3.1 (*left*) Time plots of a three-period and 12-period moving average on 29 annual values of a housing starts series.

Figure 3.2 (*right*) Time plots of a three-period and 12-period moving average on 29 annual values of a mortgage rate series.

When describing complexity (e.g., reality in terms of simplified methods such as moving averages), clearly no single approach can be considered universally adaptable to any given forecasting situation. The assumptions and theories on which the extrapolative techniques are based limit their appropriateness, reliability, and credibility. The forecaster should be careful to avoid using techniques for which the data characteristics do not match the assumptions of the method.

Later, when dealing with linear regression models (in Chapter 10), we will develop a relationship between the annual housing starts data and the annual mortgage rates. Logically, these two variables should be related in the sense that in the construction industry mortgage rates influence housing starts.

On the surface, there does not appear to be much similarity when comparing the basic time plots (Figures 3.1 and 3.2). However, after applying some business and modeling domain knowledge, we uncover a potentially useful, predictive relationship between the two variables.



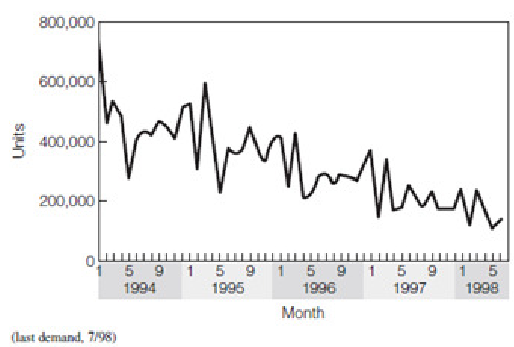


Figure 3.3 (*left)* Time plot of year-by-year revenue changes in the pharmaceutical product.
Figure 3.4 (*right* Time plot of a monthly revenue series for a pharmaceutical product over a four-year period. (Source: Figure 3.4)

Figures 3.3 and 3.4 depict the year-over-year percentage changes in units sold (shipped) of a monthly series of a pharmaceutical product and the revenues during the same period for a 54-month period. Figure 3.3 shows a revenue series dominated by large fluctuations around a constant level of approximately -800. Figure 3.4 is dominated by a declining trend, whereas the annual changes are quite volatile.

If the trend in the original data are predominantly linear, the annual changes would fluctuate about a constant level. Could there be any economic, demographic, or political influences of an additive or multiplicative nature? What projection techniques should be used in planning a forecasts for these data?

Bear in mind first that a greater number of techniques are appropriate for the time horizon one year ahead than are appropriate for two-year-ahead forecasts. As we approach forecasts two or more years out, exponential smoothing and ARIMA time series models become less applicable.

Also apparent is that more techniques handle trending data than handle cyclical data. If we assume a turning point will occur in the second year, exponential smoothing and trending models are no longer adequate, because they do not have the appropriate forecast profile.

In terms of accuracy of a forecast for the one-year-ahead horizon, the State Space approach (exponential smoothing and ARIMA models), regression analysis and econometrics are the most useful. If there is a turning point expected in the forecast period, univariate exponential smoothing and ARIMA models may not be useful.

If we consider time constraints and the desire to present an easily understood technique, the exponential smoothing and linear regression approaches should also be considered tor two-year-ahead forecasts. Different conclusions might result, however, when

- shorter time horizons are involved
- data gathering and computational costs are important
- accuracy requirements are less stringent
- time is not a constraint
- the ease of understanding and explaining forecasting approaches is extremely important.

A Multimethod Approach to Forecasting

The purpose of using more than one technique is to ensure that the forecasting approach will be as flexible as possible and that the forecaster's judgment (which is so critical to the demand forecasting process) is not overly dependent on one particular forecasting technique. It is not uncommon to see forecasters develop a search for one “best“ forecasting technique and then use that technique almost exclusively, even in an ongoing forecasting process. Such a preference can become easily established because of the highly specialized nature of some of the techniques.

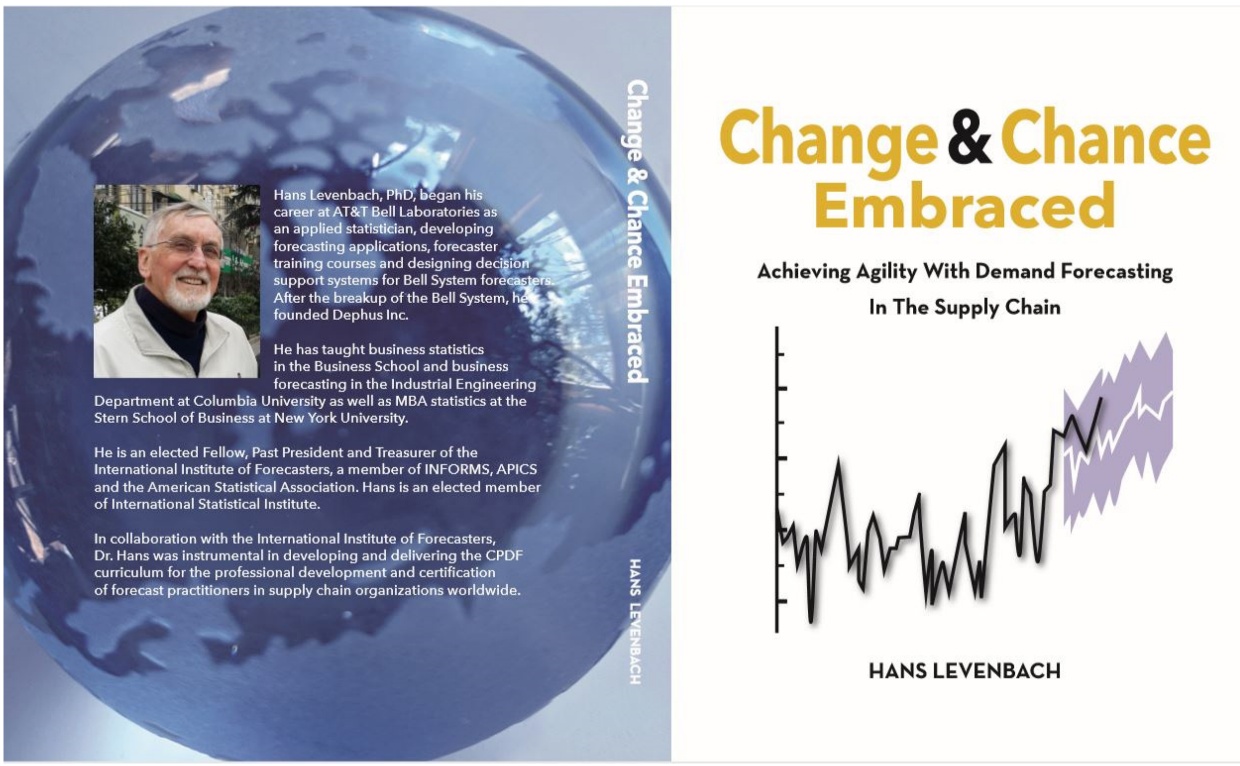
One of the lasting myths about forecasting is that complex models should be more accurate than simple models. Some forecasters uncritically prefer the most sophisticated statistical techniques that can be found. Remember Einstein’s quote at the head of this chapter: “Everything should be made as simple as possible, but not simpler.”

The accuracy of an extrapolative technique, however, is not necessarily a direct function of the degree of its sophistication. In many cases, this tendency can greatly reduce the effectiveness and credibility of a forecasting model because complex models may become unbelievable when unexpected pattern changes occur in the time series. A simpler model, on the other hand, may remain relatively unaffected by the change.

We recommend that two or more approaches be used every time to describe the historical behavior of the data and to predict future behavior. In essence, this allows us to evaluate alternative views of the future.

When "running" models, it is essential to provide uncertainty and risk level estimates, in terms of forecast prediction limits, associated with plausible alternatives. A comparison can be made of the alternative views of the future, hence increasing the chances that the derived forecast numbers are useful and credible.

The Complete Chapter 3 can be found in the book:



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