Many companies still view quantitative forecasting methods as a "black box" or unknown approach that adds little value to improving overall demand forecast accuracy. Fortunately, there is a new awareness emerging across many industries of the value of integrating demand data into the demand forecasting process. Equipping you with solutions that can sense, shape, and predict demand using highly sophisticated methods and tools, internationally renowned author and thought leader Charles Chase provides you with a basic understanding of the methods and processes required to implement a demand-driven forecasting process in Demand-Driven Forecasting: A Structured Approach to Forecasting.

From a review of the most basic forecasting methods, to the most advanced time-series methods, and innovative techniques in use today, this guide defines demand-driven forecasting, uniquely offering a fundamental understanding of the quantitative methods used to sense, shape, and predict demand within a structured process.

A must-read for CEOs, CMOs, CFOs, supply chain managers, sales managers, marketing brand managers, and demand forecasting analysts, Demand-Driven Forecasting: A Structured Approach to Forecasting covers:

• Myths versus realities of forecasting
• Causes of forecast error
• Purposes for measuring forecasting performance

Charles W. Chase, Jr., is the Business Enablement Manager at SAS Manufacturing and Supply Chain Global Practice, where he is the principal architect and strategist for delivering demand planning and forecasting solutions to improve SAS customers’ supply chain efficiencies. He has more than twenty-six years of experience in the consumer packaged goods industry, and is an expert in sales forecasting, market response modeling, econometrics, and supply chain management.


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Demand-Driven Forecasting
A Structured Approach to Forecasting

Charles Chase

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Foreword

Demand-Driven Forecasting is a long-overdue practical book on business forecasting written by one of the industry’s top business forecasters. I have been involved in business forecasting—the demand forecasting that is done by industry forecasters—for over 30 years.

Business forecasting during my early years was largely based on the exponential smoothing forecasting methods developed by an industry practitioner, Robert G. (Bob) Brown, who published several books starting in the late 1950s. These exponential smoothing methods live on today and are often the under-the-hood statistical forecasting engines powering many software packages. Forecasting methods have evolved since that time to include a wide variety of statistical time series methods, many of which were discussed in several revisions of forecasting books written by two leading academic forecasters, Spyros Makridakis and Steven C. Wheelwright, starting in the late 1970s.

A Journey Down Memory Lane

During the first half of my career, advanced methods focused on what might be termed history-driven forecasting, because the methods involved analyzing years of historical data in order to identify recurring patterns from which to project the future. The focus started changing midway in my career, toward demand-driven forecasting.

The last two decades or so have been a period of increased consumerism, especially in the United States, during which time marketing and sales organizations developed more sophisticated and effective ways to simulate demand for the products they were promoting. Industry forecasters, by necessity, started to experiment with and utilize methods that no longer
assumed that demand just magically happened and could be estimated only from understanding what happened in the past. They started leveraging cause-effect methods, such as multiple regression methods, and time series methods incorporating causal factors, such as ARIMA (autoregressive integrated moving average) models with explanatory variables in order to reflect the fact that promotional activities would shape and create demand and therefore needed to be understood and incorporated into a forecast.

Coincidently, midway in my career I was fortunate enough to meet a pioneer in demand-driven forecasting, the author of this book, Charles (Charlie) Chase, while researching ways to do promotional forecasting for a consulting engagement that I was working on for a large drugstore chain. Professionally it was a watershed event for me, as my advocacy moved from largely espousing history-driven forecasting to including advanced demand-driven forecasting.

I had heard that Charlie had successfully implemented multivariate statistical methods to incorporate the effects of promotions at Polaroid, where he was employed at the time. Our consulting team visited him and learned a lot about how to use these sophisticated methods (which we all learned about in a college classroom) in a real-world setting. From that day on our relationship has blossomed, and Charlie and I have become close colleagues and friends. We have shared a variety of ideas over time, such as multi-tiered forecasting concepts. Charlie introduced me to the Institute of Business Forecasters (IBF), an organization whose mission he was helping to recast at the time. From those efforts, the IBF has successfully evolved into the preeminent organization for business forecasters.

Qualified to Define Demand-Driven Forecasting

Today, Charlie Chase is known to be one of the top thought leaders in the business forecasting community, making him eminently qualified to write this groundbreaking book. He bears many scars from the battles it took to get this type of forecasting implemented at a variety of consumer products companies, where the shaping of demand is critical to long-term market success. At these companies, running promotional campaigns, advertising,
continually altering prices, and launching new products is a way of life. Thus, not only has Charlie had to leverage the forecasting methods learned in the classroom, but he has also had to develop innovative yet practical methods while in the heat of the battle at these dynamic companies. This is why I believe the demand-driven concepts discussed in this book are immediately applicable to business forecasters working in product industries as well as to those working at service-oriented and public sector organizations.

With the rise in consumerism during the past 20 years or so, a business forecaster’s job has become much more difficult. The dramatic growth in the entities that need to be forecast by multinational organizations have made demand forecasting methods and systems larger in scale. Business planning has become more complex in terms of having to deal with the myriad of products being sold, many with short life cycles (e.g., stock-keeping unit proliferation), the number of countries into which they are sold, as well as the number of channels sold through. Technology has been evolving to keep up with this dramatic growth in scale, and Charlie has played an influential role in this area as well. That he writes in this book about forecasting technology comes from a wealth of experience in helping to develop and implement sophisticated forecasting systems enabled by leading edge-technology.

A Primer on Advanced Forecasting

When I first reviewed a draft of this book, my initial reaction was that it represents a primer on advanced forecasting. My second reaction was: Is that statement an oxymoron? It isn’t, because Demand-Driven Forecasting takes the reader on a journey from the basic methods espoused by forecasting pioneer Bob Brown over 50 years ago to some of the most innovative business forecasting methods in use today.

After clearly defining demand-driven forecasting, Charlie takes for sense reader from a review of the most basic forecasting methods, to the most advanced time series methods, and then on to the most innovative techniques in use today, such as the linking of supply and demand to support multi-tiered forecasting and the incorporation of downstream demand signals. I suspect that much as Bob Brown’s books turbocharged the evolution of history-driven forecasting, Charlie’s book might do the same for
demand-driven forecasting. To the readers of this book, enjoy reading it and be prepared to become demand-driven.

Larry Lapide, Ph.D.
Director, Demand Management
MIT Center for Transportation & Logistics
Preface

Demand-driven forecasting is a new structured approach to forecasting that focuses on analytics to sense, shape, and predict demand. Although it is new in design, the quantitative methods that support it have been around since the early 1900s. In addition, with recent improvements in data collection, storage, and processing technologies, it is now possible to implement demand-driven forecasting across thousands of products within a business hierarchy. Unfortunately, many companies still view quantitative forecasting methods as a black box, or unknown approach, that adds little value to improving overall demand forecast accuracy. Fortunately, there is a new awareness emerging across many industries regarding the value of integrating demand data (point-of-sale and syndicated scanner data) into the demand forecasting process. Many are now looking for enabling solutions that can sense, shape, and predict demand using more sophisticated methods and tools. Industry leaders that have been striving toward demand-driven networks include consumer packaged goods, pharmaceuticals, automotive, and heavy manufacturing companies.

The purpose of this book is to provide practitioners with a detailed blueprint and road map that will help them better understand this new structured approach as well as real-life examples to build a business case for the justification of demand-driven forecasting. Although I have spent most of my career in the consumer packaged goods industry, I have found that a majority of the practical analytics described in this book are applicable across all industries. Some of my colleagues may not completely agree with such a structured approach that puts so much emphasis on analytics rather than on what is referred to as the art of forecasting. Throughout my career, I have not been an advocate of judgment-based forecasting methods due to the inevitable political bias, which tends to add error rather than improve
demand forecast accuracy. Therefore, many may view this book as implicitly biased toward forecasting situations in which data are plentiful and accessible. Although this may seem to be the case, given the current data collection capabilities and improvements in processing, it is no longer a legitimate reason to dismiss analytics in favor of judgment, particularly when judgment has such a poor track record when it comes to demand forecasting. Given this situation, I believe there is a need for a book that shares practical applications in quantitative analytics from a practitioner’s perspective.

The contents may not necessarily be for novice practitioners who have limited quantitative training, although many of the examples are explained in simple business terms. Nevertheless, many may feel that the emphasis on regression and causal modeling targets a more advanced practitioner. I have found in my experience that most practitioners have been exposed to regression methods during work on their undergraduate degree or when attending postgraduate classes. In fact, most universities require one semester of regression analysis in their undergraduate business programs, and many now require one semester of business forecasting in postgraduate MBA programs. During my tenure with Reckitt & Benckiser, an international household products manufacturer, and Polaroid, an instant camera and film manufacturer, I hired several people from local universities with statistical degrees who were able to apply their quantitative analytic knowledge with minimal training in business acumen. However, I have found that it is much more difficult to train people who have only strong business acumen in the application of quantitative methods. Given my personal experience, I recommend that companies invest in quantitative analytics training for those personnel who are responsible for demand forecasting or invest in personnel who have quantitative degrees from local universities.

The underlying message throughout this book is that the combination of analytics and domain knowledge in a structured framework in many cases adds significant improvement to demand forecast accuracy. I do not advocate more sophisticated analyses but rather applying the appropriate method, given the purpose and potential value to the overall corporate product portfolio. The book provides forecast practitioners with a basic understanding of the methods and processes required to implement a demand-driven forecasting process. My intent is to provide practitioners with a fundamental understanding of the quantitative methods used to
sense, shape, and predict demand within a structured process. Unfortunately, many companies put little value on training individuals who are responsible for creating demand forecasts in quantitative methods. In fact, they are far too quick to dismiss any quantitative results that do not meet their expectations and downplay the value of analytics as a black box. As practitioners, it is our responsibility to demonstrate the value of analytics to senior-level managers and gain their trust over time through performance metrics that link demand forecast accuracy to key performance indicators.
Acknowledgments

This book began with a chance meeting with SAS Publications sales manager Lou Metzger, whom I met when I was speaking at an annual SAS publications conference at the University of Louisville in 2007. We spoke several times during that event about my 20 years of experience in forecasting as well as the many lectures I have given and articles I have published. Lou was convinced that my practical experience working in the consumer packaged goods industry prior to coming to SAS would translate into valuable lessons worth sharing with others. A few months later I received a call from SAS Press editor-in-chief Julie Platt, who arranged for the submission of a book outline to John Wiley & Sons. The rest is history, as they say.

I have been extremely fortunate in my career, meeting people who have had a profound impact on me not only from a career perspective but also on my personal life. I have developed a strong network of friends who have been very supportive and in many cases have provided me with newfound lessons. As a result, I have become a better person as well as an advocate for helping others in the field of demand forecasting. Among that network of friends are Dr. Chaman Jain, founder of the Institute of Business Forecasting and editor-in-chief of the Journal of Business Forecasting; Dr. Oral Capps Jr. Texas A&M University; Dr. Larry Lapide, MIT; Dr. Ken Kahn, Purdue University; Dr. John (Tom) Mentzer, University of Tennessee, Knoxville; Dr. Roy Pearson, William & Mary University; Moo Fen Hiew, CEO and president of the Virtual Company; Todd Kirk, CEO and president of Mindgame Analytics; and Dr. Peter Mueller, COO and director of research of Amarillo Biosciences, Inc.. Over the years they have been mentors and best friends, and without their support and encouragement, I would have not written this book.
I express my deepest thanks to Dr. Ken Kahn; Mike Gilliland, SAS Institute Inc.; and Stacey Hamilton, SAS Institute Inc., for their relentless work editing the book; their input and suggestions have only enhanced the quality of the book. A very special thanks goes to my manager, Mark Demers, who encouraged and supported the writing of this book from the very moment we discussed it. Mark has been my biggest supporter at SAS.

Finally, I thank my wife, Cheryl Ann Whitmyer, for keeping the faith all these years and supporting my career during the good and not-so-good times. She has never wavered and has always been my biggest supporter. Without her support and encouragement over the years, I would not have been in a position to write this book.
It is an exciting time for the field of demand forecasting. For the first time in history, all the elements are in place to support demand forecasting from a fact-based perspective. Although advanced analytics have been around for well over 100 years and data collection has improved significantly over the past decade, data storage and processing capabilities have continued to lag behind. With improvements in data storage and processing over the past several years, demand forecasting is now poised to take center stage to drive real value within the supply chain.

Subsequently, predictive analytics has been gaining wide acceptance globally across all industries. Companies are now leveraging predictive analytics to uncover patterns in consumer behavior, measure the effectiveness of their marketing investment strategies, and optimize financial performance. Using advanced analytics, companies can now sense demand by uncovering consumer behavior patterns using data mining technology. Then they can measure how effective their marketing campaigns are in driving consumer demand for their products and services and therefore can optimize their marketing spending across their product portfolios. As a result, a new buzz phrase has emerged within the demand forecasting discipline: sensing, shaping, and responding to demand, or what is now being called demand-driven forecasting.

With all these improvements, there has been a renewed focus on demand forecasting as the driver of the supply chain. As a result, demand forecasting methods and applications have been changing, emphasizing...
predictive analytics using what-if simulations and scenario planning to shape and proactively drive, rather than react to, demand. The widespread acceptance of these new methods and applications is being driven by pressures to synchronize demand with supply to gain more insights into why consumers buy manufacturers’ products. The wide swings in replenishment of demand based on internal shipments to warehouses and the corresponding effects on supply can no longer be ignored or managed effectively without great stress on the downstream planning functions within the supply chain.

New enabling technologies combined with data storage capabilities have now made it easier to store causal factors that influence demand in corporate enterprise data warehouses, such as price, advertising, in-store merchandising, sales promotions, external events, competitor activities, and others, and then use advanced analytics to proactively shape demand utilizing what-if analysis or simulations based on the parameters of the models to test different marketing strategies. This has been driven primarily by senior management to gain more insights into the business while growing unit volume and profit with fewer marketing dollars. Those companies that are shaping demand using what-if analysis are experiencing additional efficiencies upstream in the supply chain. For example, senior managers are now able to measure the effects of a 5 percent price increase with a good degree of accuracy and ask additional questions, such as: What if we increase advertising by 10 percent and add another sales promotion in the month of June? How will that affect demand both from a unit volume and profit perspective? Answers to such questions are now available in real time for nonstatistical users employing advanced analytics with user-friendly point-and-click interfaces. The heavy-lifting algorithms are embedded behind the scenes, requiring quarterly or semiannual recalibration by statisticians who are either on staff or purchased through outside service providers. The results of these what-if simulations are used to enhance or shape demand forecasts by validating or invalidating assumptions developed by domain knowledge acquired through actual sales and marketing statistics.

With all the new enhancements, there are still challenges ahead for demand forecasting. Many organizations struggle with how to analyze and make practical use of the mass of data being collected and stored. Others are still struggling to understand how to synchronize and share external information with internal data across their technology architectures.
Nevertheless, they are all looking for solutions that provide actionable insights to make better decisions that improve corporate performance through improved intelligence.

Improvement in demand forecasting accuracy has been a key ingredient in allowing companies to gain exponential improvements in supply chain efficiencies. Unfortunately, demand forecasting still suffers from misconceptions that have plagued the discipline for decades and have become entrenched in many corporate cultures. The core misconception that has troubled companies for years is that simple forecasting methods, such as exponential smoothing, which measure the effects of trend, seasonality, and randomness (or what is known as unexplained), can be used to create statistical baseline forecasts and enhanced (or improved) by adding judgmental overrides. Those overrides usually are based on inflated assumptions reflecting personal bias. The second misconception is that these judgmental overrides can be managed at aggregated levels (higher levels in the product hierarchy) without paying attention to the lower-level mix of products that make up the aggregate. The aggregation is required to manage the large scale of data that usually span multiple geographic regions, channels, brands, product groups, and products. The sheer size of the data makes it difficult to manage the overrides at the lowest level of granularity. Companies compromise; they make judgmental overrides at higher aggregate levels and disaggregate it down using Excel spreadsheets and very simplistic, static averaging techniques. In other words, the averages are constant into the future and do not account for seasonality and trends. In many cases, products within the same product group are trending in different directions.

Another misconception is political bias based on the needs of the person or purpose of the department making the judgmental overrides. For example, depending on the situation, some sales departments will lower the forecast to reduce their sales quota in order to ensure that they make bonus. This is known as sandbagging. Other sales departments that have experienced lost sales due to backorders (not having the inventory available in the right place and the right time) will raise the forecast in the hopes of managing inventory levels via the sales department forecast. This creates excess inventory as the operations planning department is also raising safety stocks to cover the increase in the sales department forecast. The problem is compounded, creating excess finished goods inventory, not to mention
increased inventory carrying costs. The finance department always tries to hold to the original budget or financial plan, particularly when sales are declining. Finally, the marketing department almost always raises its forecast in anticipation of the deployment of all the marketing activities driving incremental sales. The marketing department also receives additional marketing investment dollars if it shows that its brands and products are growing. So it tends to be overly optimistic with marketing forecasts.

These misconceptions are difficult to overcome without a great deal of change management led by a corporate “champion.” A corporate champion is usually a senior-level manager (e.g., director, vice president, or higher) who has the authority to influence change within the company. This person usually has the ear of the chief executive officer, chief financial officer, or chief marketing officer and is also regarded within the organization as a domain knowledge expert in demand forecasting with a broad knowledge base that spans multiple disciplines. He or she usually has some practical knowledge of and experience in statistical forecasting methods and a strong understanding of how forecasting affects all facets of the company.

The aim of this book is to put to rest many of the misconceptions and bad habits that have plagued the demand forecasting discipline. Also, it provides readers with a structured alternative that combines data, analytics, and domain knowledge to improve the overall performance of their company’s demand forecasting process.

Data Collection, Storage, and Processing Reality

Over the past five years, we have seen a great improvement in data storage. For example, companies that only a few years ago were struggling with 1 terabyte of data are now managing in excess of 19 terabytes of data with hundreds of thousands of stock-keeping units (SKUs). Data storage costs have gone down substantially, making it easier to justify the collection of additional data in a more granular format that reflects complex supply chain networks of companies.

Most companies review their forecasts in a product hierarchy that mirrors the way they manage their supply chain or product portfolio. In the past, most companies’ product hierarchies were simple, reflecting the
business at the national, brand, product group, product line, and SKU levels. These product hierarchies ranged from hundreds to a few thousand SKUs, spanning a small number of countries or sales regions and a handful of distribution points, making them fairly easy to manage. During the past two decades, however, many industries have consolidated. Larger companies found it easier to swallow up smaller companies to increase their economies of scale from a sales, marketing, and operations perspective rather than growing their business organically. They realized additional benefits as they flushed out inefficiencies in their supply chains while increasing their revenue and global reach. Unfortunately, with all this expansion came complexities in the way they needed to view their businesses.

Today, with global reach across multiple countries, markets, channels, brands, and products, the degree of granularity has escalated tenfold or more. Companies’ product portfolios have increased dramatically in size, and their SKU base has expanded into the thousands and in some cases hundreds of thousands. It is not unusual to see companies with more than 10,000 SKUs that span across 100 or more countries. Further escalation has occurred as marketing departments redefined their consumer base by ethnicity, channels of distribution, and purchase behavior. The resulting increased granularity has further complicated product hierarchies of companies. All this proliferation in business complexity has made it difficult not only to manage the data but also to process the data in a timely manner.

Given all this complexity and increase in the number of SKUs, Excel spreadsheets are no longer viable tools to manage the demand forecasting process. Excel is simply not scalable enough to handle the data and processing requirements. Excel’s analytics capabilities are limited to some time-series techniques and basic simple regression that model trend, seasonality, and unexplainable historical patterns. Nevertheless, over 40 percent of forecasters still use Excel to do forecasting, according to several surveys conducted over the past decade by academic- and practitioner-based organizations. In fact, a recent survey conducted by Purdue University and the SAS Institute found that over 85 percent of the respondents still use Excel as a work around to existing Enterprise Resource Planning and Supply Chain Management solutions due to the lack of ad hoc reporting capabilities and other related functionality.¹

Over the past several years the introduction of NT servers, parallel processing, and grid computing has significantly improved the speed of
processing data and running analytics on large volumes of data. Sophisticated algorithms now can be executed on a large scale using advanced statistics and business rules across company product hierarchies for hundreds of thousands of products. In fact, a large majority of products can be forecasted automatically using new enabling technologies that allow forecasters to focus on growth products that are more dynamic due to their marketplace competitiveness. Rather than spending 80 percent of their time identifying, collecting, cleansing, and synchronizing data, forecasters can now focus on those products that need more attention due to market dynamics and other related factors.

Recent development in the area of master data management has helped standardize data structures, making it easier to manage information and untangle the years of mismanaged data storage. With all these new enhancements to data collection and processing, forecasters no longer need to worry about data quality or data availability. We can now collect, store, and process millions of data series in batch overnight and hundreds of thousands in real time in a matter of minutes and hours. Data are also streaming into enterprise data warehouses in real time via the Internet, providing forecasters with monitoring, tracking, and reporting capabilities throughout the workday.

All these improvements in data collection, storage, and processing speed have eliminated many of the barriers that prevented companies from conducting large-scale forecasts across complex supply chain networks and product hierarchies. Companies can no longer use the excuses that data availability is limited or that running statistical models across their product portfolios takes too long. Unfortunately, companies are still having problems understanding all this information. Fortunately, uncovering actionable insights in a timely manner to make better decisions is becoming easier as significant gains have been made with new technologies in data mining and text mining. Managing information to gain insights to support the decision-making process will only improve over the next several years.

“Art of Forecasting” Myth

Contrary to what you have heard or believe, there is no art in forecasting, but rather statistics and domain knowledge. Subsequently, domain knowledge is not the art of making judgmental overrides based on inflated bias
assumptions to simple statistical baseline forecasts without using analytics to validate or invalidate those assumptions. It is ironic that although we use exact science to manufacture products along structured guidelines with specifications that are within a .001 tolerance range, we use our gut feeling judgment to forecast demand for those same products. I have an advanced degree in applied econometrics and more than 20 years of experience as a forecast practitioner with more than six companies, and I still cannot take my gut feeling judgment and turn it into a number. I need to access the data and conduct the analytics to validate my assumptions. In other words, come up with a hypothesis, find the data, and conduct the analytics to determine whether you can reject the hypothesis. Then use the results to make adjustments to the statistical baseline forecast or, better yet, build those assumptions into the statistical baseline forecast by adding the additional data and revising the analytics.

Unfortunately, many companies are quick to dismiss any structured approach to demand forecasting, particularly when it requires data and analytics, or the “s” word: statistics. The excuse is that statistics are not always trustworthy because they can be manipulated to explain whatever you want. This excuse became clear to me when I was given a product forecast by a manager who then asked me to find the data and statistics to support it. As a young manager with a MBA in economics specializing in applied micro-econometrics, I found this somewhat amusing. Applied econometrics is a very structured approach to analyzing information and data using statistical methods that have been proven in practice as well as dissected with rigor by academia over the past 100 years. Unfortunately, the manager was not joking.

Granted, some element of domain knowledge, not art, always is required to predict the demand for any product. Unfortunately, most people misinterpret the “art” to mean gut feelings rather than a true understanding of marketplace dynamics. Let us look at a real-life example I encountered while working at a beverage company in the late 1990s to illustrate the true meaning of domain knowledge.

**End-Cap Display Dilemma**

As senior manager for global marketing research at the beverage company, I was asked to support the national brand team, which was responsible for
growing its sports drink business. Our goal was to provide the brand team
with a way to measure the effects of marketing dollars and use the findings
to shape and predict future demand as an input into the monthly Sales &
Operations Planning process. We decided to develop several advanced
statistical models by brand and package size to predict the effects of market-
ing tactics on consumer demand using ACNielsen syndicated scanner data
(point-of-sale data). The purpose of this exercise was twofold: (1) to mea-
sure the effects of the marketing mix elements (price, advertising, mer-
chandising, sales promotions, competitive activities, and any other external
factors) on consumer demand, and (2) to use those measures to conduct
what-if simulations to shape demand, resulting in a more accurate demand
forecast that reflected the sports drink brand team marketing strategy.

The first series of models was developed for the sports drink 64-ounce
product group. We identified several internal marketing elements as signifi-
cant business drivers influencing consumer demand. All the key business
drivers were significant at a 95 percent confidence level, which explained
roughly 92 percent of the variation in consumer demand for the 64-ounce
product. However, when we added end-cap displays\(^2\) to the model, all
the other key business drivers were no longer significant and the end-cap
displays alone explained over 96 percent of the variation in consumer de-
mand. This was puzzling and, from a practical standpoint, somewhat suspi-
cious. So we scheduled a meeting with the sports drink brand team to
determine whether this made sense from a domain knowledge perspective.

The brand team explained to us that this was an anomaly in the data,
most likely an error on the part of ACNielsen. When ACNielsen con-
ducted its store audit that week to capture the in-store merchandising
activities of all the manufacturers and retailers, the auditor saw the one
64-ounce sports drink bottle on the end-cap display and entered it into the
system as a sports drink 64-ounce bottle end-cap promotion. The brand
team continued to explain that it never runs end-cap display promotions
for 64-ounce bottles of any beverage because the bottles are too large to fit
enough on the display to justify the cost. So what happened? The end-cap
display was most likely an 8-ounce sports drink 12-pack promotion with
only one 12-pack left. A consumer picked up a sports drink 64-ounce bot-
tle in the aisle and continued on to the end-cap display. The shopper saw
the last 8-ounce 12-pack on promotion and decided to exchange the 64-
ounce bottle for the 8-ounce 12-pack. The consumer left the 64-ounce
bottle on the end-cap display, and the ACNielsen auditor saw it and recorded it.

Such anomalies occur occasionally and need to be identified during the final staging and cleansing of the data. After removing the end-cap display variable from the sports drink 64-ounce bottle model, all the other key business drivers fell into place, thus making the model more reflective of the actual marketing activities being implemented to drive consumer demand. As a result, we created a set of business rules for future model development. The primary rule advised modelers to exclude end-cap displays in any 64-ounce bottle models to explain consumer demand.

From this story, we learned that (1) demand forecasting requires a collaborative effort between a statistician and a domain knowledge expert, and (2) domain knowledge is very different from pure judgment.

**Reality of Judgmental Overrides**

Many companies still value judgment over analytics, and as such, judgment is used almost exclusively to manipulate the statistical baseline demand forecast to meet their needs. There are still situations where the demand forecasting process is used to generate and justify sales targets based on stretch goals. The end result is a forecast that reflects someone’s wishes rather than reality. As an econometrician with over 20 years of experience, I have never been able to turn my gut feelings into a number to enhance the accuracy of a forecast. However, if you provide me with a hypothesis based on your domain knowledge, I can identify the appropriate data and, using analytics, validate or invalidate your hypothesis. If the hypothesis is validated, we would add the data as an explanatory variable to a more sophisticated model to improve the accuracy of the statistical baseline forecast. As a result, there would be no need to make a judgmental override because we already would have incorporated your domain knowledge into the statistical baseline forecast.

Unfortunately, those individuals making manual overrides to the statistical baseline forecast actually feel that they are enhancing the accuracy of the forecast by touching it with their judgment. At least this is one of the major reasons forecasters made adjustments to 75 percent of statistical baseline forecasts at four U.K. companies, according to a recent study by Goodwin and Fildes. In fact, at these companies, the researchers found that when
Forecasters and/or planners raise the forecast, they are almost always wrong, thus making the forecast less accurate. Often they are overly optimistic when raising the forecast. Conversely, when forecasters or planners make judgmental overrides that lower the forecast, they tend to enhance its accuracy because they are more conservative. But senior management tends to frown on disclosing that a business is declining rather than growing. Overall, Goodwin and Fildes found that very small changes to the forecast, up or down, had virtually no impact on forecast accuracy and were simply a waste of time.

The real issue is that most companies have been sold a bad bill of goods by academics, practitioners, and software vendors. It is popular to advocate that you can take a simple time series statistical model, such as exponential smoothing, and enhance the forecasts by making manual overrides based on pure judgment. Simple methods such as this can work with well-behaved and easy-to-forecast demand but can produce highly inaccurate forecasts in more challenging forecasting situations. I have rarely seen the accuracy of a statistical baseline forecast improve by making a manual override using gut feeling judgment rather than informed judgment using domain knowledge. Nevertheless, almost every process designed and supported by software vendors advocates this method as it is easy to systematize these simple time series statistical methods. It is also easy to collect, store, and manage the historical data required to enable such methods.

The accepted demand forecasting process of making manual overrides using pure judgment needs to be modified to incorporate more analytics by creating a hypothesis using domain knowledge, not judgment. Demand forecasting is a collaborative process that requires a statistician and a domain knowledge expert. More sophisticated methods should be introduced, such as autoregressive integrated moving average (ARIMA), autoregressive integrated moving average with exogenous input (ARIMAX), dynamic regression, and unobserved component models. These models can capture the relationships and influences of factors other than trend and seasonality, such as price, advertising, sales promotions, marketing events, and economic information. Domain knowledge could then be used to identify the factors that affect those particular brands, product groups, and products, providing a hypothesis as to why and how they may be influencing demand. Finally, the hypothesis should be tested to determine which factors are influencing demand and incorporate them into the statistical baseline.