

Consumption-Based Forecasting and Planning

Predicting Changing Demand Patterns
in the New Digital Economy

Charles W. Chase



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***Predicting Changing Demand
Patterns in the New Digital Economy***

Charles W. Chase

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Foreword

I have the honor of writing the foreword to Charles Chase's new book *Consumption-Based Forecasting and Planning: Predicting Shifting Demand Patterns in the New Digital Economy*. I have known Mr. Chase ("Charlie") for roughly 35 years. Charlie and I have common interests in business forecasting and market analytics. In addition, Charlie and I are close friends, and he and his wife Cheryl are adopted members of my immediate family.

The purpose of a foreword is to confer credibility to the author(s) and to provide context and background of the book in question. Let's start with credibility. Charles Chase is unquestionably a leader in forecasting/modeling and advanced marketing analytics. Currently employed at SAS Institute, Inc., he is the author of *Next Generation Demand Management: People, Process, Analytics, and Technology*; *Demand-Driven Forecasting: A Structured Approach to Forecasting*; and coauthor of *Bricks Matter: The Role of Supply Chains in Building Market-Driven Differentiation*. Each of these books is required reading in my Business Forecasting PhD-level class at Texas A&M University. Moreover, Charlie has served as president of the International Association of Business Forecasting and currently writes a quarterly column in the *Journal of Business Forecasting* entitled "Innovations in Business Forecasting."

Concerning the context of his new pithy tome, the book is divided into seven chapters: (1) The Digital Economy and Unexpected Disruptions; (2) A Wake-up Call for Demand Management; (3) Why Data and Analytics Are Important; (4) Consumption-Based Forecasting and Planning; (5) AI/Machine Learning Is Disrupting Demand Forecasting;

(6) Intelligent Automation Is Disrupting Demand Planning; and (7) The Future Is Cloud Analytics and Analytics at the Edge. Targeting principally business executives, the main objective is to describe how the new digital economy and the disruption attributed to COVID-19 have changed the way companies deploy demand forecasting. As such, this book is very timely. Further, Chase argues for repositioning demand planning downstream in the supply chain closer to customers (ultimately consumers) to maximize sales. While not necessarily a novel concept, the emphasis on this repositioning is important operationally to firms, especially those engaged in the consumer-packaged goods industry. Additionally, the case is made for applying predictive analytics and machine learning to available data sources to ameliorate modeling efforts associated with customer demand patterns. Improvements in the ability to model demand lead to efficiencies, the reduction of costs and hence advances in the bottom line. Finally, a unique contribution of the book is the introduction of cloud analytic solutions and edge analytics, what Chase calls the future of demand forecasting and planning. On all fronts, Chase provides information on various key topics not presently evident in the extant literature.

Data are the lifeblood of the digital economy providing business insights and supporting real-time delivery of critical information to enable decision making. Massive amounts of data are routinely collected from sensors and devices operating in real-time from remote locations operating globally. As supply chain executives face the new digital economy, Chase argues that the appropriate vision for data and analytics is to harness relevant information not only to make better decisions but also to react faster to disruptions like the unprecedented COVID-19 pandemic. Chase states that “Intelligent automation supported by machine learning is changing the game, particularly for

demand forecasting and planning.” Chase makes clear that “when shaping business plans and strategy, consumption-based forecasting and planning can serve as a great counterweight to gut feelings and biases.”

Given that demand forecasting and planning generally have been designated as the areas that likely will deliver the most benefits from predictive analytics, it is not unreasonable to assume that cloud computing would also be the preferred technology platform. As this technology continues to grow, Chase points out that there will be incessant debate surrounding the best approaches to utilizing cloud computing due to the demand for advanced analytics skills. Analytics at the edge is a technology-based approach to data collection and analysis where automated-analytical calculations are performed using sensors, network switches, or other devices instead of utilizing centralized data repositories.

In agreement with Chase, the virtual flood of data is changing the way businesses handle data storage, processing, and analytics. The traditional computing paradigm built on centralized data warehouses with conventional Internet connectivity is not well suited for dealing with huge volumes of data. Bandwidth limitations and unpredictable system disruptions all contribute to network bottlenecks. Chase notes that companies are responding to these data challenges related to the new digital economy by deploying edge computing applications. Chase opines that the cloud is a key component for a successful digital transformation. Further, he observes that open-source cloud solutions now allow companies to monitor consumer demand on a daily and/or weekly basis providing real-time updates regarding ever-changing consumer demand patterns based on current market conditions.

Not surprisingly, Chase astutely provides a concise and cogent blueprint for how business executives should deal with the digital economy and unexpected disruptions. Indeed, his contribution provides a wake-up call for demand management. Without question, Chase illustrates why data and analytics are important, challenging business operations to embrace consumption-based forecasting and planning. Additionally, Chase notes that artificial intelligence, machine learning, and automation are vital capabilities in the digital economy. This pronouncement is not only important to the business community but also to the academic community as well. Finally, Chase accurately surmises that applications of cloud analytics and analytics at the edge will grow in the future as businesses continue to grapple in a time-sensitive manner with the ever-present challenges of demand forecasting and planning. Simply put, business executives who read carefully and take copious notes of the concepts set forth in this book will have a decided advantage in coping with the full potential of the digital economy.

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Preface

Retail and consumer goods executives know that when shaping business plans forecasts serve to temper and balance gut feelings and judgmental bias. Yet, most will admit that their forecasts are still disgracefully inaccurate. There are signs, however, based on early adoption of applying intelligent automation supported by machine learning and traditional predictive analytics that are changing the playing field, particularly for demand forecasting and planning. For example, a large global consumer goods company reduced its global days of finished goods inventory by 1.2 days after improving their overall forecast accuracy from 70% to 81% on average across their product portfolio. That corresponded to a 50 basis points improvement in overall customer service levels. So, you don't need to move the needle that much to gain significant improvements in overall supply chain performance.

The past year of the pandemic has highlighted that companies don't respond quickly to shifting consumer demand patterns, as well as other market disruptions. Companies were already facing many new challenges because of the new digital economy. The unforeseen disruption of COVID-19 worsened the economic uncertainty and market volatility. This perfect supply chain storm has become even more important for commercial teams to explore predictive analytics and automation. Those teams will need new systems to turbocharge their demand forecasting and planning capabilities to capture those shifting consumer demand patterns that are taking place as consumers move through the four phases of the pandemic—preliminary, outbreak, stabilization, and recovery. They

will need efficient ways to generate and disseminate real-time consumer demand forecasts that reflect rapidly shifting market conditions. Likewise, it will be imperative for analysts and demand planning teams to embrace automated digital applications and dashboards to allow data to be refreshed frequently and incorporate multiple scenarios.

WHY IS THIS IMPORTANT?

We all know that not all forecasts will be 100% accurate, 100% of the time. That's also reflective of best-made plans and strategic initiatives. No statistical formula can predict the surge, outcome, or exact length of a black swan event like COVID-19—or can it? There's no data available for an unforeseen disruption—or is there? Nor will analytics generate optimal forecasts every time, maybe not when using traditional time series methods. In the wake of COVID-19, for example, retailers and consumer goods companies had to reset their traditional algorithms and data sets in an attempt to understand the effects of multiple phases of self-isolation, lockdowns, and reopenings over the past 10 months in an attempt to understand shifting consumption patterns.

The COVID-19 pandemic has disrupted the usual demand forecasting and planning processes. Consumer demand patterns for different products and services have shifted from the norm, given the uneven spread of the virus, and continuing economic and health uncertainties. Traditional statistical models that rely heavily only on shipments (supply) historical data alone were unable to capture the effects of the crisis for both current demand and into the next normal. However, some early adopter demand planning teams were using predictive analytics and were able to stress-test their demand forecasts and create “What

If” scenarios. The technology allowed them to drill down on the impact of the crisis across specific product categories using different parameters. For instance, one consumer goods company used a combination of precrisis data, postcrisis assumptions across specific business drivers, and consumer-behavior research to model the shifting consumer demand patterns for their products across categories under various scenarios. One early finding showed that the next 1–8 weeks compound annual growth rate in the “pasta goods” category changed from a single-digit growth percent in a business-as-usual setting to a double-digit percent increase based on the scenarios. The behavior was linked to POS (point-of-sale), Google trends, epidemiological, stringency index, and regional economic data. By contrast, non-essential products were not influenced as much by the current situation, as demand remained unchanged across all scenarios and assumptions.

Once opportunities have been identified and benefits targeted, organizations implementing predictive analytics and machine learning on a large-scale basis must invest in the following core requirements:

- **Clean, quality, accessible data.** Perhaps more than other functional groups, the demand planning organization implementing or scaling up a predictive analytics process must ensure the reliability and accuracy of data. When business information isn't adequately sourced, aggregated, reconciled, or secured, demand analysts and planners spend more time on redundant tasks that don't add value. Business leaders must work with IT and the business to set the governance rules for data usage, what good data looks like, who owns the data, and who can access the data.
- **Organizational training, protocols, and structure.** Demand Planning, IT, and business leaders must ensure

that employees at all levels are trained to understand the systems required to collect, access, and maintain the data. It doesn't matter how clean or how easy it is to access the data if the demand planning function doesn't have the right operational and organizational training and structure to implement predictive analytics programs. It needs supporting processes and protocols to gather insights from the data, share those insights, and develop action plans in unison across all the other functions.

- **Cultural challenges.** The executive team will also need to focus on corporate cultural challenges; for example, by highlighting “lighthouse cases” that might inspire other parts of the business to use predictive analytics. The company and demand planning team will most likely need to hire data scientists and data-visualization specialists. They will need to retrain internal demand planners to work with data scientists, as well. Otherwise, execution will stall, and in many cases, fail.
- **Process and model sustainability.** Analytics and machine learning models are never 100% stable over time, so they need to be adjusted continually, which strengthens the case for in-house competences. It is worth assembling a small hybrid group of data scientists and demand planners with strong business acumen to work together on special projects that make the case for deeper investments in analytics talent.
- **The importance of having a strategic vision.** The SVP supply chain, or CAO (Chief Analytics Officer), of companies must have a clear vision of how they will use new technologies. In my experience, CAOs are well positioned to provide that vision and to lead the widespread adoption of advanced analytics. They have

most of the necessary data in hand, as well as the traditional quantitative expertise to assess the real value to be gained from analytics programs. Project teams and senior leaders may suspect that their companies could streamline processes or export products more efficiently. For example, the CAO can put these ideas in the proper context.

At investor days or in quarterly earnings reports, C-suite leaders tend to talk about analytics programs in broad terms. For instance, how they will change the industry, how the company will work with customers differently, or how digitization will affect the financials. In doing so, they can help fulfill the repeated request, from both senior management and the board, that they serve not only as traditional transaction managers but also as key strategy partners and as value managers. Of course, CAOs cannot lead digital transformations all alone; they should serve as global collaborators, encouraging everyone, including leaders in IT, sales, and marketing, to own the process. CAOs on the cutting edge of advanced analytics are positioning themselves not just as forward-thinking analytics leaders but also as valued business partners to other leaders in their companies. Those who aren't will need to think about how analytics programs could change the way they work, and then lead by example.

TRACKING SHIFTING CONSUMER DEMAND PATTERNS

Without a doubt, consumer behavior has changed several dimensions across product categories, channel selection, shopper trip frequency, brand preferences, and omnichannel consumption. These shifts, combined with projections for virus containment and economic recovery,

are critical for retail and consumer goods strategies. Leading retail and consumer goods companies are using traditional predictive analytics and machine learning algorithms with multiple sources of insights including point-of-sale data, primary consumer research, social media, and online search trends to understand how consumer demand could evolve during and after the crisis at a granular level (SKU/Ship-to-location).

Leading executives are planning to rapidly adapt their sales and marketing plans to reflect changing consumption patterns as well as consumer sentiment. The overall consumer outlook seems to vary depending on the stage of the pandemic response, causing executives to adjust the intensity of their marketing, including ad copy and calls to action, and to stay in sync with the evolving situation. Changing consumer demand patterns for essential purchases and non-essentials is leading retail and consumer goods companies to consider shifting marketing spending in channels such as digital and social media. All these actions are beneficial due to real-time testing and measurement. Just because the crisis is unprecedented does not mean rapid analytic testing should be abandoned. Many companies are using it surgically to gather data regarding the effectiveness of ongoing marketing efforts and adjust promotional campaigns accordingly given the resulting insights.

Consumer goods companies can maximize the impact of their new demand plans by collaborating with key customers (retailers) to refine, deploy, and revamp commercial plans. Flexibility and compassion have been found to be important elements in this collaboration. The pandemic has changed the retail landscape, especially for smaller retail outlets that have been hit the hardest. Making daily calls and adjusting payment terms as needed are setting the right tone. Changes in sales techniques are

being considered to adapt, as well. Companies are considering providing additional support and technologies to their sales force to improve virtual-selling techniques. Similarly, companies are reallocating field sales and brokerage resources to the channels, key customers, and geographies that are experiencing the highest demand. Retail and consumer goods companies who successfully execute these strategies will have a clear view of how the market will unfold and positioned to come out of the COVID-19 crisis ahead of their competitors. By contrast, those companies who wait until after the crisis to act on these opportunities will find themselves lagging their counterparts.

To be successful in the rapidly changing digital economy, companies need to properly tackle digital transformation. This is not possible if it's not part of their business agenda. The speed of digitalization will only continue to increase as consumers of demand forecasts throughout the business ecosystem mandate answers in real time. As more and more companies reinvent the way they do business, the efficiency of the digital economy will see its full potential.

This book describes the organizational, operational, and leadership requirements necessary to use predictive analytics and AI/machine learning technologies to generate more accurate consumption-based forecasts and demand plans. Some leading-edge companies are already well on their way in the digital journey, providing several case studies. Their stories and approaches will be a testament to the effectiveness of predictive analytics and machine learning providing a path forward for others.

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