CHAPTER 1

Introduction to Business Analytics


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LEARNING OBJECTIVES

After studying this chapter, you will be able to:

- Define business analytics.
- Explain why analytics is important in today's business environment.
- State some typical examples of business applications in which analytics would be beneficial.
- Summarize the evolution of business analytics and explain the concepts of business intelligence, operations research and management science, and decision support systems.
- Explain the difference between descriptive, predictive, and prescriptive analytics.
- State examples of how data are used in business.
- Explain the concept of a model and various ways a model can be characterized.
- Define and list the elements of a decision model.
- Illustrate examples of descriptive, predictive, and prescriptive models.
- Explain the difference between uncertainty and risk.
- Define the terms *optimization*, *objective function*, and *optimal solution*.
- Explain the difference between a deterministic and stochastic decision model.
- List and explain the steps in the problem-solving process.

The purpose of this book is to provide you with a basic introduction to the concepts, methods, and models used in business analytics so that you will develop an appreciation not only for its capabilities to support and enhance business decisions, but also for the ability to use business analytics at an elementary level in your work. In this chapter, we introduce you to the field of business analytics and set the foundation for many of the concepts and techniques that you will learn. Let's start with a rather innovative example.

Most of you have likely been to a zoo, seen the animals, had something to eat, and bought some souvenirs. You probably wouldn't think that managing a zoo is very difficult; after all, it's just feeding and taking care of the animals, right? A zoo might be the last place that you would expect to find business analytics being used, but not anymore. The Cincinnati Zoo & Botanical Garden has been an "early adopter" and one of the first organizations of its kind to exploit business analytics.[1]

Despite generating more than two-thirds of its budget through its own fund-raising efforts, the zoo wanted to reduce its reliance on local tax subsidies even further by increasing visitor attendance and revenues from secondary sources such as membership, food, and retail outlets. The zoo's senior management surmised that the best way to realize more value from each visit was to offer visitors a truly transformed customer experience. By using business analytics to gain greater insight into visitors' behavior and tailoring operations to their preferences, the zoo expected to increase attendance, boost membership, and maximize sales.

The project team—which consisted of consultants from IBM and Brightstar Partners, as well as senior executives from the zoo—began translating the organization's goals into technical solutions. The zoo worked to create a business analytics platform that was capable of delivering the desired goals by combining data from ticketing and point-of-sale systems throughout the zoo with membership information and geographical data gathered from the ZIP codes of all visitors. This enabled the creation of reports and dashboards that gave everyone from senior managers to zoo staff access to real-time information that helped them optimize operational management and transform the customer experience.

By integrating weather forecast data, the zoo is now able to compare current forecasts with historic attendance and sales data, supporting better decision making for labor scheduling and inventory planning. Another area where the solution delivers new insight is food service. By opening food outlets at specific times of day when demand is highest (for example, keeping ice cream kiosks open in the

[1]IBM Software Business Analtyics, "Cincinnati Zoo transforms customer experience and boosts profits," © IBM Corporation 2012.

final hour before the zoo closes), the zoo has been able to increase sales significantly. In addition, attendance and revenues have dramatically increased, resulting in annual return on investment of 411%. The business analytics initiative paid for itself within three months and delivers, on average, benefits of $738,212 per year. Specifically,

- The zoo has seen a 4.2% rise in ticket sales by targeting potential visitors who live in specific ZIP codes.
- Food revenues increased 25% by optimizing the mix of products on sale and adapting selling practices to match peak purchase times.
- Eliminating slow-selling products and targeting visitors with specific promotions enabled an 18% increase in merchandise sales.
- The zoo was able to cut its marketing expenditure, saving $40,000 in the first year, and reduce advertising expenditure by 43% by eliminating ineffective campaigns and segmenting customers for more targeted marketing.

Because of the zoo's success, other organizations such as Point Defiance Zoo & Aquarium in Tacoma, Washington, and History Colorado Center, a museum in Denver, have embarked on similar initiatives.

What Is Business Analytics?

Everyone makes decisions. Individuals face personal decisions such as choosing a college or graduate program, making product purchases, selecting a mortgage instrument, and investing for retirement. Managers in business organizations make numerous decisions every day. Some of these decisions include what products to make and how to price them, where to locate facilities, how many people to hire, where to allocate advertising budgets, whether or not to outsource a business function or make a capital investment, and how to schedule production. Many of these decisions have significant economic consequences; moreover, they are difficult to make because of uncertain data and imperfect information about the future.

Managers today no longer make decisions based on pure judgment and experience; they rely on factual data and the ability to manipulate and analyze data to supplement their intuition and experience, and to justify their decisions. What makes business decisions complicated today is the overwhelming amount of available data and information. Data to support business decisions—including those specifically collected by firms as well as through the Internet and social media such as Facebook—are growing exponentially and becoming increasingly difficult to understand and use. As a result, many companies have recently established analytics departments; for instance, IBM reorganized its consulting business and established a new 4,000-person organization focusing on analytics. Companies are increasingly seeking business graduates with the ability to understand and use analytics. The demand for professionals with analytics expertise has skyrocketed, and many universities now have programs in analytics.[2]

[2]Matthew J. Liberatore and Wenhong Luo, "The Analytics Movement: Implications for Operations Research," Interfaces, 40, 4 (July–August 2010): 313–324.

Business analytics, or simply **analytics**, is the use of data, information technology, statistical analysis, quantitative methods, and mathematical or computer-based models to help managers gain improved insight about their business operations and make better, fact-based decisions. Business analytics is "a process of transforming data into actions through analysis and insights in the context of organizational decision making and problem solving."[3] Business analytics is supported by various tools such as Microsoft Excel and various Excel add-ins, commercial statistical software packages such as SAS or Minitab, and more complex business intelligence suites that integrate data with analytical software.

Using Business Analytics

Tools and techniques of business analytics are used across many areas in a wide variety of organizations to improve the management of customer relationships, financial and marketing activities, human capital, supply chains, and many other areas. Leading banks use analytics to predict and prevent credit fraud. Investment firms use analytics to select the best client portfolios to manage risk and optimize return. Manufacturers use analytics for production planning, purchasing, and inventory management. Retailers use analytics to recommend products to customers and optimize marketing promotions. Pharmaceutical firms use analytics to get life-saving drugs to market more quickly. The leisure and vacation industries use analytics to analyze historical sales data, understand customer behavior, improve Web site design, and optimize schedules and bookings. Airlines and hotels use analytics to dynamically set prices over time to maximize revenue. Even sports teams are using business analytics to determine both game strategy and optimal ticket prices.[4] For example, teams use analytics to decide on ticket pricing, who to recruit and trade, what combinations of players work best, and what plays to run under different situations.

Among the many organizations that use analytics to make strategic decisions and manage day-to-day operations are Caesars Entertainment, the Cleveland Indians baseball, Phoenix Suns basketball, and New England Patriots football teams, Amazon.com, Procter & Gamble, United Parcel Service (UPS), and Capital One bank. It was reported that nearly all firms with revenues of more than $100 million are using some form of business analytics.

Some common types of business decisions that can be enhanced by using analytics include

- pricing (for example, setting prices for consumer and industrial goods, government contracts, and maintenance contracts),
- customer segmentation (for example, identifying and targeting key customer groups in retail, insurance, and credit card industries),
- merchandising (for example, determining brands to buy, quantities, and allocations),
- location (for example, finding the best location for bank branches and ATMs, or where to service industrial equipment),
- supply chain design (for example, determining the best sourcing and transportation options and finding the best delivery routes),

[3]Liberatore and Luo, "The Analytics Movement".

[4]Jim Davis, "8 Essentials of Business Analytics," in "Brain Trust—Enabling the Confident Enterprise with Business Analytics" (Cary, NC: SAS Institute, Inc., 2010): 27–29. www.sas.com/bareport

- staffing (for example, ensuring the appropriate staffing levels and capabilities and hiring the right people—sometimes referred to as "people analytics"),
- health care (for example, scheduling operating rooms to improve utilization, improving patient flow and waiting times, purchasing supplies, predicting health risk factors),

and many others in operations management, finance, marketing, and human resources—in fact, in every discipline of business.[5]

Various research studies have discovered strong relationships between a company's performance in terms of profitability, revenue, and shareholder return and its use of analytics. Top-performing organizations (those that outperform their competitors) are three times more likely to be sophisticated in their use of analytics than lower performers and are more likely to state that their use of analytics differentiates them from competitors.[6] However, research has also suggested that organizations are overwhelmed by data and struggle to understand how to use data to achieve business results and that most organizations simply don't understand how to use analytics to improve their businesses. Thus, understanding the capabilities and techniques of analytics is vital to managing in today's business environment.

So, no matter what your job position in an organization is or will be, the study of analytics will be quite important to your future success. You may find many uses in your everyday work for the Excel-based tools that we will study. You may not be skilled in all the technical nuances of analytics and supporting software, but you will, at the very least, be a consumer of analytics and work with analytics professionals to support your analyses and decisions. For example, you might find yourself on project teams with managers who know very little about analytics and analytics experts such as statisticians, programmers, and economists. Your role might be to ensure that analytics is used properly to solve important business problems.

Impacts and Challenges

The benefits of applying business analytics can be significant. Companies report reduced costs, better risk management, faster decisions, better productivity, and enhanced bottom-line performance such as profitability and customer satisfaction. For example, 1-800-Flowers.com used analytic software to target print and online promotions with greater accuracy; change prices and offerings on its Web site (sometimes hourly); and optimize its marketing, shipping, distribution, and manufacturing operations, resulting in a $50 million cost savings in one year.[7]

Business analytics is changing how managers make decisions.[8] To thrive in today's business world, organizations must continually innovate to differentiate themselves from competitors, seek ways to grow revenue and market share, reduce costs, retain existing customers and acquire new ones, and become faster and leaner. IBM suggests that traditional management

[5]Thomas H. Davenport, "How Organizations Make Better Decisions," edited excerpt of an article distributed by the International Institute for Analytics published in "Brain Trust—Enabling the Confident Enterprise with Business Analytics" (Cary, NC: SAS Institute, Inc., 2010): 8–11. www.sas.com/bareport

[6]Thomas H. Davenport and Jeanne G. Harris, *Competing on Analytics* (Boston: Harvard Business School Press, 2007): 46; Michael S. Hopkins, Steve LaValle, Fred Balboni, Nina Kruschwitz, and Rebecca Shockley, "10 Data Points: Information and Analytics at Work," *MIT Sloan Management Review*, 52, 1 (Fall 2010): 27–31.

[7]Jim Goodnight, "The Impact of Business Analytics on Performance and Profitability," in "Brain Trust—Enabling the Confident Enterprise with Business Analytics" (Cary, NC: SAS Institute, Inc., 2010): 4–7. www.sas.com/bareport

[8]*Analytics: The New Path to Value*, a joint MIT Sloan Management Review and IBM Institute for Business Value study.

approaches are evolving in today's analytics-driven environment to include more fact-based decisions as opposed to judgment and intuition, more prediction rather than reactive decisions, and the use of analytics by everyone at the point where decisions are made rather than relying on skilled experts in a consulting group.[9] Nevertheless, organizations face many challenges in developing analytics capabilities, including lack of understanding of how to use analytics, competing business priorities, insufficient analytical skills, difficulty in getting good data and sharing information, and not understanding the benefits versus perceived costs of analytics studies. Successful application of analytics requires more than just knowing the tools; it requires a high-level understanding of how analytics supports an organization's competitive strategy and effective execution that crosses multiple disciplines and managerial levels.

In 2011, a survey by Bloomberg Businessweek Research Services and SAS concluded that business analytics was still in the "emerging stage" and was used only narrowly within business units, not across entire organizations. The study also noted that many organizations lacked analytical talent, and those that did have analytical talent often didn't know how to apply the results properly. While analytics was used as part of the decision-making process in many organizations, most business decisions are still based on intuition.[10] Today, business analytics has matured in many organizations, but many more opportunities still exist. These opportunities are reflected in the job market for analytics professionals, or "data scientists," as some call them. McKinsey & Company suggested that there is a shortage of qualified data scientists.[11]

CHECK YOUR UNDERSTANDING

1. Explain why analytics is important in today's business environment.
2. Define business analytics.
3. State three examples of how business analytics is used in organizations.
4. What are the key benefits of using business analytics?
5. What challenges do organizations face in using analytics?

Evolution of Business Analytics

Analytical methods, in one form or another, have been used in business for more than a century. The core of business analytics consists of three disciplines: business intelligence and information systems, statistics, and modeling and optimization.

Analytic Foundations

The modern evolution of analytics began with the introduction of computers in the late 1940s and their development through the 1960s and beyond. Early computers provided the ability to store and analyze data in ways that were either very difficult or impossible to do manually. This facilitated the collection, management, analysis, and reporting of data, which

[9] "Business Analytics and Optimization for the Intelligent Enterprise" (April 2009). www.ibm.com/qbs/intelligent-enterprise

[10] Bloomberg Businessweek Research Services and SAS, "The Current State of Business Analytics: Where Do We Go From Here?" (2011).

[11] Andrew Jennings, "What Makes a Good Data Scientist?" *Analytics Magazine* (July–August 2013): 8–13. www.analytics-magazine.org

is often called **business intelligence (BI)**, a term that was coined in 1958 by an IBM researcher, Hans Peter Luhn.[12] Business intelligence software can answer basic questions such as "How many units did we sell last month?" "What products did customers buy and how much did they spend?" "How many credit card transactions were completed yesterday?" Using BI, we can create simple rules to flag exceptions automatically; for example, a bank can easily identify transactions greater than $10,000 to report to the Internal Revenue Service.[13] BI has evolved into the modern discipline we now call **information systems (IS)**.

Statistics has a long and rich history, yet only rather recently has it been recognized as an important element of business, driven to a large extent by the massive growth of data in today's world. Google's chief economist noted that statisticians surely have one of the best jobs.[14] Statistical methods allow us to gain a richer understanding of data that goes beyond business intelligence reporting by not only summarizing data succinctly but also finding unknown and interesting relationships among the data. Statistical methods include the basic tools of description, exploration, estimation, and inference, as well as more advanced techniques like regression, forecasting, and data mining.

Much of modern business analytics stems from the analysis and solution of complex decision problems using mathematical or computer-based models—a discipline known as operations research, or management science. *Operations research (OR)* was born from efforts to improve military operations prior to and during World War II. After the war, scientists recognized that the mathematical tools and techniques developed for military applications could be applied successfully to problems in business and industry. A significant amount of research was carried on in public and private think tanks during the late 1940s and through the 1950s. As the focus on business applications expanded, the term *management science (MS)* became more prevalent. Many people use the terms *operations research* and *management science* interchangeably, so the field became known as **Operations Research/Management Science (OR/MS)**. Many OR/MS applications use **modeling and optimization**—techniques for translating real problems into mathematics, spreadsheets, or various computer languages, and using them to find the best ("optimal") solutions and decisions. INFORMS, the Institute for Operations Research and the Management Sciences, is the leading professional society devoted to OR/MS and analytics and publishes a bimonthly magazine called *Analytics* (http://analytics-magazine.org/). Digital subscriptions may be obtained free of charge at the Web site.

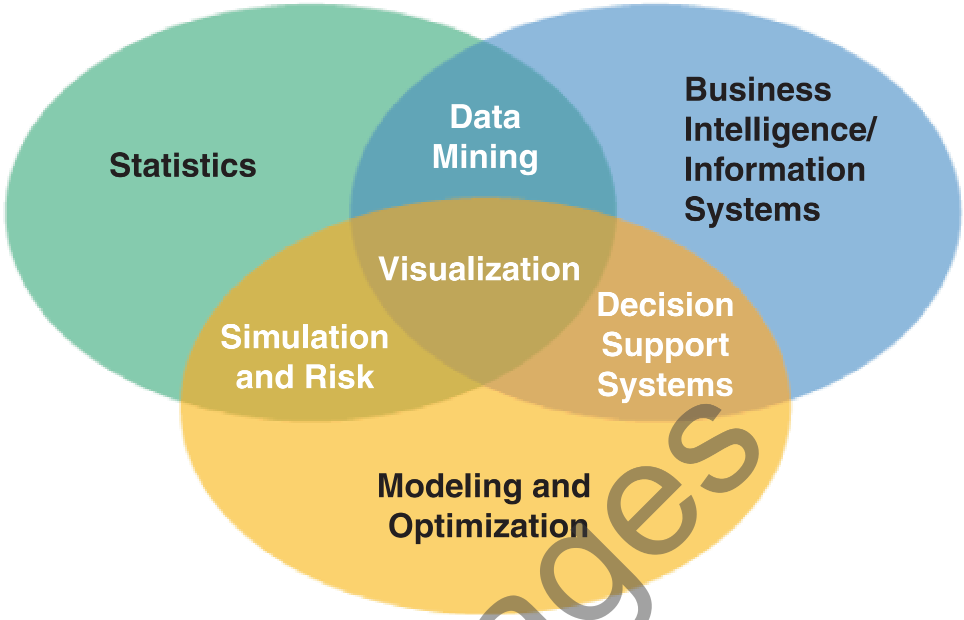
Modern Business Analytics

Modern business analytics can be viewed as an integration of BI/IS, statistics, and modeling and optimization, as illustrated in Figure 1.1. While these core topics are traditional and have been used for decades, the uniqueness lies in their intersections. For example, **data mining** is focused on better understanding characteristics and patterns among variables in large databases using a variety of statistical and analytical tools. Many standard statistical tools as well as more advanced ones are used extensively in data mining. **Simulation and risk analysis** relies on spreadsheet models and statistical analysis to examine the impacts of uncertainty in estimates and their potential interaction with one another on the output variable of interest.

[12] H. P. Luhn, "A Business Intelligence System." *IBM Journal* (October 1958).
[13] Jim Davis, "Business Analytics: Helping You Put an Informed Foot Forward," in "Brain Trust—Enabling the Confident Enterprise with Business Analytics," (Cary, NC: SAS Institute, Inc., 2010): 4–7. www.sas.com/bareport
[14] James J. Swain, "Statistical Software in the Age of the Geek," *Analytics Magazine* (March -April 2013): 48–55.

Figure 1.1

A Visual Perspective of Business Analytics



Decision support systems (DSSs) began to evolve in the 1960s by combining business intelligence concepts with OR/MS models to create analytical-based computer systems to support decision making. DSSs include three components:

1. *Data management*. The data management component includes databases for storing data and allows the user to input, retrieve, update, and manipulate data.
2. *Model management*. The model management component consists of various statistical tools and management science models and allows the user to easily build, manipulate, analyze, and solve models.
3. *Communication system*. The communication system component provides the interface necessary for the user to interact with the data and model management components.[15]

DSSs have been used for many applications, including pension fund management, portfolio management, work-shift scheduling, global manufacturing and facility location, advertising-budget allocation, media planning, distribution planning, airline operations planning, inventory control, library management, classroom assignment, nurse scheduling, blood distribution, water pollution control, ski-area design, police-beat design, and energy planning.[16]

A key feature of a DSS is the ability to perform **what-if analysis**—how specific combinations of inputs that reflect key assumptions will affect model outputs. What-if analysis is also used to assess the sensitivity of optimization models to changes in data inputs and provide better insight for making good decisions.

Perhaps the most useful component of business analytics, which makes it truly unique, is the center of Figure 1.1—**visualization**. Visualizing data and results of analyses provides a way of easily communicating data at all levels of a business and can reveal surprising patterns and relationships. Software such as IBM's Cognos system exploits data visualization

[15]William E. Leigh and Michael E. Doherty, *Decision Support and Expert Systems* (Cincinnati, OH: South-Western Publishing Co., 1986).

[16]H. B. Eom and S. M. Lee, "A Survey of Decision Support System Applications (1971–April 1988)," *Interfaces*, 20, 3 (May–June 1990): 65–79.

for query and reporting, data analysis, dashboard presentations, and scorecards linking strategy to operations. The Cincinnati Zoo, for example, has used this on an iPad to display hourly, daily, and monthly reports of attendance, food and retail location revenues and sales, and other metrics for prediction and marketing strategies. UPS uses telematics to capture vehicle data and display them to help make decisions to improve efficiency and performance. You may have seen a **tag cloud** (see the graphic at the beginning of this chapter), which is a visualization of text that shows words that appear more frequently with larger fonts.

Software Support and Spreadsheet Technology

Many companies, such as IBM, SAS, and Tableau Software, have developed a variety of software and hardware solutions to support business analytics. For example, IBM's Cognos Express, an integrated business intelligence and planning solution designed to meet the needs of midsize companies, provides reporting, analysis, dashboard, scorecard, planning, budgeting, and forecasting capabilities. It is made up of several modules, including Cognos Express Reporter, for self-service reporting and ad hoc query; Cognos Express Advisor, for analysis and visualization; and Cognos Express Xcelerator, for Excel-based planning and business analysis. Information is presented to users in a context that makes it easy to understand; with an easy-to-use interface, users can quickly gain the insight they need from their data to make the right decisions and then take action for effective and efficient business optimization and outcome. SAS provides a variety of software that integrate data management, business intelligence, and analytics tools. SAS Analytics covers a wide range of capabilities, including predictive modeling and data mining, visualization, forecasting, optimization and model management, statistical analysis, text analytics, and more. Tableau Software provides simple drag and drop tools for visualizing data from spreadsheets and other databases. We encourage you to explore many of these products as you learn the basic principles of business analytics in this book.

Although commercial software often have powerful features and capabilities, they can be expensive, generally require advanced training to understand and apply, and may work only on specific computer platforms. Spreadsheet software, on the other hand, is widely used across all areas of business and used by nearly everyone. Spreadsheets are an effective platform for manipulating data and developing and solving models; they support powerful commercial add-ins and facilitate communication of results. Spreadsheets provide a flexible modeling environment and are particularly useful when the end user is not the designer of the model. Teams can easily use spreadsheets and understand the logic upon which they are built. Information in spreadsheets can easily be copied from spreadsheets into other documents and presentations. A recent survey identified more than 180 commercial spreadsheet products that support analytics efforts, including data management and reporting, data- and model-driven analytical techniques, and implementation.[17] Many organizations have used spreadsheets extremely effectively to support decision making in marketing, finance, and operations. Some illustrative applications include the following:[18]

- Analyzing supply chains (Hewlett-Packard)
- Determining optimal inventory levels to meet customer service objectives (Procter & Gamble)

[17]Thomas A. Grossman, "Resources for Spreadsheet Analysts," *Analytics Magazine* (May/June 2010): 8. www.analytics-magazine.org
[18]Larry J. LeBlanc and Thomas A. Grossman, "Introduction: The Use of Spreadsheet Software in the Application of Management Science and Operations Research," *Interfaces*, 38, 4 (July–August 2008): 225–227.

- Selecting internal projects (Lockheed Martin Space Systems)
- Planning for emergency clinics in response to a sudden epidemic or bioterrorism attack (Centers for Disease Control)
- Analyzing the default risk of a portfolio of real estate loans (Hypo International)
- Assigning medical residents to on-call and emergency rotations (University of Vermont College of Medicine)
- Performance measurement and evaluation (American Red Cross)

Some optional software packages for statistical applications that your instructor might use are SAS, Minitab, *XLSTAT* and *StatCrunch*. These provide many powerful procedures as alternatives or supplements to Excel.

Spreadsheet technology has been influential in promoting the use and acceptance of business analytics. Spreadsheets provide a convenient way to manage data, calculations, and visual graphics simultaneously, using intuitive representations instead of abstract mathematical notation. Although the early applications of spreadsheets were primarily in accounting and finance, spreadsheets have developed into powerful general-purpose managerial tools for applying techniques of business analytics. The power of analytics in a personal computing environment was noted decades ago by business consultants Michael Hammer and James Champy, who said, “When accessible data is combined with easy-to-use analysis and modeling tools, frontline workers—when properly trained—suddenly have sophisticated decision-making capabilities.”[19]

ANALYTICS IN PRACTICE: Social Media Analytics

One of the emerging applications of analytics is helping businesses learn from social media and exploit social media data for strategic advantage.[20] Using analytics, firms can integrate social media data with traditional data sources such as customer surveys, focus groups, and sales data; understand trends and customer perceptions of their products; and create informative reports to assist marketing managers and product designers.

Social media analytics is useful in decision making in many business domains to understand how user-generated content spreads and influences user interactions, how information is transmitted, and how it influences decisions. A review of research published in social media analytics provides numerous examples:[21]

- The analysis of public responses from social media before, during, and after disasters, such as the 2010 Haiti earthquake and Hurricane Sandy in New York City in 2012, has the potential to improve situational knowledge in emergency and disaster management practices.
- Social media platforms enable citizens' engagement with politicians, governments, and other citizens. Studies have examined how voters discuss the candidates during an election, how candidates are adopting Twitter for campaigning and influencing conversations in the public space, and how presidential candidates in the United States used Twitter to engage people and identify the topics mentioned by candidates during their campaigns. Others have used analytics to track political preference by monitoring online popularity.
- In the entertainment industry, one study analyzed viewer ratings to predict the impact on revenue for upcoming movies. Another developed a web intelligence application to aggregate the news about popular TV serials and identify emerging storylines.

[19]Michael Hammer and James Champy, *Reengineering the Corporation* (New York: HarperBusiness, 1993): 96.

[20]Jim Davis, “Convergence—Taking Social Media from Talk to Action,” SASCOM (First Quarter 2011): 17.

[21]Ashish K. Rathore, Arpan K. Kar, and P. Vigneswara Ilavarasana, “Social Media Analytics: Literature Review and Directions for Future Research,” *Decision Analysis*, 14, 4 (December 2017): 229–249.

- Retail organizations monitor and analyze social media data about their own products and services and also about their competitors' products and services to stay competitive. For instance, one study analyzed different product features based on rankings from users' online reviews.
- The integration of social media application and health care leads to better patient management and empowerment. One researcher classified various online health communities, such as a diabetes patients' community, using posts from WebMD.com. Another analyzed physical activity–related tweets for a better understanding of physical activity behaviors. To predict the spread of influenza, one researcher developed a forecasting approach using flu-related tweets.

In this book, we use Microsoft Excel as the primary platform for implementing analytics. In the Chapter 1 Appendix, we review some key Excel skills that you should have before moving forward in this book.

The main chapters in this book are designed using Excel 2016 for Windows or Excel 2016 for Mac. Earlier versions of Excel do not have all the capabilities that we use in this book. In addition, some key differences exist between Windows and Mac versions that we will occasionally point out. Thus, some Excel tools that we will describe in chapter appendixes require you to use Excel for Windows, Office 365, or Google Sheets, and will not run on Excel for Mac; these are optional to learn, and are not required for any examples or problems. Your instructor may use optional software, such as XLSTAT and StatCrunch, which are provided by the publisher (Pearson), or Analytic Solver, which is described in online supplements to this book.

CHECK YOUR UNDERSTANDING

1. Provide two examples of questions that business intelligence can address.
2. How do statistical methods enhance business intelligence reporting?
3. What is operations research/management science?
4. How does modern business analytics integrate traditional disciplines of BI, statistics, and modeling/optimization?
5. What are the components of a decision support system?

Descriptive, Predictive, and Prescriptive Analytics

Business analytics begins with the collection, organization, and manipulation of data and is supported by three major components:[22]

1. *Descriptive analytics*. Most businesses start with **descriptive analytics**—the use of data to understand past and current business performance and make informed decisions. Descriptive analytics is the most commonly used and most well-understood type of analytics. These techniques categorize, characterize, consolidate, and classify data to convert them into useful information for the purposes of understanding and analyzing business performance. Descriptive

[22]Parts of this section are adapted from Irv Lustig, Brenda Dietric, Christer Johnson, and Christopher Dziekan, "The Analytics Journey," *Analytics* (November/December 2010). http://analytics-magazine.org/novemberdecember-2010-table-of-contents/

analytics summarizes data into meaningful charts and reports, for example, about budgets, sales, revenues, or cost. This process allows managers to obtain standard and customized reports and then drill down into the data and make queries to understand the impact of an advertising campaign, such as reviewing business performance to find problems or areas of opportunity, and identifying patterns and trends in data. Typical questions that descriptive analytics helps answer are "How much did we sell in each region?" "What was our revenue and profit last quarter?" "How many and what types of complaints did we resolve?" "Which factory has the lowest productivity?" Descriptive analytics also helps companies to classify customers into different segments, which enables them to develop specific marketing campaigns and advertising strategies.

2. *Predictive analytics*. **Predictive analytics** seeks to predict the future by examining historical data, detecting patterns or relationships in these data, and then extrapolating these relationships forward in time. For example, a marketer might wish to predict the response of different customer segments to an advertising campaign, a commodities trader might wish to predict short-term movements in commodities prices, or a skiwear manufacturer might want to predict next season's demand for skiwear of a specific color and size. Predictive analytics can predict risk and find relationships in data not readily apparent with traditional analyses. Using advanced techniques, predictive analytics can help detect hidden patterns in large quantities of data, and segment and group data into coherent sets to predict behavior and detect trends. For instance, a bank manager might want to identify the most profitable customers, predict the chances that a loan applicant will default, or alert a credit card customer to a potential fraudulent charge. Predictive analytics helps to answer questions such as "What will happen if demand falls by 10% or if supplier prices go up 5%?" "What do we expect to pay for fuel over the next several months?" "What is the risk of losing money in a new business venture?"
3. *Prescriptive analytics*. Many problems, such as aircraft or employee scheduling and supply chain design, simply involve too many choices or alternatives for a human decision maker to effectively consider. **Prescriptive analytics** uses optimization to identify the best alternatives to minimize or maximize some objective. Prescriptive analytics is used in many areas of business, including operations, marketing, and finance. For example, we may determine the best pricing and advertising strategy to maximize revenue, the optimal amount of cash to store in ATMs, or the best mix of investments in a retirement portfolio to manage risk. Prescriptive analytics addresses questions such as "How much should we produce to maximize profit?" "What is the best way of shipping goods from our factories to minimize costs?" "Should we change our plans if a natural disaster closes a supplier's factory, and if so, by how much?" The mathematical and statistical techniques of predictive analytics can also be combined with prescriptive analytics to make decisions that take into account the uncertainty in the data.

A wide variety of tools are used to support business analytics. These include

- Database queries and analysis
- "Dashboards" to report key performance measures
- Data visualization
- Statistical methods
- Spreadsheets and predictive models

ANALYTICS IN PRACTICE: Analytics in the Home Lending and Mortgage Industry[23]

Sometime during their lives, most Americans will receive a mortgage loan for a house or condominium. The process starts with an application. The application contains all pertinent information about the borrower that the lender will need. The bank or mortgage company then initiates a process that leads to a loan decision. It is here that key information about the borrower is provided by third-party providers. This information includes a credit report, verification of income, verification of assets, verification of employment, and an appraisal of the property. The result of the processing function is a complete loan file that contains all the information and documents needed to underwrite the loan, which is the next step in the process. Underwriting is where the loan application is evaluated for its risk. Underwriters evaluate whether the borrower can make payments on time, can afford to pay back the loan, and has sufficient collateral in the property to back up the loan. In the event the borrower defaults on their loan, the lender can sell the property to recover the amount of the loan. But if the amount of the loan is greater than the value of the property, then the lender cannot recoup their money. If the underwriting process indicates that the borrower is creditworthy and has the capacity to repay the loan and the value of the property in question is greater than the loan amount, then the loan is approved and will move to closing. Closing is the step where the borrower signs all the appropriate papers, agreeing to the terms of the loan.

In reality, lenders have a lot of other work to do. First, they must perform a quality control review on a sample of the loan files that involves a manual examination of all the documents and information gathered. This process is designed to identify any mistakes that may have been made or information that is missing from the loan file. Because lenders do not have unlimited money to lend to borrowers, they frequently sell the loan to a third party so that they have fresh capital to lend to others. This occurs in what is called the secondary market. Freddie Mac and Fannie Mae are the two largest purchasers of mortgages in the secondary market. The final step in the process is servicing. Servicing includes all the activities associated with providing the customer service on the loan, like processing payments, managing property taxes held in escrow, and answering questions about the loan.

In addition, the institution collects various operational data on the process to track its performance and efficiency, including the number of applications, loan types and amounts, cycle times (time to close the loan), bottlenecks in the process, and so on. Many different types of analytics are used:

Descriptive analytics—This focuses on historical reporting, addressing such questions as

- How many loan applications were taken in each of the past 12 months?
- What was the total cycle time from application to close?
- What was the distribution of loan profitability by credit score and loan-to-value (LTV), which is the mortgage amount divided by the appraised value of the property?

Predictive analytics—Predictive modeling uses mathematical, spreadsheet, and statistical models and addresses questions such as

- What impact on loan volume will a given marketing program have?
- How many processors or underwriters are needed for a given loan volume?
- Will a given process change reduce cycle time?

Prescriptive analytics—This involves the use of simulation or optimization to drive decisions. Typical questions include

- What is the optimal staffing to achieve a given profitability constrained by a fixed cycle time?
- What is the optimal product mix to maximize profit constrained by fixed staffing?

The mortgage market has become much more dynamic in recent years due to rising home values, falling interest rates, new loan products, and an increased desire by home owners to utilize the equity in their homes as a financial resource. This has increased the complexity and variability of the mortgage process and created an opportunity for lenders to proactively use the data that are available to them as a tool for managing their business. To ensure that the process is efficient, effective, and performed with quality, data and analytics are used every day to track what is done, who is doing it, and how long it takes.

[23]Contributed by Craig Zielazny, BlueNote Analytics, LLC.

- Scenario and "what-if" analyses
- Simulation
- Forecasting
- Data and text mining
- Optimization
- Social media, Web, and text analytics

Although the tools used in descriptive, predictive, and prescriptive analytics are different, many applications involve all three. Here is a typical example in retail operations.

EXAMPLE 1.1 Retail Markdown Decisions[24]

As you probably know from your shopping experiences, most department stores and fashion retailers clear their seasonal inventory by reducing prices. The key question they face is what prices should they set—and when should they set them—to meet inventory goals and maximize revenue? For example, suppose that a store has 100 bathing suits of a certain style that go on sale on April 1 and wants to sell all of them by the end of June. Over each week of the 12-week selling season, they can make a decision to discount the price. They face two decisions: When to reduce the price, and by how much. This results in 24 decisions to make. For a major national chain that may carry thousands of products, this can easily result in millions of decisions that store managers have to make. Descriptive analytics can be used to examine historical data for similar products, such as the number of units sold, price at each point of sale, starting and ending inventories, and special promotions, newspaper ads, direct marketing ads, and so on, to understand what the results of past decisions achieved. Predictive analytics can be used to predict sales based on pricing decisions. Finally, prescriptive analytics can be applied to find the best set of pricing decisions to maximize the total revenue.

CHECK YOUR UNDERSTANDING

1. Define descriptive analytics and provide two examples.
2. Define predictive analytics and provide two examples.
3. Define prescriptive analytics and provide two examples.

Data for Business Analytics

Since the dawn of the electronic age and the Internet, both individuals and organizations have had access to an enormous wealth of data and information. Most data are collected through some type of measurement process, and consist of numbers (e.g., sales revenues) or textual data (e.g., customer demographics such as gender). Other data might be extracted from social media, online reviews, and even audio and video files. *Information* comes from analyzing data—that is, extracting meaning from data to support evaluation and decision making.

Data are used in virtually every major function in a business. Modern organizations—which include not only for-profit businesses but also nonprofit organizations—need good data to support a variety of company purposes, such as planning, reviewing company performance, improving operations, and comparing company performance with competitors'

[24]Inspired by a presentation by Radhika Kulkarni, SAS Institute, "Data-Driven Decisions: Role of Operations Research in Business Analytics," INFORMS Conference on Business Analytics and Operations Research, April 10–12, 2011.

or best-practice benchmarks. Some examples of how data are used in business include the following:

- Annual reports summarize data about companies' profitability and market share both in numerical form and in charts and graphs to communicate with shareholders.
- Accountants conduct audits to determine whether figures reported on a firm's balance sheet fairly represent the actual data by examining samples (that is, subsets) of accounting data, such as accounts receivable.
- Financial analysts collect and analyze a variety of data to understand the contribution that a business provides to its shareholders. These typically include profitability, revenue growth, return on investment, asset utilization, operating margins, earnings per share, economic value added (EVA), shareholder value, and other relevant measures.
- Economists use data to help companies understand and predict population trends, interest rates, industry performance, consumer spending, and international trade. Such data are often obtained from external sources such as Standard & Poor's Compustat data sets, industry trade associations, or government databases.
- Marketing researchers collect and analyze extensive customer data. These data often consist of demographics, preferences and opinions, transaction and payment history, shopping behavior, and much more. Such data may be collected by surveys, personal interviews, or focus groups, or from shopper loyalty cards.
- Operations managers use data on production performance, manufacturing quality, delivery times, order accuracy, supplier performance, productivity, costs, and environmental compliance to manage their operations.
- Human resource managers measure employee satisfaction, training costs, turnover, market innovation, training effectiveness, and skills development.

Data may be gathered from primary sources such as internal company records and business transactions, automated data-capturing equipment, and customer market surveys and from secondary sources such as government and commercial data sources, custom research providers, and online research.

Perhaps the most important source of data today is data obtained from the Web. With today's technology, marketers collect extensive information about Web behaviors, such as the number of page views, visitor's country, time of view, length of time, origin and destination paths, products they searched for and viewed, products purchased, and what reviews they read. Using analytics, marketers can learn what content is being viewed most often, what ads were clicked on, who the most frequent visitors are, and what types of visitors browse but don't buy. Not only can marketers understand what customers have done, but they can better predict what they intend to do in the future. For example, if a bank knows that a customer has browsed for mortgage rates and homeowner's insurance, they can target the customer with homeowner loans rather than credit cards or automobile loans. Traditional Web data are now being enhanced with social media data from Facebook, cell phones, and even Internet-connected gaming devices.

As one example, a home furnishings retailer wanted to increase the rate of sales for customers who browsed their Web site. They developed a large data set that covered more than 7,000 demographic, Web, catalog, and retail behavioral attributes for each customer. They used predictive analytics to determine how well a customer would respond to different e-mail marketing offers and customized promotions to individual customers. This not only helped them to determine where to most effectively spend marketing resources but also doubled the response rate compared to previous marketing campaigns, with a projected and multimillion dollar increase in sales.[25]

Big Data

Today, nearly all data are captured digitally. As a result, data have been growing at an overwhelming rate, being measured by terabytes (10^{12} bytes), petabytes (10^{15} bytes), exabytes (10^{18} bytes), and even by higher-dimensional terms. Just think of the amount of data stored on Facebook, Twitter, or Amazon servers, or the amount of data acquired daily from scanning items at a national grocery chain such as Kroger and its affiliates. Walmart, for instance, has over one million transactions each hour, yielding more than 2.5 petabytes of data. Analytics professionals have coined the term **big data** to refer to massive amounts of business data from a wide variety of sources, much of which is available in real time. IBM calls these characteristics *volume*, *variety*, and *velocity*. Most often, big data revolve around customer behavior and customer experiences. Big data provide an opportunity for organizations to gain a competitive advantage—if the data can be understood and analyzed effectively to make better business decisions.

The volume of data continues to increase; what is considered "big" today will be even bigger tomorrow. In one study of information technology (IT) professionals in 2010, nearly half of survey respondents ranked data growth among their top three challenges. Big data are captured using sensors (for example, supermarket scanners), click streams from the Web, customer transactions, e-mails, tweets and social media, and other ways. Big data sets are unstructured and messy, requiring sophisticated analytics to integrate and process the data and understand the information contained in them. Because much big data are being captured in real time, they must be incorporated into business decisions at a faster rate. Processes such as fraud detection must be analyzed quickly to have value. In addition to *volume*, *variety*, and *velocity*, IBM proposed a fourth dimension: *veracity*—the level of reliability associated with data. Having high-quality data and understanding the uncertainty in data are essential for good decision making. Data veracity is an important role for statistical methods.

Big data can help organizations better understand and predict customer behavior and improve customer service. A study by the McKinsey Global Institute noted that, "The effective use of big data has the potential to transform economies, delivering a new wave of productivity growth and consumer surplus. Using big data will become a key basis of competition for existing companies, and will create new competitors who are able to attract employees that have the critical skills for a big data world."[26] However, understanding big data requires advanced analytics tools such as data mining and text analytics, and new technologies such as cloud computing, faster multi-core processors, large memory spaces, and solid-state drives.

Data Reliability and Validity

Poor data can result in poor decisions. In one situation, a distribution system design model relied on data obtained from the corporate finance department. Transportation costs were

[25]Based on a presentation by Bill Franks of Teradata, "Optimizing Customer Analytics: How Customer Level Web Data Can Help," INFORMS Conference on Business Analytics and Operations Research, April 10–12, 2011.

[26]James Manyika, Michael Chui, Brad Brown, Jacques Bughin, Richard Dobbs, Charles Roxburgh, and Angela Hung Byers, "Big Data: The Next Frontier for Innovation, Competition, and Productivity," McKinsey & Company May 2011.

determined using a formula based on the latitude and longitude of the locations of plants and customers. But when the solution was represented on a geographic information system (GIS) mapping program, one of the customers was located in the Atlantic Ocean.

Thus, data used in business decisions need to be reliable and valid. **Reliability** means that data are accurate and consistent. **Validity** means that data correctly measure what they are supposed to measure. For example, a tire pressure gauge that consistently reads several pounds of pressure below the true value is not reliable, although it is valid because it does measure tire pressure. The number of calls to a customer service desk might be counted correctly each day (and thus is a reliable measure), but it is not valid if it is used to assess customer dissatisfaction, as many calls may be simple queries. Finally, a survey question that asks a customer to rate the quality of the food in a restaurant may be neither reliable (because different customers may have conflicting perceptions) nor valid (if the intent is to measure customer satisfaction, as satisfaction generally includes other elements of service besides food).

CHECK YOUR UNDERSTANDING

1. State three examples of how data are used in different business functions.
2. How are data obtained from the Web used in marketing and business?
3. Define big data and list the four characteristics of big data.
4. Explain the concepts of data reliability and validity.

Models in Business Analytics

To make an informed decision, we must be able to specify the decision alternatives that represent the choices that can be made and criteria for evaluating the alternatives. Specifying decision alternatives might be very simple; for example, you might need to choose one of three corporate health plan options. Other situations can be more complex; for example, in locating a new distribution center, it might not be possible to list just a small number of alternatives. The set of potential locations might be anywhere in the United States or even across the globe. Decision criteria might be to maximize discounted net profits, customer satisfaction, or social benefits or to minimize costs, environmental impact, or some measure of loss.

Many decision problems can be formalized using a model. A **model** is an abstraction or representation of a real system, idea, or object. Models capture the most important features of a problem and present them in a form that is easy to interpret. A model can be as simple as a written or verbal description of some phenomenon, a visual representation such as a graph or a flowchart, or a mathematical or spreadsheet representation. Example 1.2 illustrates three ways to express a model.

A **decision model** is a logical or mathematical representation of a problem or business situation that can be used to understand, analyze, or facilitate making a decision. Decision models can be represented in various ways, most typically with mathematical functions and spreadsheets. Spreadsheets are ideal vehicles for implementing decision models because of their versatility in managing data, evaluating different scenarios, and presenting results in a meaningful fashion. We will focus on spreadsheet models beginning with Chapter 11.

EXAMPLE 1.2 Three Forms of a Model

Models are usually developed from theory or observation and establish relationships between actions that decision makers might take and results that they might expect, thereby allowing the decision makers to evaluate scenarios or to predict what might happen. For example, the sales of a new product, such as a first-generation iPad, Android phone, or 3-D television, often follow a common pattern. We might represent this in one of the three following ways:

1. A simple verbal description of sales might be: *The rate of sales starts small as early adopters begin to evaluate a new product and then begins to grow at an increasing rate over time as positive customer feedback spreads. Eventually, the market begins to become saturated, and the rate of sales begins to decrease.*
2. A sketch of sales as an S-shaped curve over time, as shown in Figure 1.2, is a visual model that conveys this phenomenon.
3. Finally, analysts might identify a mathematical model that characterizes this curve. Several different mathematical functions do this; one is called a Gompertz curve and has the formula: $S = ae^{be^{ct}}$, where S = sales, t = time, e is the base of natural logarithms, and a, b, and c are constants. Of course, you would not be expected to know this; that's what analytics professionals do.

Decision models typically have three types of input:

1. *Data*, which are assumed to be constant for purposes of the model. Some examples are costs, machine capacities, and intercity distances.
2. *Uncontrollable inputs*, which are quantities that can change but cannot be directly controlled by the decision maker. Some examples are customer demand, inflation rates, and investment returns. Often, these variables are uncertain.
3. *Decision options*, which are controllable and can be selected at the discretion of the decision maker. Some examples are production quantities, staffing levels, and investment allocations. Decision options are often called **decision variables**.

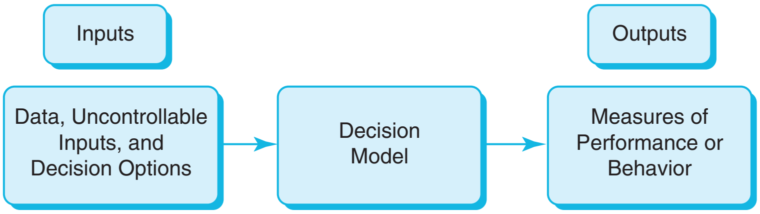
Decision models characterize the relationships among these inputs and the outputs of interest to the decision maker (see Figure 1.3). In this way, the user can manipulate the decision options and understand how they influence outputs, make predictions for the future, or use analytical tools to find the best decisions. Thus, decision models can be descriptive, predictive, or prescriptive and therefore are used in a wide variety of business analytics applications.

▸ **Figure 1.2**

New Product Sales over Time

Figure 1.3

The Nature of Decision Models



Decision models complement decision makers' intuition and often provide insights that intuition cannot. For example, one early application of analytics in marketing involved a study of sales operations. Sales representatives had to divide their time between large and small customers and between acquiring new customers and keeping old ones. The problem was to determine how the representatives should best allocate their time. Intuition suggested that they should concentrate on large customers and that it was much harder to acquire a new customer than to keep an old one. However, intuition could not tell whether they should concentrate on the 100 largest or the 1,000 largest customers, or how much effort to spend on acquiring new customers. Models of sales force effectiveness and customer response patterns provided the insight to make these decisions. However, it is important to understand that all models are only representations of the real world and, as such, cannot capture every nuance that decision makers face in reality. Decision makers must often modify the policies that models suggest to account for intangible factors that they might not have been able to incorporate into the model.

Descriptive Models

Descriptive models explain behavior and allow users to evaluate potential decisions by asking "what-if?" questions. The following example illustrates a simple descriptive mathematical model.

EXAMPLE 1.3 Gasoline Usage Model

Automobiles have different fuel economies (miles per gallon), and commuters drive different distances to work or school. Suppose that a state Department of Transportation (DOT) is interested in measuring the average monthly fuel consumption of commuters in a certain city. The DOT might sample a group of commuters and collect information on the number of miles driven per day, the number of driving days per month, the fuel economy of their vehicles, and additional miles driven per month for leisure and household activities. We may develop a simple descriptive model for calculating the amount of gasoline consumed, using the following symbols for the data:

G = gallons of fuel consumed per month
m = miles driven per day to and from work or school
d = number of driving days per month
f = fuel economy in miles per gallon (mpg)
a = additional miles for leisure and household activities per month

When developing mathematical models, it is very important to use the dimensions of the variables to ensure logical consistency. In this example, we see that

$$(m \text{ miles/day}) \times (d \text{ days/month}) = m \times d \text{ miles/month}$$

Thus, the total number of miles driven per month $= m \times d + a$. If the vehicle gets f miles/gallon, then the total number of gallons consumed per month is

$$\begin{aligned} G &= (m \times d + a \text{ miles/month})/(f \text{ miles/gallon}) \\ &= (m \times d + a)/f \text{ gallons/month} \end{aligned} \quad \textbf{(1.1)}$$

Suppose that a commuter drives 30 miles round trip to work for 20 days each month, achieves a fuel economy of 34 mpg, and drives an additional 250 miles each month. Using formula (1.1), the number of gallons consumed is

$$G = (30 \times 20 + 250)/34 = 25.0 \text{ gallons/month}$$

In the previous example, we have no decision options; the model is purely descriptive, but allows us to evaluate "what-if?" questions, for example, "What if we purchase a hybrid vehicle with a fuel economy of 45 miles/gallon?" "What if leisure and household activity driving increases to 400 miles/month?" Most of the models we will be using include decision options. As an example, suppose that a manufacturer has the option of producing a part in house or outsourcing it from a supplier (the decision options). Should the firm produce the part or outsource it? The decision depends on the costs of manufacturing and outsourcing, as well as the anticipated volume of demand (the uncontrollable inputs). By developing a model to evaluate the total cost of both alternatives (the outputs), the best decision can be made.

EXAMPLE 1.4 An Outsourcing Decision Model

Suppose that a manufacturer can produce a part for \$125/unit with a fixed cost of \$50,000. The alternative is to outsource production to a supplier at a unit cost of \$175. The total manufacturing and outsourcing costs can be expressed by simple mathematical formulas, where Q is the production volume:

$$TC\text{ (manufacturing)} = \$50{,}000 + \$125 \times Q \quad \textbf{(1.2)}$$

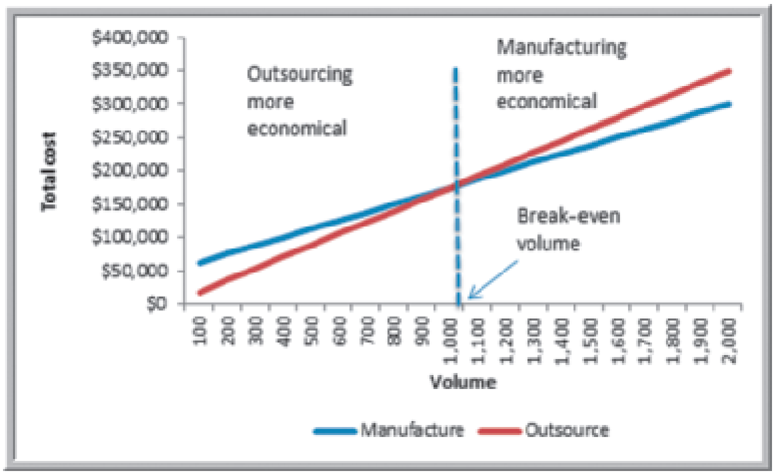
$$TC\text{ (outsourcing)} = \$175 \times Q \quad \textbf{(1.3)}$$

These formulas comprise the decision model, which simply describes what the costs of manufacturing and outsourcing are for any level of production volume. Thus, if the anticipated production volume is 1,500 units, the cost of manufacturing will be $\$50{,}000 + \$125 \times 1{,}500 = \$237{,}500$, and the cost of outsourcing would be $\$175 \times 1{,}500 = \$262{,}500$; therefore, manufacturing would be the best decision. On the other hand, if the anticipated production volume is only 800 units, the cost of manufacturing will be $\$50{,}000 + \$125 \times 800 = \$150{,}000$ and the cost of outsourcing would be $\$175 \times 800 = \$140{,}000$, and the best decision would be to outsource. If we graph the two total cost formulas, we can easily see how the costs compare for different values of Q. This is shown graphically in Figure 1.4. The point at which the total costs of manufacturing and outsourcing are equal is called the break-even volume. This can easily be found by setting TC (manufacturing) = TC (outsourcing) and solving for Q:

$$\$50{,}000 + \$125 \times Q = \$175 \times Q$$
$$\$50{,}000 = 50 \times Q$$
$$Q = 1{,}000$$

▶ **Figure 1.4**

Graphical Illustration of Break-Even Analysis



Predictive Models

Predictive models focus on what will happen in the future. Many predictive models are developed by analyzing historical data and assuming that the past is representative of the future. Example 1.5 shows how historical data might be used to develop a model that can be used to predict the impact of pricing and promotional strategies in the grocery industry.[27]

EXAMPLE 1.5 A Predictive Sales-Promotion Model

In the grocery industry, managers typically need to know how best to use pricing, coupons, and advertising strategies to influence sales. Grocers often study the relationship of sales volume to these strategies by conducting controlled experiments. That is, they implement different combinations of pricing, coupons, and advertising, observe the sales that result, and use analytics to develop predictive models of sales as a function of these decision strategies.

For example, suppose that a grocer who operates three stores in a small city varied the price, coupons (yes = 1, no = 0), and advertising expenditures in a local newspaper over a 16-week period and observed the following sales:

Week	Price ($)	Coupon (0,1)	Advertising ($)	Store1 Sales (Units)	Store 2 Sales (Units)	Store 3 Sales (Units)
1	6.99	0	0	501	510	481
2	6.99	0	150	772	748	775
3	6.99	1	0	554	528	506
4	6.99	1	150	838	785	834
5	6.49	0	0	521	519	500
6	6.49	0	150	723	790	723
7	6.49	1	0	510	556	520
8	6.49	1	150	818	773	800
9	7.59	0	0	479	491	486
10	7.59	0	150	825	822	757
11	7.59	1	0	533	513	540
12	7.59	1	150	839	791	832
13	5.49	0	0	484	480	508
14	5.49	0	150	686	683	708
15	5.49	1	0	543	531	530
16	5.49	1	150	767	743	779

To better understand the relationships among price, coupons, and advertising, an analyst might have developed the following model using business analytics tools (we will see how to do this in Chapter 8):

$$\text{Total Sales} = 1105.55 + 56.18 \times \text{Price} + 123.88 \times \text{Coupon} + 5.24 \times \text{Advertising} \quad \textbf{(1.4)}$$

In this example, the uncontrollable inputs are the sales at each store. The decision options are price, coupons, and advertising. The numerical values in the model are estimated from the data obtained from the experiment. They reflect the impact on sales of changing the decision options. For example, an increase in price of $1 results in a 56.18-unit

(continued)

[27]Roger J. Calantone, Cornelia Droge, David S. Litvack, and C. Anthony di Benedetto. "Flanking in a Price War," *Interfaces*, 19, 2 (1989): 1–12.

increase in weekly sales; using coupons (that is, setting Coupon = 1 in the model) results in a 123.88-unit increase in weekly sales. The output of the model is the predicted total sales units of the product. For example, if the price is $6.99, no coupons are offered, and no advertising is done (the experiment corresponding to week 1), the model estimates sales as

$$\text{Total Sales} = 1{,}105.55 + 56.18 \times 6.99 + 123.88 \times 0 + 5.24 \times 0 = 1{,}498.25 \text{ units}$$

We see that the actual total sales in the three stores for week 1 was 1,492. Thus, this model appears to provide good estimates for sales using the historical data. We would hope that this model would also provide good predictions of future sales. So if the grocer decides to set the price at $5.99, does not use coupons, and spends $100 in advertising, the model would predict sales to be

$$\text{Total Sales} = 1{,}105.55 + 56.18 \times 5.99 + 123.88 \times 0 + 5.24 \times 100 = 1{,}966.07 \text{ units}$$

Prescriptive Models

A prescriptive decision model helps decision makers to identify the best solution to a decision problem. **Optimization** is the process of finding a set of values for decision options that minimize or maximize some quantity of interest—profit, revenue, cost, time, and so on—called the **objective function**. Any set of decision options that optimizes the objective function is called an **optimal solution**. In a highly competitive world, where one percentage point can mean a difference of hundreds of thousands of dollars or more, knowing the best solution can mean the difference between success and failure.

EXAMPLE 1.6 A Prescriptive Model for Pricing

To illustrate an example of a prescriptive model, suppose that a firm wishes to determine the best pricing for one of its products to maximize revenue over the next year. A market research study has collected data that estimate the expected annual sales for different levels of pricing. Analysts determined that sales can be expressed by the following model:

$$\text{Sales} = -2.9485 \times \text{Price} + 3{,}240.9 \quad \textbf{(1.5)}$$

Because revenue equals price × sales, a model for total revenue is

$$\begin{aligned}\text{Total Revenue} &= \text{Price} \times \text{Sales}\\ &= \text{Price} \times (-2.9485 \times \text{Price} + 3{,}240.9)\\ &= -\,2.9485 \times \text{Price}^2 + 3{,}240.9 \times \text{Price}\end{aligned} \quad \textbf{(1.6)}$$

The firm would like to identify the price that maximizes the total revenue. One way to do this would be to try different prices and search for the one that yields the highest total revenue. This would be quite tedious to do by hand or even with a calculator; however, as we will see in later chapters, spreadsheet models make this much easier.

Although the pricing model did not, most optimization models have **constraints**—limitations, requirements, or other restrictions that are imposed on any solution, such as "Do not exceed the allowable budget" or "Ensure that all demand is met." For instance, a consumer products company manager would probably want to ensure that a specified level of customer service is achieved with the redesign of the distribution system. The presence of constraints makes modeling and solving optimization problems more challenging; we address constrained optimization problems later in this book, starting in Chapter 13.

For some prescriptive models, analytical solutions—closed-form mathematical expressions or simple formulas—can be obtained using such techniques as calculus or other types of mathematical analyses. In most cases, however, some type of computer-based procedure is needed to find an optimal solution. An **algorithm** is a systematic procedure that finds a solution to a problem. Researchers have developed effective algorithms to solve many types of optimization problems. For example, Microsoft Excel has a built-in add-in called *Solver* that allows you to find optimal solutions to optimization problems formulated as spreadsheet models. We use *Solver* in later chapters. However, we will not be concerned with the detailed mechanics of these algorithms; our focus will be on the use of the algorithms to solve and analyze the models we develop.

If possible, we would like to ensure that an algorithm such as the one *Solver* uses finds the best solution. However, some models are so complex that it is impossible to solve them optimally in a reasonable amount of computer time because of the extremely large number of computations that may be required or because they are so complex that finding the best solution cannot be guaranteed. In these cases, analysts use **search algorithms**—solution procedures that generally find good solutions without guarantees of finding the best one. Powerful search algorithms exist to obtain good solutions to extremely difficult optimization problems. One of these is discussed in Chapter 14.

Model Assumptions

All models are based on assumptions that reflect the modeler's view of the "real world." Some assumptions are made to simplify the model and make it more tractable, that is, able to be easily analyzed or solved. Other assumptions might be made to better characterize historical data or past observations. The task of the modeler is to select or build an appropriate model that best represents the behavior of the real situation. For example, economic theory tells us that demand for a product is negatively related to its price. Thus, as prices increase, demand falls, and vice versa (a phenomenon that you may recognize as price elasticity—the ratio of the percentage change in demand to the percentage change in price). Different mathematical models can describe this phenomenon. In the following examples, we illustrate two of them.

EXAMPLE 1.7 A Linear Demand Prediction Model

A simple model to predict demand as a function of price is the linear model

$$D = a - bP \tag{1.7}$$

where D is the demand, P is the unit price, a is a constant that estimates the demand when the price is zero, and b is the slope of the demand function. This model is most applicable when we want to predict the effect of small changes around the current price. For example, suppose we know that when the price is \$100, demand is 19,000 units and that demand falls by 10 for each dollar of price increase. Using simple algebra, we can determine that $a = 20{,}000$ and $b = 10$. Thus, if the price is \$80, the predicted demand is

$$D = 20{,}000 - 10(80) = 19{,}200 \text{ units}$$

If the price increases to \$90, the model predicts demand as

$$D = 20{,}000 - 10(90) = 19{,}100 \text{ units}$$

If the price is \$100, demand would be

$$D = 20{,}000 - 10(100) = 19{,}000 \text{ units}$$

and so on. A graph of demand as a function of price is shown in Figure 1.5 as price varies between \$80 and \$120. We see that there is a constant decrease in demand for each \$10 increase in price, a characteristic of a linear model.

Figure 1.5

Graph of Linear Demand Model $D = a - bP$