com/watch?v=NXEL5F4_aKA. Watch the video that appears on YouTube. Essentially, you have to assume the role of a customer service center professional. An incoming flight is running late, and several passengers are likely to miss their connecting flights. There are seats on one outgoing flight that can accommodate two of the four passengers. Which two passengers should be given priority? You are given information about customers' profiles and relationships with the airline. Your decisions might change as you learn more about those customers' profiles.

Watch the video, pause it as appropriate, and answer the questions on which passengers should be given priority. Then resume the video to get more information. After the video is complete, you can see the slides related to this video and how the analysis was prepared on a slide set at **www.slideshare.net/teradata/bsi-how-we-did-it-the-case-of-the-misconnecting-passengers**.

This multimedia excursion provides an example of how additional available information through an enterprise DW can assist in decision making.

Although some people equate DSS with BI, these systems are not, at present, the same. It is interesting to note that some people believe that DSS is a part of BI—one of its analytical tools. Others think that BI is a special case of DSS that deals mostly with reporting, communication, and collaboration (a form of data-oriented DSS). Another explanation (Watson, 2005) is that BI is a result of a continuous revolution, and as such, DSS is one of BI's original elements. Further, as noted in the next section onward, in many circles, BI has been subsumed by the new terms *analytics* or *data science*.

APPROPRIATE PLANNING AND ALIGNMENT WITH THE BUSINESS STRATEGY First and foremost, the fundamental reasons for investing in BI must be aligned with the company's business strategy. BI cannot simply be a technical exercise for the information systems department. It has to serve as a way to change the manner in which the company conducts business by improving its business processes and transforming decision-making processes to be more data driven. Many BI consultants and practitioners involved in successful BI initiatives advise that a framework for planning is a necessary precondition. One framework, proposed by Gartner, Inc. (2004), decomposed planning and execution into *business, organization, functionality*, and *infrastructure* components. At the business and organizational levels, strategic and operational objectives must be defined while considering the available organizational skills to achieve those objectives. Issues of organizational culture surrounding BI initiatives and building enthusiasm for those initiatives and procedures for the intra-organizational sharing of BI best practices must be considered by upper management—with plans in place to prepare the organization for change. One of the first steps in that process is to assess the IS organization, the skill sets of the potential classes of users, and whether the culture is amenable to change. From this assessment, and assuming there are justification and the need to move ahead, a company can prepare a detailed action plan. Another critical issue for BI implementation success is the integration of several BI projects (most enterprises use several BI projects) among themselves and with the other IT systems in the organization and its business partners.

Gartner and many other analytics consulting organizations promoted the concept of a BI competence center that would serve the following functions:

- A center can demonstrate how BI is clearly linked to strategy and execution of strategy.
- A center can serve to encourage interaction between the potential business user communities and the IS organization.
- A center can serve as a repository and disseminator of best BI practices between and among the different lines of business.
- Standards of excellence in BI practices can be advocated and encouraged throughout the company.
- The IS organization can learn a great deal through interaction with the user communities, such as knowledge about the variety of types of analytical tools that are needed.

- The business user community and IS organization can better understand why the DW platform must be flexible enough to provide for changing business requirements.
- The center can help important stakeholders like high-level executives see how BI can play an important role.

Over the last 10 years, the idea of a BI competence center has been abandoned because many advanced technologies covered in this book have reduced the need for a central group to organize many of these functions. Basic BI has now evolved to a point where much of it can be done in "self-service" mode by the end users. For example, many data visualizations are easily accomplished by end users using the latest visualization packages (Chapter 3 will introduce some of these). As noted by Duncan (2016), the BI team would now be more focused on producing curated data sets to enable self-service BI. Because analytics is now permeating across the whole organization, the BI competency center could evolve into an analytics community of excellence to promote best practices and ensure overall alignment of analytics initiatives with organizational strategy.

BI tools sometimes needed to be integrated among themselves, creating synergy. The need for integration pushed software vendors to continuously add capabilities to their products. Customers who buy an all-in-one software package deal with only one vendor and do not have to deal with system connectivity. But they may lose the advantage of creating systems composed from the "best-of-breed" components. This led to major chaos in the BI market space. Many of the software tools that rode the BI wave (e.g., Savvion, Vitria, Tibco, MicroStrategy, Hyperion) have either been acquired by other companies or have expanded their offerings to take advantage of six key trends that have emerged since the initial wave of surge in business intelligence:

- Big Data.
- Focus on customer experience as opposed to just operational efficiency.
- Mobile and even newer user interfaces—visual, voice, mobile.
- Predictive and prescriptive analytics, machine learning, artificial intelligence.
- Migration to cloud.
- Much greater focus on security and privacy protection.

This book covers many of these topics in significant detail by giving examples of how the technologies are evolving and being applied, and the managerial implications.

SECTION 1.4 REVIEW QUESTIONS

1. List three of the terms that have been predecessors of analytics.
2. What was the primary difference between the systems called MIS, DSS, and Executive Information Systems?
3. Did DSS evolve into BI or vice versa?
4. Define *BI*.
5. List and describe the major components of BI.
6. Define *OLTP*.
7. Define *OLAP*.
8. List some of the implementation topics addressed by Gartner's report.
9. List some other success factors of BI.

1.5 ANALYTICS OVERVIEW

The word *analytics* has largely replaced the previous individual components of computerized decision support technologies that have been available under various labels in the past. Indeed, many practitioners and academics now use the word *analytics* in place of BI. Although many authors and consultants have defined it slightly differently, one can view **analytics** as the process of developing actionable decisions or recommendations for actions based on insights generated from historical data. According to the Institute for Operations Research and Management Science (INFORMS), analytics represents the combination of computer technology, management science techniques, and statistics to solve real problems. Of course, many other organizations have proposed their own interpretations and motivations for analytics. For example, SAS Institute Inc. proposed eight levels of analytics that begin with standardized reports from a computer system. These reports essentially provide a sense of what is happening with an organization. Additional technologies have enabled us to create more customized reports that can be generated on an ad hoc basis. The next extension of reporting takes us to OLAP-type queries that allow a user to dig deeper and determine specific sources of concern or opportunities. Technologies available today can also automatically issue alerts for a decision maker when performance warrants such alerts. At a consumer level, we see such alerts for weather or other issues. But similar alerts can also be generated in specific settings when sales fall above or below a certain level within a certain time period or when the inventory for a specific product is running low. All of these applications are made possible through analysis and queries of data being collected by an organization. The next level of analysis might entail statistical analysis to better understand patterns. These can then be taken a step further to develop forecasts or models for predicting how customers might respond to a specific marketing campaign or ongoing service/product offerings. When an organization has a good view of what is happening and what is likely to happen, it can also employ other techniques to make the best decisions under the circumstances.

This idea of looking at all the data to understand what is happening, what will happen, and how to make the best of it has also been encapsulated by INFORMS in proposing three levels of analytics. These three levels are identified as descriptive, predictive, and prescriptive. Figure 1.9 presents a graphical view of these three levels of analytics. It suggests that these three are somewhat independent steps and one type of analytics

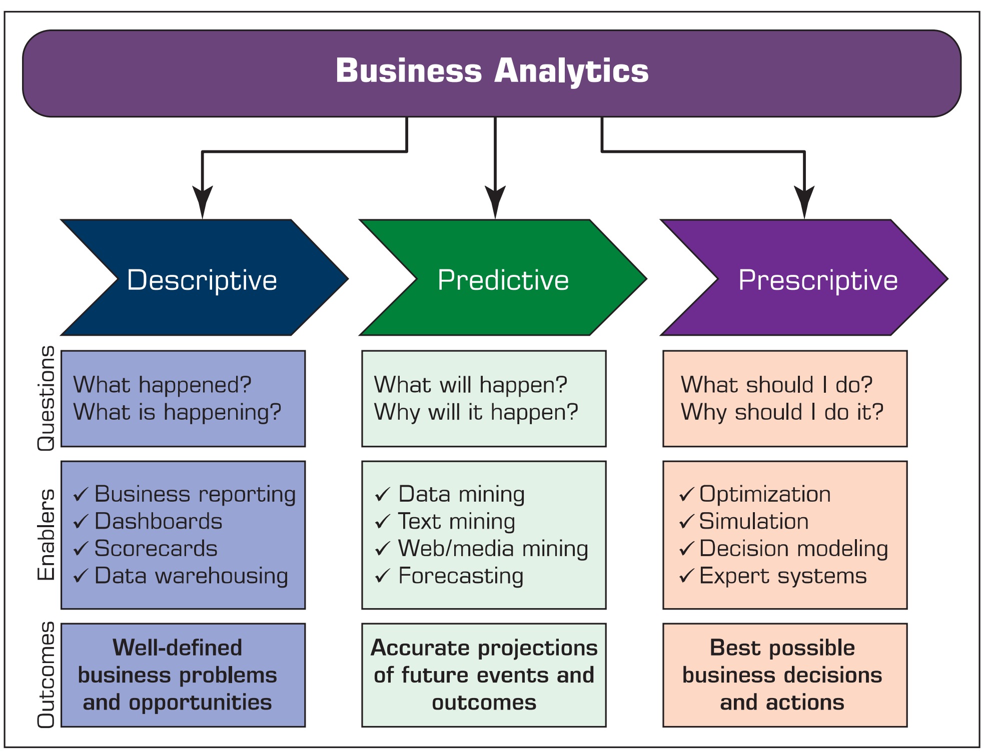

FIGURE 1.9 **Three Types of Analytics.**

applications leads to another. It also suggests that there is actually some overlap across these three types of analytics. In either case, the interconnected nature of different types of analytics applications is evident. We next introduce these three levels of analytics.

Descriptive Analytics

Descriptive (or reporting) analytics refers to knowing what is happening in the organization and understanding some underlying trends and causes of such occurrences. First, this involves the consolidation of data sources and availability of all relevant data in a form that enables appropriate reporting and analysis. Usually, the development of this data infrastructure is part of DWs. From this data infrastructure, we can develop appropriate reports, queries, alerts, and trends using various reporting tools and techniques.

A significant technology that has become a key player in this area is visualization. Using the latest visualization tools in the marketplace, we can now develop powerful insights in the operations of our organization. Two examples of the application of advanced visualization tools in business operations, available to both private and public companies, are analyzed in the Application Cases 1.3 and 1.4.

Application Case 1.3 An Post and the Use of Data Visualization in Daily Postal Operations

An Post, the state-owned corporation that manages postal services in the Republic of Ireland, presents an interesting and well-documented case of successful innovation in the public sector, which is often plagued by inefficiency and lackluster performance. Established in 1984, An Post is now one of Ireland's largest public employers. For most of its history, An Post's operations did not meet the breakeven point, let alone make a profit. This only changed in 2014, after eight years of losses.

This is why it came as a surprise when An Post made the headlines in 2018 as one of the rare public services to have successfully adopted advanced technological solutions to address customers' orders and feedback and make them significantly more manageable and streamlined.

Interaction with customers can be particularly tricky and time-consuming, and this is where platform innovation and visualization tools can help. For An Post, this service is provided by the Oracle Analytics Cloud platform and An Post's own Customer Experience Management portal. Oracle Analytics Cloud is one of the most comprehensive cloud analytics platforms, offering self-service visualization, powerful inline data preparation to enterprise reporting, and self-learning analytics.

Today, An Post's portal allows a select few corporate customers, including Amazon, Sky TV, and the Inditex Group (which owns brands such as Massimo Dutti and Zara), to visualize their parcel traffic on An Post's cloud service. There are plans to make this data visualization tool available to more of An Post's customers.

The move to data visualization services was so successful that the state-owned public service was honored with the 2018 Analytics Innovation—Global Excellence Award, celebrated in October 2018 at the Oracle Open World ceremony in San Francisco.

Sources: An Post Media centre. "Oracle Says 'An Post You're a Winner'." **https://www.anpost.com/Media-Centre/News/Oracle-says-An-Post-you-re-a-winner.** Oracle.com. "Oracle Analytics Cloud Overview." **https://www.oracle.com/technetwork/middleware/oac/overview/index.html.**

Questions for Case 1.3

1. Why was Oracle's system important for An Post?
2. What additional challenges does a state-owned service face when adopting innovative solutions?

What We Can Learn from This Application Case

While the adoption of innovation technology might at times appear daunting, it is always advantageous to streamline processes. As the case shows, public services can also benefit from adopting them in their operations.

Application Case 1.4 Siemens Reduces Cost with the Use of Data Visualization

Siemens is a German company headquartered in Berlin, Germany. It is one of the world's largest companies focusing on the areas of electrification, automation, and digitalization. It has an annual revenue of 76 billion euros.

The visual analytics group of Siemens is tasked with end-to-end reporting solutions and consulting for all of Siemens internal BI needs. This group was facing the challenge of providing reporting solutions to the entire Siemens organization across different departments while maintaining a balance between governance and self-service capabilities. Siemens needed a platform that could analyze its multiple cases of customer satisfaction surveys, logistic processes, and financial reporting. This platform should be easy to use for their employees so that they could use these data for analysis and decision making. In addition, the platform should be easily integrated with existing Siemens systems and give employees a seamless user experience.

Siemens started using Dundas BI, a leading global provider of BI and data visualization solutions. It allowed Siemens to create highly interactive dashboards that enabled it to detect issues early and thus save a significant amount of money. The dashboards developed by Dundas BI helped Siemens global logistics organization answer questions like how different supply rates at different locations affect the operation, thus helping the company reduce cycle time by 12 percent and scrap cost by 25 percent.

Questions for Case 1.4

1. What challenges were faced by Siemens visual analytics group?
2. How did the data visualization tool Dundas BI help Siemens in reducing cost?

What We Can Learn from This Application Case

Many organizations want tools that can be used to analyze data from multiple divisions. These tools can help them improve performance and make data discovery transparent to their users so that they can identify issues within the business easily.

Sources: **Dundas.com**. "How Siemens Drastically Reduced Cost with Managed BI Applications." **https://www.dundas.com/Content/pdf/siemens-case-study.pdf** (accessed September 2018); Wikipedia.org. "SIEMENS." **https://en.wikipedia.org/wiki/Siemens** (accessed September 2018); **Siemens.com**. "About Siemens." **http://www.siemens.com/about/en/** (accessed September 2018).

Predictive Analytics

Predictive analytics aims to determine what is likely to happen in the future. This analysis is based on statistical techniques as well as other more recently developed techniques that fall under the general category of **data mining**. The goal of these techniques is to be able to predict whether the customer is likely to switch to a competitor ("churn"), what and how much the customer would likely buy next, what promotions the customer would respond to, whether the customer is a creditworthy risk, and so forth. A number of techniques are used in developing predictive analytical applications, including various classification algorithms. For example, as described in Chapters 4 and 5, we can use classification techniques such as logistic regression, decision tree models, and neural networks to predict how well a motion picture will do at the box office. We can also use clustering algorithms for segmenting customers into different clusters to be able to target specific promotions to them. Finally, we can use association mining techniques (Chapters 4 and 5) to estimate relationships between different purchasing behaviors. That is, if a customer buys one product, what else is the customer likely to purchase? Such analysis can assist a retailer in recommending or promoting related products. For example, any product search on **Amazon.com** results in the retailer also suggesting similar products that a customer may be interested in. We will study these techniques and their applications in Chapters 3 through 6. Application Case 1.5 illustrates how Asian companies have made use of predictive analytics.

Application Case 1.5

SagaDigits and the Use of Predictive Analytics

Predictive analytics is widely held to be the most actionable form of business intelligence. As IBM famously stated, if business can be considered a "numbers game," predictive analytics is the way this game is best played and won.

Many companies in China and Hong Kong are increasingly using data mining and predictive analytics to better cater to their customers' needs. This has led to the growth, in the last ten years, of enterprises specializing in these IT solutions. Among them is the award-winning SagaDigits Group.

Incorporated in 2016 in Hong Kong, the group consists of two sister organizations that work together to offer services to Asian businesses. SagaDigits Limited provides data mining, cleansing, extraction, and analytics services based on a series of methods, including natural language processing, big data, and AI technologies. Compathnion Technology Limited specializes instead in data collection, visual recognition, predictive analytics, and statistical modeling for indoor and outdoor uses.

One of the most interesting scalable solutions that SagaDigits offers its customers is Smart Box, an original, highly configurable AI solution for online and offline retail stores. When a company adopts this product for its retail business, it gets a real-time zone detection service in selected retail stores to predict the number of shoppers in those specific areas and learn their preferences based on the spatial information collected.

To successfully predict customer behavior, Smart Box employs a mixed set of indicators and information tools, including advanced visual recognition. Its sensors can detect consumers' gender, emotion, and approximate age group with a high level of accuracy. Finally, based on its own behavioral models' predictions and the historical records of similar customers' transaction histories, Smart Box provides automatic recommendations for advertisement and product selection for display.

Smart Box is one among many of SagaDigits' solutions that use predictive analytics. Another system is Smart User Pro, which uses a variety of public data and internal data to predict various marketing trends in retail and marketing for consumer goods.

Sources: Eric Seigel (2015). "Seven Reasons You Need Predictive Analytics Today." Prediction Impact, Inc. **https://www.ibm.com/downloads/cas/LKMPR8AJ** (accessed October 2019). Saga Digits. **https://sagadigits.com/about** (accessed October 2019). **https://sagadigits.com** (accessed October 2019).

Questions for Case 1.5

1. Why is predictive analytics becoming increasingly common?
2. What is the most interesting feature of Smart Box?
3. To which kind of corporate organization is Smart Box targeted?
4. Describe alternative uses of predictive analytics that Saga Digits has developed solutions for.

What We Can Learn from This Application Case

Innovative IT solutions and sophisticated tools such as predictive analytics are being increasingly used across the world. East Asia was one of the first regions to adopt them, especially places such as Hong Kong, which has many links with North American universities focused on technology and computer science. Saga Digits is one of many companies that offer predictive analytics for consumers' behaviors and future marketing trends.

Prescriptive Analytics

The third category of analytics is termed **prescriptive analytics**. The goal of prescriptive analytics is to recognize what is going on as well as the likely forecast and make decisions to achieve the best performance possible. This group of techniques has historically been studied under the umbrella of OR or management sciences and is generally aimed at optimizing the performance of a system. The goal here is to provide a decision or a recommendation for a specific action. These recommendations can be in the form of a specific yes/no decision for a problem, a specific amount (say, price for a specific item or airfare to charge), or a complete set of production plans. The decisions may be presented to a decision maker in a report or may be used directly in an automated decision rules system (e.g., in airline pricing systems). Thus, these types of analytics can also be termed **decision or normative analytics**. Application Case 1.6 gives an example of such prescriptive analytic applications. We will learn about some aspects of prescriptive analytics in Chapter 8.

ANALYTICS APPLIED TO DIFFERENT DOMAINS Applications of analytics in various industry sectors have spawned many related areas or at least buzzwords. It is almost fashionable to attach the word *analytics* to any specific industry or type of data. Besides the general category of text analytics—aimed at getting value out of text (to be studied in Chapter 7)—or Web analytics—analyzing Web data streams (also in

Application Case 1.6

A Specialty Steel Bar Company Uses Analytics to Determine Available-to-Promise Dates

This application case is based on a project that involved one of the coauthors. A company that does not wish to disclose its name (or even its precise industry) was facing a major problem of making decisions on which inventory of raw materials to use to satisfy which customers. This company supplies custom configured steel bars to its customers. These bars may be cut into specific shapes or sizes and may have unique material and finishing requirements. The company procures raw materials from around the world and stores them in its warehouse. When a prospective customer calls the company to request a quote for the specialty bars meeting specific material requirements (composition, origin of the metal, quality, shapes, sizes, etc.), the salesperson usually has just a little bit of time to submit such a quote including the date when the product can be delivered, prices, and so on. It must make available-to-promise (ATP) decisions, which determine in real time the dates when the salesperson can promise delivery of products that customers requested during the quotation stage. Previously, a salesperson had to make such decisions by analyzing reports on available inventory of raw materials. Some of the available raw material may have already been committed to another customer's order. Thus, the inventory in stock might not really be inventory available. On the other hand, there may be raw material that is expected to be delivered in the near future that could also be used for satisfying the order from this prospective customer. Finally, there might even be an opportunity to charge a premium for a new order by repurposing previously committed inventory to satisfy this new order while delaying an already committed order. Of course, such decisions should be based on the cost–benefit analyses of delaying a previous order. The system should thus be able to pull real-time data about inventory, committed orders, incoming raw material, production constraints, and so on.

To support these ATP decisions, a real-time DSS was developed to find an optimal assignment of the available inventory and to support additional what-if analysis. The DSS uses a suite of mixed-integer programming models that are solved using commercial software. The company has incorporated the DSS into its enterprise resource planning system to seamlessly facilitate its use of business analytics.

Questions for Case 1.6

1. Why would reallocation of inventory from one customer to another be a major issue for discussion?
2. How could a DSS help make these decisions?

Source: M. Pajouh Foad, D. Xing, S. Hariharan, Y. Zhou, B. Balasundaram, T. Liu, & R. Sharda, R. (2013). "Available-to-Promise in Practice: An Application of Analytics in the Specialty Steel Bar Products Industry." *Interfaces, 43*(6), pp. 503–517. **http://dx.doi.org/10.1287/inte.2013.0693** (accessed September 2018).

Chapter 7)—many industry- or problem-specific analytics professions/streams have been developed. Examples of such areas are marketing analytics, retail analytics, fraud analytics, transportation analytics, health analytics, sports analytics, talent analytics, behavioral analytics, and so forth. For example, we will soon see several applications in *sports analytics*. The next section will introduce health analytics and market analytics broadly. Literally, any systematic analysis of data in a specific sector is being labeled as "(fill-in-blanks)" analytics. Although this may result in overselling the concept of analytics, the benefit is that more people in specific industries are aware of the power and potential of analytics. It also provides a focus to professionals developing and applying the concepts of analytics in a vertical sector. Although many of the techniques to develop analytics applications may be common, there are unique issues within each vertical segment that influence how the data may be collected, processed, analyzed, and the applications implemented. Thus, the differentiation of analytics based on a vertical focus is good for the overall growth of the discipline.

ANALYTICS OR DATA SCIENCE? Even as the concept of analytics is receiving more attention in industry and academic circles, another term has already been introduced and is becoming popular. The new term is *data science*. Thus, the practitioners of data science are data scientists. D. J. Patil of LinkedIn is sometimes credited with creating the term *data science*. There have been some attempts to describe the differences between data analysts and data scientists (e.g., see "Data Science Revealed," 2018) (**emc.com/collateral/about/news/emc-data-science-study-wp.pdf**). One view is that *data analyst* is just another term for professionals who were doing BI in the form of data compilation, cleaning, reporting, and perhaps some visualization. Their skill sets included Excel use, some SQL knowledge, and reporting. You would recognize those capabilities as descriptive or reporting analytics. In contrast, data scientists are responsible for predictive analysis, statistical analysis, and use of more advanced analytical tools and algorithms. They may have a deeper knowledge of algorithms and may recognize them under various labels—data mining, knowledge discovery, or machine learning. Some of these professionals may also need deeper programming knowledge to be able to write code for data cleaning/analysis in current Web-oriented languages such as Java or Python and statistical languages such as R. Many analytics professionals also need to build significant expertise in statistical modeling, experimentation, and analysis. Again, our readers should recognize that these fall under the predictive and prescriptive analytics umbrella. However, prescriptive analytics also includes more significant expertise in OR including optimization, simulation, and decision analysis. Those who cover these fields are more likely to be called *data scientists* than *analytics professionals*.

Our view is that the distinction between analytics professional and data scientist is more of a degree of technical knowledge and skill sets than functions. It may also be more of a distinction across disciplines. Computer science, statistics, and applied mathematics programs appear to prefer the data science label, reserving the analytics label for more business-oriented professionals. As another example of this, applied physics professionals have proposed using *network science* as the term for describing analytics that relate to groups of people—social networks, supply chain networks, and so forth. See **http://barabasi.com/networksciencebook/** for an evolving textbook on this topic.

Aside from a clear difference in the skill sets of professionals who only have to do descriptive/reporting analytics versus those who engage in all three types of analytics, the distinction between the two labels is fuzzy at best. We observe that graduates of our analytics programs tend to be responsible for tasks that are more in line with data science professionals (as defined by some circles) than just reporting analytics. This book is clearly aimed at introducing the capabilities and functionality of all analytics (which include data science), not just reporting analytics. From now on, we will use these terms interchangeably.

WHAT IS BIG DATA? Any book on analytics and data science has to include significant coverage of what is called **Big Data analytics**. We cover it in Chapter 9 but here is a very brief introduction. Our brains work extremely quickly and efficiently and are versatile in processing large amounts of all kinds of data: images, text, sounds, smells, and video. We process all different forms of data relatively easily. Computers, on the other hand, are still finding it hard to keep up with the pace at which data are generated, let alone analyze them quickly. This is why we have the problem of Big Data. So, what is Big Data? Simply put, Big Data refers to data that cannot be stored in a single storage unit. Big Data typically refers to data that come in many different forms: structured, unstructured, in a stream, and so forth. Major sources of such data are clickstreams from Web sites, postings on social media sites such as Facebook, and data from traffic, sensors, or weather. A Web search engine such as Google needs to search and index billions of Web pages to give you relevant search results in a fraction of a second. Although this is not done in real time, generating an index of all the Web pages on the Internet is not an easy task. Luckily for Google, it was able to solve this problem. Among other tools, it has employed Big Data analytical techniques.

There are two aspects to managing data on this scale: storing and processing. If we could purchase an extremely expensive storage solution to store all this at one place on one unit, making this unit fault tolerant would involve a major expense. An ingenious solution was proposed that involved storing these data in chunks on different machines connected by a network—putting a copy or two of this chunk in different locations on the network, both logically and physically. It was originally used at Google (then called the Google File System) and later developed and released by an Apache project as the Hadoop Distributed File System (HDFS).

However, storing these data is only half of the problem. Data are worthless if they do not provide business value, and for them to provide business value, they must be analyzed. How can such vast amounts of data be analyzed? Passing all computation to one powerful computer does not work; this scale would create a huge overhead on such a powerful computer. Another ingenious solution was proposed: Push computation to the data instead of pushing data to a computing node. This was a new paradigm and gave rise to a whole new way of processing data. This is what we know today as the MapReduce programming paradigm, which made processing Big Data a reality. MapReduce was originally developed at Google, and a subsequent version was released by the Apache project called *Hadoop MapReduce*.

Today, when we talk about storing, processing, or analyzing Big Data, HDFS and MapReduce are involved at some level. Other relevant standards and software solutions have been proposed. Although the major toolkit is available as an open source, several companies have been launched to provide training or specialized analytical hardware or software services in this space. Some examples are HortonWorks, Cloudera, and Teradata Aster.

Over the past few years, what was called Big Data changed more and more as Big Data applications appeared. The need to process data coming in at a rapid rate added velocity to the equation. An example of fast data processing is algorithmic trading. This uses electronic platforms based on algorithms for trading shares on the financial market, which operates in microseconds. The need to process different kinds of data added variety to the equation. Another example of a wide variety of data is sentiment analysis, which uses various forms of data from social media platforms and customer responses to gauge sentiments. Today, Big Data is associated with almost any kind of large data that have the characteristics of volume, velocity, and variety. As noted before, these are evolving quickly to encompass stream analytics, IoT, cloud computing, and deep learning–enabled AI. We will study these in various chapters in the book.

SECTION 1.5 REVIEW QUESTIONS

1. Define *analytics*.
2. What is descriptive analytics? What are the various tools that are employed in descriptive analytics?
3. How is descriptive analytics different from traditional reporting?
4. What is a DW? How can DW technology help enable analytics?
5. What is predictive analytics? How can organizations employ predictive analytics?
6. What is prescriptive analytics? What kinds of problems can be solved by prescriptive analytics?
7. Define *modeling* from the analytics perspective.
8. Is it a good idea to follow a hierarchy of descriptive and predictive analytics before applying prescriptive analytics?
9. How can analytics aid in objective decision making?
10. What is Big Data analytics?
11. What are the sources of Big Data?
12. What are the characteristics of Big Data?
13. What processing technique is applied to process Big Data?

1.6 ANALYTICS EXAMPLES IN SELECTED DOMAINS

You will see examples of analytics applications throughout various chapters. That is one of the primary approaches (exposure) of this book. In this section, we highlight three application areas—sports, healthcare, and retail—where there have been the most reported applications and successes.

Sports Analytics—An Exciting Frontier for Learning and Understanding Applications of Analytics

The application of analytics to business problems is a key skill, one that you will learn in this book. Many of these techniques are now being applied to improve decision making in all aspects of sports, a very hot area called *sports analytics*. It is the art and science of gathering data about athletes and teams to create insights that improve sports decisions, such as deciding which players to recruit, how much to pay them, who to play, how to train them, how to keep them healthy, and when they should be traded or retired. For teams, it involves business decisions such as ticket pricing as well as roster decisions, analysis of each competitor's strengths and weaknesses, and many game-day decisions.

Indeed, sports analytics is becoming a specialty within analytics. It is an important area because sport is a big business, generating about $145 billion in revenues each year plus an additional $100 billion in legal and $300 billion in illegal gambling, according to Price Waterhouse ("Changing the Game: Outlook for the Global Sports Market to 2015" (2015)). In 2014, only $125 million was spent on analytics (less than 0.1 percent