CHAPTER 1
Introduction: Data-Analytic Thinking

Dream no small dreams for they have no power to move the hearts of men.

—Johann Wolfgang von Goethe

The past fifteen years have seen extensive investments in business infrastructure, which have improved the ability to collect data throughout the enterprise. Virtually every aspect of business is now open to data collection and often even instrumented for data collection: operations, manufacturing, supply-chain management, customer behavior, marketing campaign performance, workflow procedures, and so on. At the same time, information is now widely available on external events such as market trends, industry news, and competitors' movements. This broad availability of data has led to increasing interest in methods for extracting useful information and knowledge from data—the realm of data science.

The Ubiquity of Data Opportunities

With vast amounts of data now available, companies in almost every industry are focused on exploiting data for competitive advantage. In the past, firms could employ teams of statisticians, modelers, and analysts to explore datasets manually, but the volume and variety of data have far outstripped the capacity of manual analysis. At the same time, computers have become far more powerful, networking has become ubiquitous, and algorithms have been developed that can connect datasets to enable broader and deeper analyses than previously possible. The convergence of these phenomena has given rise to the increasingly widespread business application of data science principles and data-mining techniques.

Probably the widest applications of data-mining techniques are in marketing for tasks such as targeted marketing, online advertising, and recommendations for cross-selling.

Data mining is used for general customer relationship management to analyze customer behavior in order to manage attrition and maximize expected customer value. The finance industry uses data mining for credit scoring and trading, and in operations via fraud detection and workforce management. Major retailers from Walmart to Amazon apply data mining throughout their businesses, from marketing to supply-chain management. Many firms have differentiated themselves strategically with data science, sometimes to the point of evolving into data mining companies.

The primary goals of this book are to help you view business problems from a data perspective and understand principles of extracting useful knowledge from data. There is a fundamental structure to data-analytic thinking, and basic principles that should be understood. There are also particular areas where intuition, creativity, common sense, and domain knowledge must be brought to bear. A data perspective will provide you with structure and principles, and this will give you a framework to systematically analyze such problems. As you get better at data-analytic thinking you will develop intuition as to how and where to apply creativity and domain knowledge.

Throughout the first two chapters of this book, we will discuss in detail various topics and techniques related to data science and data mining. The terms "data science" and "data mining" often are used interchangeably, and the former has taken a life of its own as various individuals and organizations try to capitalize on the current hype surrounding it. At a high level, *data science* is a set of fundamental principles that guide the extraction of knowledge from data. Data mining is the extraction of knowledge from data, via technologies that incorporate these principles. As a term, "data science" often is applied more broadly than the traditional use of "data mining," but data mining techniques provide some of the clearest illustrations of the principles of data science.

It is important to understand data science even if you never intend to apply it yourself. Data-analytic thinking enables you to evaluate proposals for data mining projects. For example, if an employee, a consultant, or a potential investment target proposes to improve a particular business application by extracting knowledge from data, you should be able to assess the proposal systematically and decide whether it is sound or flawed. This does not mean that you will be able to tell whether it will actually succeed—for data mining projects, that often requires trying—but you should be able to spot obvious flaws, unrealistic assumptions, and missing pieces.

Throughout the book we will describe a number of fundamental data science principles, and will illustrate each with at least one data mining technique that embodies the principle. For each principle there are usually many specific techniques that embody it, so in this book we have chosen to emphasize the basic principles in preference to specific techniques. That said, we will not make a big deal about the difference between data

science and data mining, except where it will have a substantial effect on understanding the actual concepts.

Let's examine two brief case studies of analyzing data to extract predictive patterns.

Example: Hurricane Frances

Consider an example from a *New York Times* story from 2004:

> Hurricane Frances was on its way, barreling across the Caribbean, threatening a direct hit on Florida's Atlantic coast. Residents made for higher ground, but far away, in Bentonville, Ark., executives at Wal-Mart Stores decided that the situation offered a great opportunity for one of their newest data-driven weapons … predictive technology.
>
> A week ahead of the storm's landfall, Linda M. Dillman, Wal-Mart's chief information officer, pressed her staff to come up with forecasts based on what had happened when Hurricane Charley struck several weeks earlier. Backed by the trillions of bytes' worth of shopper history that is stored in Wal-Mart's data warehouse, she felt that the company could 'start predicting what's going to happen, instead of waiting for it to happen,' as she put it. (Hays, 2004)

Consider *why* data-driven prediction might be useful in this scenario. It might be useful to predict that people in the path of the hurricane would buy more bottled water. Maybe, but this point seems a bit obvious, and why would we need data science to discover it? It might be useful to project the *amount of increase* in sales due to the hurricane, to ensure that local Wal-Marts are properly stocked. Perhaps mining the data could reveal that a particular DVD sold out in the hurricane's path—but maybe it sold out that week at Wal-Marts across the country, not just where the hurricane landing was imminent. The prediction could be somewhat useful, but is probably more general than Ms. Dillman was intending.

It would be more valuable to discover patterns due to the hurricane that were not obvious. To do this, analysts might examine the huge volume of Wal-Mart data from prior, similar situations (such as Hurricane Charley) to identify *unusual* local demand for products. From such patterns, the company might be able to anticipate unusual demand for products and rush stock to the stores ahead of the hurricane's landfall.

Indeed, that is what happened. *The New York Times* (Hays, 2004) reported that: "… the experts mined the data and found that the stores would indeed need certain products —and not just the usual flashlights. 'We didn't know in the past that strawberry Pop-Tarts increase in sales, like seven times their normal sales rate, ahead of a hurricane,' Ms. Dillman said in a recent interview. 'And the pre-hurricane top-selling item was beer.'"[1]

1. Of course! What goes better with strawberry Pop-Tarts than a nice cold beer?

Example: Predicting Customer Churn

How are such data analyses performed? Consider a second, more typical business scenario and how it might be treated from a data perspective. This problem will serve as a running example that will illuminate many of the issues raised in this book and provide a common frame of reference.

Assume you just landed a great analytical job with MegaTelCo, one of the largest telecommunication firms in the United States. They are having a major problem with customer retention in their wireless business. In the mid-Atlantic region, 20% of cell phone customers leave when their contracts expire, and it is getting increasingly difficult to acquire new customers. Since the cell phone market is now saturated, the huge growth in the wireless market has tapered off. Communications companies are now engaged in battles to attract each other's customers while retaining their own. Customers switching from one company to another is called *churn*, and it is expensive all around: one company must spend on incentives to attract a customer while another company loses revenue when the customer departs.

You have been called in to help understand the problem and to devise a solution. Attracting new customers is much more expensive than retaining existing ones, so a good deal of marketing budget is allocated to prevent churn. Marketing has already designed a special retention offer. Your task is to devise a precise, step-by-step plan for how the data science team should use MegaTelCo's vast data resources to decide which customers should be offered the special retention deal prior to the expiration of their contracts.

Think carefully about what data you might use and how they would be used. Specifically, how should MegaTelCo choose a set of customers to receive their offer in order to best reduce churn for a particular incentive budget? Answering this question is much more complicated than it may seem initially. We will return to this problem repeatedly through the book, adding sophistication to our solution as we develop an understanding of the fundamental data science concepts.

In reality, customer retention has been a major use of data mining technologies—especially in telecommunications and finance businesses. These more generally were some of the earliest and widest adopters of data mining technologies, for reasons discussed later.

Data Science, Engineering, and Data-Driven Decision Making

Data science involves principles, processes, and techniques for understanding phenomena via the (automated) analysis of data. In this book, we will view the ultimate goal

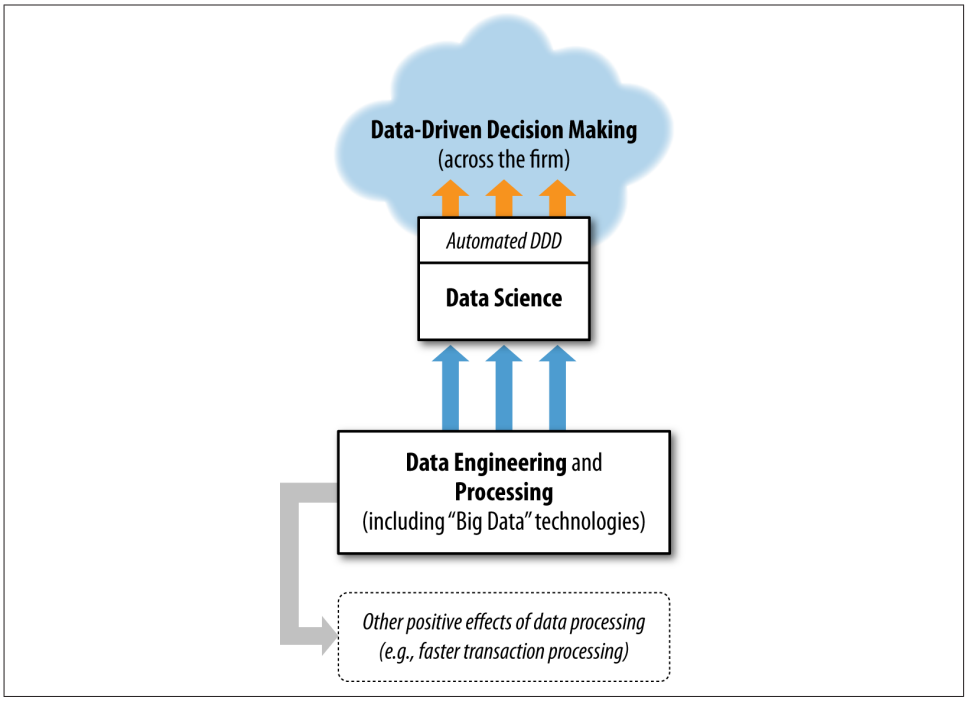

Figure 1-1. Data science in the context of various data-related processes in the organization.

of data science as improving decision making, as this generally is of direct interest to business.

Figure 1-1 places data science in the context of various other closely related and data-related processes in the organization. It distinguishes data science from other aspects of data processing that are gaining increasing attention in business. Let's start at the top.

Data-driven decision-making (DDD) refers to the practice of basing decisions on the analysis of data, rather than purely on intuition. For example, a marketer could select advertisements based purely on her long experience in the field and her eye for what will work. Or, she could base her selection on the analysis of data regarding how consumers react to different ads. She could also use a combination of these approaches. DDD is not an all-or-nothing practice, and different firms engage in DDD to greater or lesser degrees.

The benefits of data-driven decision-making have been demonstrated conclusively. Economist Erik Brynjolfsson and his colleagues from MIT and Penn's Wharton School conducted a study of how DDD affects firm performance (Brynjolfsson, Hitt, & Kim, 2011). They developed a measure of DDD that rates firms as to how strongly they use

data to make decisions across the company. They show that statistically, the more data-driven a firm is, the more productive it is—even controlling for a wide range of possible confounding factors. And the differences are not small. One standard deviation higher on the DDD scale is associated with a 4%–6% increase in productivity. DDD also is correlated with higher return on assets, return on equity, asset utilization, and market value, and the relationship seems to be causal.

The sort of decisions we will be interested in in this book mainly fall into two types: (1) decisions for which "discoveries" need to be made within data, and (2) decisions that repeat, especially at massive scale, and so decision-making can benefit from even small increases in decision-making accuracy based on data analysis. The Walmart example above illustrates a type 1 problem: Linda Dillman would like to discover knowledge that will help Walmart prepare for Hurricane Frances's imminent arrival.

In 2012, Walmart's competitor Target was in the news for a data-driven decision-making case of its own, also a type 1 problem (Duhigg, 2012). Like most retailers, Target cares about consumers' shopping habits, what drives them, and what can influence them. Consumers tend to have inertia in their habits and getting them to change is very difficult. Decision makers at Target knew, however, that the arrival of a new baby in a family is one point where people do change their shopping habits significantly. In the Target analyst's words, "As soon as we get them buying diapers from us, they're going to start buying everything else too." Most retailers know this and so they compete with each other trying to sell baby-related products to new parents. Since most birth records are public, retailers obtain information on births and send out special offers to the new parents.

However, Target wanted to get a jump on their competition. They were interested in whether they could *predict* that people *are expecting* a baby. If they could, they would gain an advantage by making offers before their competitors. Using techniques of data science, Target analyzed historical data on customers who *later* were revealed to have been pregnant, and were able to extract information that could predict which consumers were pregnant. For example, pregnant mothers often change their diets, their wardrobes, their vitamin regimens, and so on. These indicators could be extracted from historical data, assembled into predictive models, and then deployed in marketing campaigns. We will discuss predictive models in much detail as we go through the book. For the time being, it is sufficient to understand that a predictive model abstracts away most of the complexity of the world, focusing in on a particular set of indicators that correlate in some way with a quantity of interest (who will churn, or who will purchase, who is pregnant, etc.). Importantly, in both the Walmart and the Target examples, the

data analysis was not testing a simple hypothesis. Instead, the data were explored with the hope that something useful would be discovered.[2]

Our churn example illustrates a type 2 DDD problem. MegaTelCo has hundreds of millions of customers, each a candidate for defection. Tens of millions of customers have contracts expiring each month, so each one of them has an increased likelihood of defection in the near future. If we can improve our ability to estimate, for a given customer, how profitable it would be for us to focus on her, we can potentially reap large benefits by applying this ability to the millions of customers in the population. This same logic applies to many of the areas where we have seen the most intense application of data science and data mining: direct marketing, online advertising, credit scoring, financial trading, help-desk management, fraud detection, search ranking, product recommendation, and so on.

The diagram in Figure 1-1 shows data science supporting data-driven decision-making, but also overlapping with data-driven decision-making. This highlights the often overlooked fact that, increasingly, business decisions are being made *automatically* by computer systems. Different industries have adopted automatic decision-making at different rates. The finance and telecommunications industries were early adopters, largely because of their precocious development of data networks and implementation of massive-scale computing, which allowed the aggregation and modeling of data at a large scale, as well as the application of the resultant models to decision-making.

In the 1990s, automated decision-making changed the banking and consumer credit industries dramatically. In the 1990s, banks and telecommunications companies also implemented massive-scale systems for managing data-driven fraud control decisions. As retail systems were increasingly computerized, merchandising decisions were automated. Famous examples include Harrah's casinos' reward programs and the automated recommendations of Amazon and Netflix. Currently we are seeing a revolution in advertising, due in large part to a huge increase in the amount of time consumers are spending online, and the ability online to make (literally) split-second advertising decisions.

Data Processing and "Big Data"

It is important to digress here to address another point. There is a lot to data processing that is not data science—despite the impression one might get from the media. Data engineering and processing are critical to support data science, but they are more general. For example, these days many data processing skills, systems, and technologies often are mistakenly cast as data science. To understand data science and data-driven

2. Target was successful enough that this case raised ethical questions on the deployment of such techniques. Concerns of ethics and privacy are interesting and very important, but we leave their discussion for another time and place.

businesses it is important to understand the differences. Data science needs access to data and it often benefits from sophisticated data engineering that data processing technologies may facilitate, but these technologies are not data science technologies per se. They support data science, as shown in Figure 1-1, but they are useful for much more. Data processing technologies are very important for many data-oriented business tasks that do not involve extracting knowledge or data-driven decision-making, such as efficient transaction processing, modern web system processing, and online advertising campaign management.

"Big data" technologies (such as Hadoop, HBase, and MongoDB) have received considerable media attention recently. *Big data* essentially means datasets that are too large for traditional data processing systems, and therefore require new processing technologies. As with the traditional technologies, big data technologies are used for many tasks, including data engineering. Occasionally, big data technologies are actually used for *implementing* data mining techniques. However, much more often the well-known big data technologies are used for data processing *in support of* the data mining techniques and other data science activities, as represented in Figure 1-1.

Previously, we discussed Brynjolfsson's study demonstrating the benefits of data-driven decision-making. A separate study, conducted by economist Prasanna Tambe of NYU's Stern School, examined the extent to which *big data* technologies seem to help firms (Tambe, 2012). He finds that, after controlling for various possible confounding factors, using big data technologies is associated with significant additional productivity growth. Specifically, one standard deviation higher utilization of big data technologies is associated with 1%–3% higher productivity than the average firm; one standard deviation lower in terms of big data utilization is associated with 1%–3% lower productivity. This leads to potentially very large productivity differences between the firms at the extremes.

From Big Data 1.0 to Big Data 2.0

One way to think about the state of big data technologies is to draw an analogy with the business adoption of Internet technologies. In Web 1.0, businesses busied themselves with getting the basic internet technologies in place, so that they could establish a web presence, build electronic commerce capability, and improve the efficiency of their operations. We can think of ourselves as being in the era of Big Data 1.0. Firms are busying themselves with building the capabilities to process large data, largely in support of their current operations—for example, to improve efficiency.

Once firms had incorporated Web 1.0 technologies thoroughly (and in the process had driven down prices of the underlying technology) they started to look further. They began to ask what the Web could do for them, and how it could improve things they'd always done—and we entered the era of Web 2.0, where new systems and companies began taking advantage of the interactive nature of the Web. The changes brought on by this shift in thinking are pervasive; the most obvious are the incorporation of social-

networking components, and the rise of the "voice" of the individual consumer (and citizen).

We should expect a Big Data 2.0 phase to follow Big Data 1.0. Once firms have become capable of processing massive data in a flexible fashion, they should begin asking: "*What can I now do that I couldn't do before, or do better than I could do before?*" This is likely to be the golden era of data science. The principles and techniques we introduce in this book will be applied far more broadly and deeply than they are today.

It is important to note that in the Web 1.0 era some precocious companies began applying Web 2.0 ideas far ahead of the mainstream. Amazon is a prime example, incorporating the consumer's "voice" early on, in the rating of products, in product reviews (and deeper, in the rating of product reviews). Similarly, we see some companies already applying Big Data 2.0. Amazon again is a company at the forefront, providing data-driven recommendations from massive data. There are other examples as well. Online advertisers must process extremely large volumes of data (billions of ad impressions per day is not unusual) and maintain a very high throughput (real-time bidding systems make decisions in tens of milliseconds). We should look to these and similar industries for hints at advances in big data and data science that subsequently will be adopted by other industries.

Data and Data Science Capability as a Strategic Asset

The prior sections suggest one of the fundamental principles of data science: *data, and the capability to extract useful knowledge from data, should be regarded as key strategic assets.* Too many businesses regard data analytics as pertaining mainly to realizing value from some existing data, and often without careful regard to whether the business has the appropriate analytical talent. Viewing these as assets allows us to think explicitly about the extent to which one should invest in them. Often, we don't have exactly the right data to best make decisions and/or the right talent to best support making decisions from the data. Further, thinking of these as assets should lead us to the realization that they are *complementary*. The best data science team can yield little value without the appropriate data; the right data often cannot substantially improve decisions without suitable data science talent. As with all assets, it is often necessary to make investments. Building a top-notch data science team is a nontrivial undertaking, but can make a huge difference for decision-making. We will discuss strategic considerations involving data science in detail in Chapter 13. Our next case study will introduce the idea that thinking explicitly about how to invest in data assets very often pays off handsomely.

The classic story of little Signet Bank from the 1990s provides a case in point. Previously, in the 1980s, data science had transformed the business of consumer credit. Modeling the probability of default had changed the industry from personal assessment of the

likelihood of default to strategies of massive scale and market share, which brought along concomitant economies of scale. It may seem strange now, but at the time, credit cards essentially had uniform pricing, for two reasons: (1) the companies did not have adequate information systems to deal with differential pricing at massive scale, and (2) bank management believed customers would not stand for price discrimination. Around 1990, two strategic visionaries (Richard Fairbanks and Nigel Morris) realized that information technology was powerful enough that they could do more sophisticated predictive modeling—using the sort of techniques that we discuss throughout this book—and offer different terms (nowadays: pricing, credit limits, low-initial-rate balance transfers, cash back, loyalty points, and so on). These two men had no success persuading the big banks to take them on as consultants and let them try. Finally, after running out of big banks, they succeeded in garnering the interest of a small regional Virginia bank: Signet Bank. Signet Bank's management was convinced that modeling profitability, not just default probability, was the right strategy. They knew that a small proportion of customers actually account for *more than* 100% of a bank's profit from credit card operations (because the rest are break-even or money-losing). If they could model profitability, they could make better offers to the best customers and "skim the cream" of the big banks' clientele.

But Signet Bank had one really big problem in implementing this strategy. They did not have the appropriate data to model profitability with the goal of offering different terms to different customers. No one did. Since banks were offering credit with a specific set of terms and a specific default model, they had the data to model profitability (1) for the terms they actually have offered in the past, and (2) for the sort of customer who was actually offered credit (that is, those who were deemed worthy of credit by the existing model).

What could Signet Bank do? They brought into play a fundamental strategy of data science: acquire the necessary data at a cost. Once we view data as a business asset, we should think about whether and how much we are willing to invest. In Signet's case, data could be generated on the profitability of customers given different credit terms by conducting experiments. Different terms were offered at random to different customers. This may seem foolish outside the context of data-analytic thinking: you're likely to lose money! This is true. In this case, losses are the cost of data acquisition. The data-analytic thinker needs to consider whether she expects the data to have sufficient value to justify the investment.

So what happened with Signet Bank? As you might expect, when Signet began randomly offering terms to customers for data acquisition, the number of bad accounts soared. Signet went from an industry-leading "charge-off" rate (2.9% of balances went unpaid) to almost 6% charge-offs. Losses continued for a few years while the data scientists worked to build predictive models from the data, evaluate them, and deploy them to improve profit. Because the firm viewed these losses as investments in data, they persisted despite complaints from stakeholders. Eventually, Signet's credit card operation

turned around and became so profitable that it was spun off to separate it from the bank's other operations, which now were overshadowing the consumer credit success.

Fairbanks and Morris became Chairman and CEO and President and COO, and proceeded to apply data science principles throughout the business—not just customer acquisition but retention as well. When a customer calls looking for a better offer, data-driven models calculate the potential profitability of various possible actions (different offers, including sticking with the status quo), and the customer service representative's computer presents the best offers to make.

You may not have heard of little Signet Bank, but if you're reading this book you've probably heard of the spin-off: Capital One. Fairbanks and Morris's new company grew to be one of the largest credit card issuers in the industry with one of the lowest charge-off rates. In 2000, the bank was reported to be carrying out 45,000 of these "scientific tests" as they called them.[3]

Studies giving clear quantitative demonstrations of the value of a data asset are hard to find, primarily because firms are hesitant to divulge results of strategic value. One exception is a study by Martens and Provost (2011) assessing whether data on the specific transactions of a bank's consumers can improve models for deciding what product offers to make. The bank built models from data to decide whom to target with offers for different products. The investigation examined a number of different types of data and their effects on predictive performance. Sociodemographic data provide a substantial ability to model the sort of consumers that are more likely to purchase one product or another. However, sociodemographic data only go so far; after a certain volume of data, no additional advantage is conferred. In contrast, detailed data on customers' individual (anonymized) transactions improve performance substantially over just using sociodemographic data. The relationship is clear and striking and—significantly, for the point here—the predictive performance continues to improve as more data are used, increasing throughout the range investigated by Martens and Provost with no sign of abating. This has an important implication: banks with bigger data assets may have an important strategic advantage over their smaller competitors. If these trends generalize, and the banks are able to apply sophisticated analytics, banks with bigger data assets should be better able to identify the best customers for individual products. The net result will be either increased adoption of the bank's products, decreased cost of customer acquisition, or both.

The idea of data as a strategic asset is certainly not limited to Capital One, nor even to the banking industry. Amazon was able to gather data early on online customers, which has created significant switching costs: consumers find value in the rankings and recommendations that Amazon provides. Amazon therefore can retain customers more easily, and can even charge a premium (Brynjolfsson & Smith, 2000). Harrah's casinos

3. You can read more about Capital One's story (Clemons & Thatcher, 1998; McNamee 2001).

famously invested in gathering and mining data on gamblers, and moved itself from a small player in the casino business in the mid-1990s to the acquisition of Caesar's Entertainment in 2005 to become the world's largest gambling company. The huge valuation of Facebook has been credited to its vast and unique data assets (Sengupta, 2012), including both information about individuals and their likes, as well as information about the structure of the social network. Information about network structure has been shown to be important to predicting and has been shown to be remarkably helpful in building models of who will buy certain products (Hill, Provost, & Volinsky, 2006). It is clear that Facebook has a remarkable data asset; whether they have the right data science strategies to take full advantage of it is an open question.

In the book we will discuss in more detail many of the fundamental concepts behind these success stories, in exploring the principles of data mining and data-analytic thinking.

Data-Analytic Thinking

Analyzing case studies such as the churn problem improves our ability to approach problems "data-analytically." Promoting such a perspective is a primary goal of this book. When faced with a business problem, you should be able to assess whether and how data can improve performance. We will discuss a set of fundamental concepts and principles that facilitate careful thinking. We will develop frameworks to structure the analysis so that it can be done systematically.

As mentioned above, it is important to understand data science even if you never intend to do it yourself, because data analysis is now so critical to business strategy. Businesses increasingly are driven by data analytics, so there is great professional advantage in being able to interact competently with and within such businesses. Understanding the fundamental concepts, and having frameworks for organizing data-analytic thinking not only will allow one to interact competently, but will help to envision opportunities for improving data-driven decision-making, or to see data-oriented competitive threats.

Firms in many traditional industries are exploiting new and existing data resources for competitive advantage. They employ data science teams to bring advanced technologies to bear to increase revenue and to decrease costs. In addition, many new companies are being developed with data mining as a key strategic component. Facebook and Twitter, along with many other "Digital 100" companies (*Business Insider*, 2012), have high valuations due primarily to data assets they are committed to capturing or creating.[4] Increasingly, managers need to oversee analytics teams and analysis projects, marketers have to organize and understand data-driven campaigns, venture capitalists must be

4. Of course, this is not a new phenomenon. Amazon and Google are well-established companies that get tremendous value from their data assets.

able to invest wisely in businesses with substantial data assets, and business strategists must be able to devise plans that exploit data.

As a few examples, if a consultant presents a proposal to mine a data asset to improve your business, you should be able to assess whether the proposal makes sense. If a competitor announces a new data partnership, you should recognize when it may put you at a strategic disadvantage. Or, let's say you take a position with a venture firm and your first project is to assess the potential for investing in an advertising company. The founders present a convincing argument that they will realize significant value from a unique body of data they will collect, and on that basis are arguing for a substantially higher valuation. Is this reasonable? With an understanding of the fundamentals of data science you should be able to devise a few probing questions to determine whether their valuation arguments are plausible.

On a scale less grand, but probably more common, data analytics projects reach into all business units. Employees throughout these units must interact with the data science team. If these employees do not have a fundamental grounding in the principles of data-analytic thinking, they will not really understand what is happening in the business. This lack of understanding is much more damaging in data science projects than in other technical projects, because the data science is supporting improved decision-making. As we will describe in the next chapter, this requires a close interaction between the data scientists and the business people responsible for the decision-making. Firms where the business people do not understand what the data scientists are doing are at a substantial disadvantage, because they waste time and effort or, worse, because they ultimately make wrong decisions.

The need for managers with data-analytic skills

The consulting firm McKinsey and Company estimates that "there will be a shortage of talent necessary for organizations to take advantage of big data. By 2018, the United States alone could face a shortage of 140,000 to 190,000 people with deep analytical skills as well as 1.5 million managers and analysts with the know-how to use the analysis of big data to make effective decisions." (Manyika, 2011). Why 10 times as many managers and analysts than those with deep analytical skills? Surely data scientists aren't so difficult to manage that they need 10 managers! The reason is that a business can get leverage from a data science team for making better decisions in multiple areas of the business. However, as McKinsey is pointing out, the managers in those areas need to understand the fundamentals of data science to effectively get that leverage.

This Book

This book concentrates on the fundamentals of data science and data mining. These are a set of principles, concepts, and techniques that structure thinking and analysis. They allow us to understand data science processes and methods surprisingly deeply, without needing to focus in depth on the large number of specific data mining algorithms.

There are many good books covering data mining algorithms and techniques, from practical guides to mathematical and statistical treatments. This book instead focuses on the fundamental concepts and how they help us to think about problems where data mining may be brought to bear. That doesn't mean that we will ignore the data mining techniques; many algorithms are exactly the embodiment of the basic concepts. But with only a few exceptions we will not concentrate on the deep technical details of how the techniques actually work; we will try to provide just enough detail so that you will understand what the techniques do, and how they are based on the fundamental principles.

Data Mining and Data Science, Revisited

This book devotes a good deal of attention to the extraction of useful (nontrivial, hopefully actionable) patterns or models from large bodies of data (Fayyad, Piatetsky-Shapiro, & Smyth, 1996), and to the fundamental data science principles underlying such data mining. In our churn-prediction example, we would like to *take the data* on prior churn and *extract patterns*, for example patterns of behavior, *that are useful*—that can help us to predict those customers who are more likely to leave in the future, or that can help us to design better services.

The fundamental concepts of data science are drawn from many fields that study data analytics. We introduce these concepts throughout the book, but let's briefly discuss a few now to get the basic flavor. We will elaborate on all of these and more in later chapters.

Fundamental concept: *Extracting useful knowledge from data to solve business problems can be treated systematically by following a process with reasonably well-defined stages.* The Cross Industry Standard Process for Data Mining, abbreviated CRISP-DM (CRISP-DM Project, 2000), is one codification of this process. Keeping such a process in mind provides a framework to structure our thinking about data analytics problems. For example, in actual practice one repeatedly sees analytical "solutions" that are not based on careful analysis of the problem or are not carefully evaluated. Structured thinking about analytics emphasizes these often under-appreciated aspects of supporting decision-making with data. Such structured thinking also contrasts critical points where human creativity is necessary versus points where high-powered analytical tools can be brought to bear.

Fundamental concept: *From a large mass of data, information technology can be used to find informative descriptive attributes of entities of interest.* In our churn example, a customer would be an entity of interest, and each customer might be described by a large number of attributes, such as usage, customer service history, and many other factors. Which of these actually gives us information on the customer's likelihood of leaving the company when her contract expires? How much information? Sometimes this process is referred to roughly as finding variables that "correlate" with churn (we will discuss this notion precisely). A business analyst may be able to hypothesize some and test them, and there are tools to help facilitate this experimentation (see "Other Analytics Techniques and Technologies" on page 35). Alternatively, the analyst could apply information technology to automatically discover informative attributes—essentially doing large-scale automated experimentation. Further, as we will see, this concept can be applied recursively to build models to predict churn based on multiple attributes.

Fundamental concept: *If you look too hard at a set of data, you will find something—but it might not generalize beyond the data you're looking at.* This is referred to as *overfitting* a dataset. Data mining techniques can be very powerful, and the need to detect and avoid overfitting is one of the most important concepts to grasp when applying data mining to real problems. The concept of overfitting and its avoidance permeates data science processes, algorithms, and evaluation methods.

Fundamental concept: *Formulating data mining solutions and evaluating the results involves thinking carefully about the context in which they will be used.* If our goal is the extraction of potentially *useful* knowledge, how can we formulate what is useful? It depends critically on the application in question. For our churn-management example, how exactly are we going to use the patterns extracted from historical data? Should the value of the customer be taken into account in addition to the likelihood of leaving? More generally, does the pattern lead to better decisions than some reasonable alternative? How well would one have done by chance? How well would one do with a smart "default" alternative?

These are just four of the fundamental concepts of data science that we will explore. By the end of the book, we will have discussed a dozen such fundamental concepts in detail, and will have illustrated how they help us to structure data-analytic thinking and to understand data mining techniques and algorithms, as well as data science applications, quite generally.

Chemistry Is Not About Test Tubes: Data Science Versus the Work of the Data Scientist

Before proceeding, we should briefly revisit the engineering side of data science. At the time of this writing, discussions of data science commonly mention not just analytical skills and techniques for understanding data but popular tools used. Definitions of data

scientists (and advertisements for positions) specify not just areas of expertise but also specific programming languages and tools. It is common to see job advertisements mentioning data mining techniques (e.g., random forests, support vector machines), specific application areas (recommendation systems, ad placement optimization), alongside popular software tools for processing big data (Hadoop, MongoDB). There is often little distinction between the science and the technology for dealing with large datasets.

We must point out that data science, like computer science, is a young field. The particular concerns of data science are fairly new and general principles are just beginning to emerge. The state of data science may be likened to that of chemistry in the mid-19th century, when theories and general principles were being formulated and the field was largely experimental. Every good chemist had to be a competent lab technician. Similarly, it is hard to imagine a working data scientist who is not proficient with certain sorts of software tools.

Having said this, this book focuses on the science and not on the technology. You will not find instructions here on how best to run massive data mining jobs on Hadoop clusters, or even what Hadoop is or why you might want to learn about it.[5] We focus here on the general principles of data science that have emerged. In 10 years' time the predominant technologies will likely have changed or advanced enough that a discussion here would be obsolete, while the general principles are the same as they were 20 years ago, and likely will change little over the coming decades.

Summary

This book is about the extraction of useful information and knowledge from large volumes of data, in order to improve business decision-making. As the massive collection of data has spread through just about every industry sector and business unit, so have the opportunities for mining the data. Underlying the extensive body of techniques for mining data is a much smaller set of fundamental concepts comprising *data science*. These concepts are general and encapsulate much of the essence of data mining and business analytics.

Success in today's data-oriented business environment requires being able to think about how these fundamental concepts apply to particular business problems—to think data-analytically. For example, in this chapter we discussed the principle that data should be thought of as a business asset, and once we are thinking in this direction we start to ask whether (and how much) we should invest in data. Thus, an understanding of these fundamental concepts is important not only for data scientists themselves, but for any-

5. OK: Hadoop is a widely used open source architecture for doing highly parallelizable computations. It is one of the current "big data" technologies for processing massive datasets that exceed the capacity of relational database systems. Hadoop is based on the MapReduce parallel processing framework introduced by Google.

one working with data scientists, employing data scientists, investing in data-heavy ventures, or directing the application of analytics in an organization.

Thinking data-analytically is aided by conceptual frameworks discussed throughout the book. For example, the automated extraction of patterns from data is a process with well-defined stages, which are the subject of the next chapter. Understanding the process and the stages helps to structure our data-analytic thinking, and to make it more systematic and therefore less prone to errors and omissions.

There is convincing evidence that data-driven decision-making and big data technologies substantially improve business performance. Data science supports data-driven decision-making—and sometimes conducts such decision-making automatically—and depends upon technologies for "big data" storage and engineering, but its principles are separate. The data science principles we discuss in this book also differ from, and are complementary to, other important technologies, such as statistical hypothesis testing and database querying (which have their own books and classes). The next chapter describes some of these differences in more detail.