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CHAPTER SEVEN

Working with Quants

From ***Keeping Up with the Quants****: Your Guide to Understanding and Using Analytics*

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Working with Quants

Since this book is for non-quants, we thought it would be useful to describe how you can best deal with analytical professionals and data scientists. Even though you will have learned a lot by reading this book and by doing some of the knowledge-building activities suggested in the previous chapter, it won't be enough for you to do sophisticated analytics by yourself. You'll have to occasionally work with specialists in quantitative fields. Quantitative analysts and data scientists often have PhDs or master's degrees in quantitative fields like statistics, math, and even physics. That tells you something about the level of quant skills necessary to do serious work.

What we are primarily describing in this chapter is a set of relationships between three sets of players:

- Business or organizational decision makers
- Business professionals or team members
- Quantitative analysts or data scientists

Our assumption in this book is that you are in one of the first two categories and need to work closely with people in the third category. If you are in the third category, you may also find this chapter useful, as it will give you some guidance as to how to work effectively with non-quants.

There is a good reason for a mutual accommodation of these three groups, rather than one of them turning things over fully to another. We are, if you haven't noticed this far in the book, big advocates of analytics and data as a basis for decision making. However, intuition and experience are still important decision resources for many executives. They can lead to bias in decisions, but they are undeniably helpful in establishing the appropriate financial metrics, proposing crucial "what-if" business scenarios, and setting the conditions for which analytical models are relevant.

The goal, then, is to make analytical decisions while preserving the role of the executive's gut. Few executives are skilled at both analytics and intuition. This means that they will need to work closely with quantitative analysts if they are going to be effective decision makers. In fact, we would argue that the quality of relationships between executives and their quantitatively oriented advisers is a key factor in effective decision making.

As Karl Kempf, an Intel Fellow (one of those roles for distinguished scientific types who have earned a lot of autonomy in their work) who heads a decision engineering group at the company puts it, effective quantitative decisions "are not about the math; they're about the relationships."[1] This is a notable statement from Kempf, who is known informally around Intel as the "UberQuant" and the "Chief Mathematician." If someone referred to as the Chief Mathematician declares that it's not about the math, we should pay attention.

Kempf has observed that the mathematical and statistical algorithms that quantitative analysts apply when performing analytics can be very simple or staggeringly complex. But in all cases the algorithms have resulted from the very careful work of very smart people over decades (or centuries, as we have noted in some of our examples) and have been checked, cross-checked, and dissected over and over by other very smart people.

The math works, but the human side of these decisions is typically much less refined. Organizations that maintain quantitative analyst groups—and all should in this analytical age—need to carefully address the types of analysts they hire and the roles they play relative to executives. Analysts with the right combination of skills are likely to be in short supply. In addition, executives need to change their expectations of, and relationships with, analysts. Finally, the methods and tools that such quantitative groups employ need to be expanded and refined to seamlessly integrate with how people and organizations really make decisions.

Business-Quant Relationships in Decision Engineering at Intel

Karl Kempf and his analytical team at Intel have observed firsthand many of the lessons we describe in this section. The group is highly focused on relationships between analysts and decision makers. It strives to find ways to build mutual respect—to get the business decision maker to have a little interest and respect for the skills of the quantitative analyst, and to get the math person to have a big interest and a lot of respect for the insights of the business decision maker. The asymmetry in the relationship is intentional. While it is good for the business decision maker to get a bit of a feel for the math, Kempf and his group feel it is absolutely vital for the math person to get as deep an understanding of the intuition of the business person as possible. This does not equate to the decision maker becoming a math expert, but it may equate to the math person becoming a business expert.

While the math person can never fully understand the origins of the business intuition—by definition—the math person must understand what the intuition is and speak the language of the business person. Intel's approach is to send one of its "math people" off into the business—at least to listen, learn, and after a suitable time, ask questions. At most, the analyst can be trained, as a new hire would be, to participate in the business process. In both cases the mission is to understand the formal and informal organization, how the group is incentivized and rewarded, and so forth.

Kempf judges the low bar for success as when the math person thinks he or she understands the business problem. The high bar is when the business person thinks the math person understands the business problem. This generally builds some business respect for the math person ("first time anyone has actually come and spent time to understand our problems—this person is genuinely interested in helping us"), and very often builds some math respect for the business person ("not as easy as I thought it would be—this guy is actually pretty clever").

Assuming the greatest advocate of employing analytics made it possible for the math person to temporarily observe or join the business group, a useful side goal here is to identify and engage the biggest naysayers in the group. In the worst case they may be right, and it can't be done; in the best case you already know the most important candidates to critique demonstrations of results or solutions. Anne Robinson, who has led an analytics group at Cisco Systems and now does so at Verizon Wireless, also emphasizes the importance of incorporating skeptics into the list of stakeholders. "They keep you honest and keep the team high-performing," she says. “If you can convince them, you can convince anybody.” (We describe an example of Anne’s work at Cisco at the end of this chapter.)

At Intel, the next step in the relationship is for decision makers and quants to collaborate to build the basic model. The key quant person drives these brainstorms to elicit inputs (data elements, sources of data, ideas for detecting and fixing bad data), outputs (what solution slices and dices are most desirable, what display methods are most intuitively satisfying to the intended business users), what are the key variables, and what are the key relationships between variables.

Again, in such exercises, the business person doesn’t have to understand, for example, hyperbolic partial differential equations, but at minimum there has to be a diagram on the white board setting out such questions as:

- Since A and X are related, if A goes up, in what direction does X go?
- What are the highest and lowest values key variable B can take?
- If there is a time lag between cause Y and effect Q, how long might it be?

As with any other type of model, a few concrete examples (historical or made up) are extremely useful to step through in structuring the basic model. In this exercise, the quant must listen carefully, ask clarifying questions, and absorb as much of the knowledge of the business decision maker as possible. This is as much about relationship building as it is model building.

At this point the quant team should be ready to spring into action. It needs to select the right math approach, formalize the model so it can be represented in the computer, collect the data, and get it into the computer. The analyst can then test the model by performing sensitivity analysis on variables and relationships, and trying alternatives. When the business decision maker can supply some test problems, the analyst can begin to detect biases in the perceptions of either the decision maker or the analyst and adjust the model appropriately. The most important aspect of this stage is to get a prototype to run as soon as possible and show it to the intended users for feedback. It is usually a good idea to do a couple of rounds of this with different people from the business to test the completeness of the model and the consensus of the business team.

The model and the system are then refined based on feedback and redemonstrated. In other words, it's important to fail early and often. At each round, there will be things the quant forgot, misunderstood, or simply got wrong; and things the business decision makers forget to say, said but don't like now that they see it, and so forth. Whether the project is a one-shot analysis or ongoing use of an analysis tool, success on the problem generally builds success in the relationship. The business decision maker probably needs to have some faith at first, but if things go well, that is quickly replaced by credibility based on experience. The development of mutual trust, respect, and understanding takes effort and time—especially from the analyst, because the business person doesn't have that much time to invest. It is often the case that an initial successful relationship leads to a sequence of powerful analyses and support tools as well as deepening trust and understanding.

The ROI of Combining Art and Science at Intel

The approach just described has been developed and continuously improved over twenty-plus years of projects covering the analytics spectrum at Intel, and it has yielded considerable benefits. Initial work focused on manufacturing, including factory design, construction, ramp-up, and operations. Problems analyzed and decision policies implemented spanned problems from determining machine quantities and layout to managing work-in-progress and equipment maintenance.

A second major body of analytics work focused on integrated production, inventory, and logistics planning across Intel's factory network. With production facilities in the United States, Costa Rica, Ireland, Israel, China, Malaysia, and most recently Vietnam—all operating 24/365—analytics in the factories spanned not only time zones but also cultures and languages.

Subsequent projects looked upstream and downstream in the supply chain. Projects on contract structures for equipment and materials focused on win-win relationships with suppliers and optimizing Intel's agility. Demand forecasting and finished product positioning projects focused on service to customers and containing supply chain costs. These systems continue to be in active use, or have been upgraded by second- and third-generation analysis systems and decision policies. Work has most recently spread into Intel's extensive product development organizations. The decision-engineering analysts are now building relationships with senior business personnel with intuition and experience about future products. Their recent analysis projects run from selecting features for future products to playing out product roadmap scenarios to allocating critical engineering resources to project portfolio management.

These projects and their impact garnered Intel the 2009 Institute for Operations Research and the Management Sciences prize for "repeatedly applied the principles of operations research and the management sciences in pioneering, varied, novel, and lasting ways." In accepting the award, Intel's then chairman of the board Craig Barrett credited the application of advanced analytics with enhancing competitiveness for the previous two decades adding billions (that's with a *b*) of dollars to the bottom line.

Your Analytical Responsibilities

If analytical problem solving is going to take place successfully, there are some specific responsibilities for both quantitative analysts and business decision makers (you). We have spent much of this book describing what quants do and how you can understand their data and reports better. Now it's time to address the analytical roles that businesspeople must play, whether they are mathematically focused or not (see "What Quantitative Analysts Should Expect of Business Decision Makers").

What Quantitative Analysts Should Expect of Business Decision Makers

As a business decision maker, you should:

- Give the analysts enough of your time and attention to ensure that they understand the problem from your perspective
- Make available the time and attention of people within your organization who can help them understand the details of the business situation
- Have a firm understanding of the time and money necessary to build the solution, and jointly agree on this as a proposal
- Learn enough about the underlying math and statistics to have a general idea of how the model works and when it might be invalid
- Politely push back if you don't understand something, and ask for a different or better explanation
- Attend all relevant briefings, demonstrations, and launch meetings
- Let your employees know that using the new model effectively is important to your success, and to theirs

Learning Something About Math and Statistics

In chapter 6, we suggested various ways that businesspeople can learn about statistics. We think that this responsibility extends to businesspeople at every level, including senior executive decision makers. Why? In this data-intensive society and business culture, you simply can't understand how data and analytics can be applied to decision making without some mathematical sophistication.

Those who lack understanding can get into trouble easily, as the Joe Cassano example at AIG Financial Products in chapter 1 illustrates. Many businesses increasingly use statistical and mathematical models in their business operations. Therefore, a key principle is that managers shouldn't build analytical models into their businesses that they don't understand. As Yale economist Robert Shiller puts it (in the context of explaining some of the reasons for the 2008–2009 financial crisis, which he anticipated), "You have to be a quantitative person if you're managing a company. The quantitative details really matter."[2]

Some organizations insist on a familiarity with math and models. Ed Clark, the CEO of TD Bank Group, who has a PhD in economics from Harvard, avoided the problems that many US banks encountered in the financial crisis. He reflected on the problem at other banks in the *Toronto Star:* "What I found frightening was, when I talked to my counterparts in the area [of structured products], I gradually realized that they didn't understand what these products actually were. They had never sat down and gone through the mathematics of the individual products. It's partly because they were delegating too far down in their organizations the understanding of these products."[3]

As all industries become more data oriented and analytical, it is incumbent upon senior executives to master some degree of analytical complexity. Otherwise, they're not going to be able to push back when some trader suggests that they take on inordinate and poorly understood risk, or when a marketer suggests a predictive model that employs too much customer data. Otherwise, they're putting their institutions and their customers in great jeopardy.

Some of the concepts that any executive needs to understand include:

- Measures of central tendency (mean, median, mode)
- Probability and distributions
- Sampling
- The basics of correlation and regression analysis
- The rudiments of experimental design
- The interpretation of visual analytics

The methods for acquiring this knowledge can be the same as for more junior personnel, except that senior executives may have the resources to bring in professors or consultants for sessions with groups of executives, or even private one-on-one tutoring.

Understanding and Questioning Assumptions

We've already mentioned statistician George Box's famous quote, "All models are wrong, but some are useful." We mentioned at the time that it's important to know when they no longer become useful. That is generally when the assumptions built into the model—and all models have them—are no longer correct or valid. The world is always changing, and the job of the skeptical executive is to determine whether it has changed in ways that call the model into question. Here are some examples of assumptions in quantitative models that have actually been used by organizations:

- The customer's willingness to buy a product at a certain price (known as a price elasticity model) hasn't changed, even though the economy has deteriorated.

- The customer sample on which we tested various versions of Web pages several years ago is similar in their preferences to the customers we have today.
- The predictive model we created on mortgage holders' likelihood of default when housing prices were going up still holds when prices are declining (obviously, this one is somewhat problematic).
- The likelihood that a hurricane will hit a region of southern Florida hasn't gone up, even though we seem to be experiencing some degree of global climate change.
- A landline telephone number still provides a valid sample for a political poll, even though many people no longer have them (as we've suggested, this one is also problematic).

Not all of these assumptions were invalid. In fact, since almost all models are based on data from the past (remember, it's hard to get good data about the future), they make the assumption that the future is going to be like the past in most respects. And those models are very often valid for long periods of time. As Charles Duhigg has noted in a recent book, *The Power of Habit,* human behavior, once established, can be remarkably persistent over time.[4] That allows us to magically predict the future on the basis of the past.

Some organizations utilize high-priced talent just to ask penetrating questions about assumptions. Take Larry Summers, for example. The former economic adviser to the Clinton and Obama adminstrations and former president of Harvard University has worked as an adviser to D.E. Shaw, a quantitative hedge fund. Tom ran into Summers at a social occasion and asked him what he did for the company. He said, "I go in once a week and walk around the desks of the quants who build mathematical trading models. I ask them what the assumptions are behind their models, and under what circumstances they would be violated. You would be surprised how often they can't give me a clear answer." Summers was reportedly paid $5 million for playing this role, so it must have been perceived as valuable.

You too can act like Larry Summers. If someone presents you with a model, you can always look smart by asking what the assumptions are behind the model and what the conditions are that would invalidate them. If the reply is overly technical, keep pursuing the issue of how the world would have to change for the model to be no longer useful.

Push Back When You Don't Understand

The last point in the previous section can be generalized; it's important to push back when you don't understand. The most important form of pushing back is to request data and analysis, rather than anecdote or opinion. As Gary Loveman, CEO of Caesars Entertainment put it, "It is not my job to have all the answers, but it is my job to ask lots of penetrating, disturbing, and occasionally almost offensive questions as part of the analytic process that leads to insight and refinement."[5]

The specific types of questions that simply encourage greater use of analytics might go like this:

- "Did you forget your data?"
- "How do you think that hypothesis could be tested with data?"
- "Have you thought about an empirical analysis of that idea?"
- "We have about XX customers. Have you tried this out on any of them?"
- "Maybe you could consider a small but rigorous experiment on that concept."

You get the idea. If enough people around an organization constantly ask questions of this type, the culture will change quickly and dramatically.

Quantitative people will often attempt to describe models and problems in highly technical terms. That doesn't mean you have to listen or converse in the same terms. As a good illustration, the movie *Margin Call* dramatizes some of the events that led to the financial crisis of 2008–2009. The movie is based on an investment bank that resembles Lehman Brothers. The quant character in the plot, who has a PhD in propulsion engineering, comes up with a new algorithm for calculating the bank's exposure to risk. When he shows the algorithm to the head of trading, played by Kevin Spacey, the blustery trading czar says, "You know I can't read these things. Just speak to me in English."[6] Every manager should be similarly demanding.[7]

Liam Fahey, a marketing and strategy professor, has described in an article in *Strategy and Leadership* the roles of executives in making analytics work through a series of recommended questions.[8] They're a good summary of the topic of what to expect from executives. Here are the overall questions he recommends that executives ask:

- What business issue or need is the analytics work intended to inform?
- What are the core insights relevant to understanding the business issue and its context?
- How can I leverage these insights in the work I do?
- How do the insights affect decisions confronting us now?
- How do the insights help shape emerging and future decisions?

When preliminary findings begin to emerge, executives should ask:

- What is surprising about this finding?
- Can you do further analysis to strengthen or refute the finding?
- Should we get others involved to challenge this emerging finding?
- Is there a significant insight emerging here?
- If the finding holds up, how should it affect my thinking on this or other topics or issues?

For each new insight, executives should ask:

- What is new in each insight?
- What was the old understanding?
- How significant is the difference?
- What is the reasoning or "argument" that connects the data set to the insight?

After the insights have been delivered, executives should ask:

- Who was/is involved in shaping the new understanding?
- How might they have influenced the outcome?
- What might be the principal differences across individuals or units?

If you as an executive ask all these questions, you will be much more engaged in the analytical work, and the analysts will perceive you as being interested and knowledgeable. And if the analysts can answer them all clearly, they're doing a good job too!

What Should You Expect of Analytical Professionals?

Having spent some time describing the responsibilities of business decision makers in solving quantitative problems, it makes sense to also describe what analytical professionals need to do in order to meet the decision makers (more than) halfway. We've summarized these activities in "What Business Decision Makers Should Expect of Quantitative Analysts."

They Will Learn Your Business and Be Interested in Business Problems

Some quantitative analysts are primarily interested in quantitative methods and analysis itself, rather than the business problem to be solved. This is partly a function of our educational system, which tends to teach math and statistics in a relatively context-free format. But if quants don't focus on the business problem, they won't be able to solve it effectively or provide much value to decision makers.

The most important time to ensure that an analyst is interested in solving business problems is at the point of hiring and recruiting. Once he or she has been hired, it may be hard to bring about change. Anne Robinson, the head of an analytics group at Verizon Wireless, for example, asks any recruit to describe a specific business problem that he or she has addressed in the past, and what was interesting about it. Karl Kempf at Intel asks similar questions. If the recruit is stuck for an answer to that question—and both Robinson and Kempf report that many are, unfortunately—that person doesn't get hired.

They Will Talk in Business Terms

We've discussed this more than once throughout the book, and it's not an easy thing to do. But quantitative professionals need to learn how to translate their analysis approaches and findings into business

What Business Decision Makers Should Expect of Quantitative Analysts

If you're a business executive who is working with quantitative analysts, here's what you should legitimately expect of them:

- They should have a good working understanding of your business overall, and of the specific business process that the quantitative analysis will support.
- They should understand your thinking style and the types of analyses and outputs that will influence your thinking.
- They should be able to develop effective working relationships with key people in your organization.
- They should use the language of your business to explain what benefits and improvements analytics can provide.
- They should provide you with an accurate estimate of the time and cost to develop a model and related capabilities.
- If you don't understand what they're proposing to do, or you're skeptical of the benefits they predict, they should be patient and try again with different language.
- They should have a structured process for eliciting the information and business rules they need to build their model.
- They should help you think about such broad aspects of the problem as the framing of the decision involved, the stakeholders for it, and the organizational capabilities necessary to implement a new solution.
- Unless there is an important reason to do otherwise, new models and tool sets should be developed with a rapid prototyping

approach, so you see something of substance very quickly and can provide feedback on it.

- They should iterate and improve the model until it meets your performance specifications.
- They should agree on a timeframe during which you will review the model, and explain to you what you should look for as signs that the model isn't working well and needs to be revisited.

terms. In many cases, that will mean using terminology with which business professionals are familiar—lift, ROI, customer behavior, money saved and earned. Talking about money all the time may strike some as a bit mercenary, but it is the language of business. In a government agency or nonprofit organization, there are usually translations that fit that context involving citizens, constituents, and budgets.

Patrick Moore, who heads a commercial analytics group at Merck (there is an example of his group's work at the end of the chapter), says that he tries to follow three rules of thumb when explaining analytical results in order to help his clients make better business decisions:

- Avoid the idea that the analysis is a "black box." That will make the client want to avoid it. So he tries to be very transparent.
- Convey the impression to business customers that the appropriate data has been looked at using appropriate methods; in other words, he and his analysts try to be and to appear confident that they have done the right thing analytically.

- Provide the client with "sound bites" or "thumbnails" of the results that they can use to turn around and communicate to their leadership.

Moore's group also makes extensive use of graphics displays to communicate, for example, the relative importance of different variables in a model. Even if clients don't fully understand the metric or statistic being used, they can grasp the relative importance of factors in a bar chart.

They Will Explain Any Technical Language

There may be times when quants will need to use some degree of technical language to explain what they have done. Even if that's true, quants should be ready with an explanation of what it means in English, and that means not being caught off guard. If there is a type of analytical tool or method that is used frequently, the quants in your organization may want to meet with colleagues and together determine a way to explain it in straightforward, clear wording. Of course, for relatively simple analyses—those involving a couple of variables—visual analytics are a powerful way to explain relationships within data.

They Are Willing to Develop a Relationship

As we mentioned earlier in this chapter, better decisions are not about the math, but about the relationships. If your quants don't want a relationship with businesspeople, perhaps they should go back to being an astrophysicist, forest ranger, or some other solitary profession, rather than being quantitative analysts in business.

This is easy to say, but it is true that many quants have historically preferred numbers to people. However, if you search for and interview for people-oriented quants and recruit at business-oriented analytics programs (such as the one at North Carolina State described in chapter 6), you can address this problem.

They Won't Make You Feel Stupid

We've seen a number of organizations in which quantitative people seemed to delight in making "normal" businesspeople feel stupid. They would say things like, "Surely you know what regression analysis is?" or, "I'm sorry, a chi-square test is just too elementary for me to have to explain." Some "heavy quants" (as one organization classified its more quantitatively sophisticated employees) even lorded it over the "light quants" in the same company.

Of course, this behavior is unacceptable and highly damaging to effective problem solving. However, like much bad behavior, we think it is often the result of people not feeling respected. In organizations where quants are intimately engaged in the business process and highly respected by decision makers, they tend to be wonderful people to work with. In organizations that somehow hired quantitative analysts but ignore them when important decisions come along, the nasty attitudes we've described often pop up. Quants, like most other people, respect others when they are respected.

Analytical Thinking Example: Demand Forecasting at Cisco

Forecasting customer demand is a problem for many firms, particularly in manufacturing.[9] It is a particularly important issue for Cisco Systems, the market-leading provider of telecommunications equipment. The company has a very complex global supply chain, and doesn't manufacture most of the products it sells. As Kevin Harrington, vice president of global business operations in Cisco's Customer

Value Chain Management organization put it: "Forecasting customer demand is, of course, a central part of supply chain management and a critical enabler of lean manufacturing. This discipline becomes ever more challenging in times like our own characterized by rapid changes in the macro-economy and volatile swings in supply and demand. In fact, Cisco's need to write off some unused inventory [$2.25 billion worth] after the dotcom bust in 2001 provided some of the impetus for the larger transformation of our value chain."[10]

The resulting project is a good illustration not only of analytical thinking, but of good relationships between quantitative analysts and business decision makers.

PROBLEM RECOGNITION AND FRAMING. The problem for Cisco was simply to create a better forecast of demand across more than ten thousand different products. Managers in various parts of the company, including Sales, Marketing, and Finance, already created a "consensus forecast" using a combination of intuition and extrapolation of previous demand trends. But Karl Braitberg, Cisco's vice president of Demand Management and Planning, felt that a statistical forecast based on known booking and historical demand patterns would make a good "second opinion" for the human-derived consensus forecast, which can be affected by excessive marketing enthusiasm. He commissioned Anne Robinson, senior manager of Analytical Forecasting and Modeling, and her six-person team to try to develop a statistical forecast. Robinson realized that in order to be successful, she needed not only to create a high-quality forecast model, but also to get Cisco management to buy into and use the statistical forecasts. So she identified the key stakeholders for the model, and employed an "agile" model development process in which progressively capable outputs would be delivered at a regular frequency over the eighteen months of the project. At each output delivery step, she would show the results to stakeholders, educate them about the workings of the model, and—she hoped—get their buy-in for using it.

REVIEW OF PREVIOUS FINDINGS. There are a variety of approaches to statistical forecasting. Previous findings suggest that the best results are achieved through a combination of approaches to forecasting—an approach called *ensemble forecasting*. Robinson knew from her research and investigation that the ensemble approach offered potential, so she made sure that any forecasting tools her team explored had that capability.

MODELING (VARIABLE SELECTION). The key variables in the model would likely be current order levels and historical demand. These variables are commonly used in forecasting processes across industries.

DATA COLLECTION (MEASUREMENT). While the variables to be used were clear from the beginning, there were various diverse sources of current orders, and the different sources had to be evaluated to determine the data that was most valuable for the model. For example, Cisco tracks customer orders by industry segments, customer size segments, geographical area, and actual customer shipments. The data don't always add up perfectly. Fortunately, all the possible data sources were present in a preexisting enterprise data warehouse. However, Robinson's team also needed to create some new metrics of customer-centric demand fulfillment that became drivers of what it meant to be customer-centric throughout the Cisco supply chain.

DATA ANALYSIS. Statisical forecasting leads to a predicted range of demand, with a confidence interval for each range estimate. It might suggest, for example, that the monthly demand for a particular router would be between three thousand and thirty-five hundred units, with a 95 percent chance that the actual demand would be within that range. The "agile" approach to developing the model dictated a series of steps, each taking two to three months, to show that a successful model was possible and that it could scale to deal with the number and variability of Cisco's products. Some of the steps involved:

- Selecting a tool that fit the requirements (Cisco selected the SAS Forecast Server, which offers support for ensemble models)
- Determining whether statistical models could achieve better forecast accuracy than the consensus forecasts, and it did that
- Tuning the models to increase their accuracy
- Determining whether the forecasting approach could scale to thousands of products in three hundred product families (it could)
- Automating the models (it would be far too labor intensive for humans to run them, but Cisco managers and experts can still override them if necessary)

At each step, there was a stakeholder review, which built commitment to the new approach throughout the process.

RESULTS PRESENTATION AND ACTION. The statistical forecasting approach now produces weekly forecast ranges for more than eighteen thousand products over a twenty-four-month time horizon. Using the combination of the statistical and consensus forecasts, forecast accuracy has been improved by 12 percent on average. According to Kevin Harrington, the project was a success:

> The results include better forecast accuracy, increased inventory turns and an overall improvement in supply demand balancing that has paid off for both Cisco and our customers in the form of reduced excess inventory and faster, more reliable service. During the worst of the recent economic downturn, Cisco was able to reduce inventory in the supply chain without write-offs or a fall-off in customer service. Today, our statistical forecasting experts are working to further refine the entire process and manage the increased demand caused by the global economic recovery.[11]

In addition to the results that Harrington describes, Robinson notes that now managers at Cisco are comfortable with using ranges and probabilities to describe demand. They expect to see ranges rather than point (single number) forecasts, and talk about ranges in every important conversation. In short, the culture of forecasting at Cisco has changed dramatically in a more analytical direction.

Throughout the project, Robinson attempted to engage the entire forecasting community in the new analytical process. She went through a structured brainstorming process with stakeholders to help identify new customer-centric metrics. She had panel discussions with larger audiences, road shows for various groups, and a "Forecasting 101" presentation that she gave many times. She created visuals to display the results of the model, and encouraged her team to "tell a story with data" from the results. Robinson also built a close partnership with Cisco's IT organization, and she noted that at times it was difficult to distinguish between the tasks of her team and the tasks of IT people.

Analytical Thinking Example: Optimizing the Sales Force at Merck

Identifying the ideal size for a sales force at a major pharmaceutical company like Merck is a difficult analytical task. New products are introduced regularly, increasing demand and the need for salespeople; existing products go off patent, which reduces demand and the need for salespeople. There is no history of demand for new products, so it's impossible to know just how to predict sales force needs exactly.

Many pharmaceutical companies employ external consultants for sales force sizing. However, when Paul Kallukaran, a quantitative PhD with experience in analyzing pharmaceutical sales data, joined the Commercial Analytics team, Merck executives decided to do the analysis in-house.

PROBLEM RECOGNITION AND FRAMING. With certain drugs coming off patent and other drugs entering the sales cycle, what should the optimal size of the sales force be? The sales force is not monolithic, but rather segmented by the brand and geography. So the problem was not to size the sales force overall, but rather to size it for each region and brand.

REVIEW OF PREVIOUS FINDINGS. Given that consulting firms offer sales force sizing services, there is some literature on it. Kallukaran's previous job was not directly in the area, but he had looked at approaches other firms had used. However, they tended to be "black box" oriented from the standpoint of sales and marketing decision makers, and Kallukaran and Patrick Moore, the head of Commercial Analytics, disliked that aspect. In the past, different groups at Merck had used different consultants and different methods for sales force sizing; this was the first time one central approach had been employed.

MODELING (VARIABLE SELECTION). Kallukaran decided to use multiple methods to determine the optimal sales force size. In addition to doing it the traditional way with statistical models, he and his team employed a more granular approach by trying to understand what it took to serve each customer. They asked the sales force about their activities with physician customers, and determined the likely workload for each one. They also computed various product forecasts and created nonlinear response models of sales force promotion and the likely change in physician prescribing as a result. They analyzed the impact of the sales force versus other factors that affect physician prescribing behaviors, including habit, brand equity, and pull by patients. The analysts also looked at patient-level data to understand adherence patterns over time; many patients exhibit significant drop-off in usage over time, which affects long-term sales of a drug. Finally, they employed an integer optimization model to optimize resources for each physician for each product for each of hundreds of territories.

DATA COLLECTION. The pharmaceuticals industry generally gets physician prescribing data from third-party syndicators, and Merck had that data. But the sales force activity model in the project required surveying salespeople on their sales behaviors and times with customers. They had to maintain the trust of the sales force—that is, survey them in a way that it didn't look like a downsizing exercise—so that salespeople wouldn't feel that their own jobs were threatened and would provide accurate answers.

DATA ANALYSIS. As we noted, the complex exercise involved a variety of analytical approaches, including integer optimization and nonparametric (not assuming a particular type of data distribution) models that computed response curves for each product segment on the basis of historical promotion responses. Since the project involved running models for each brand and territory, computing the whole model initially took sixteen hours. But Kallukaran's group wanted a faster response time, so they split the problem across hundreds of surplus laptop computers. Each laptop computed the model for a particular territory. With all that computing horsepower on tap, the entire model could be run in twenty minutes.

RESULTS PRESENTATION AND ACTION. While this was a new approach to the sales force sizing problem at Merck, it was not entirely unfamiliar to internal clients—which made it easier to get them to adopt the model and act on the results. On the sales side, the VP of Strategic Planning had an analytical orientation, and exposure to what consultants had done in this area in the past. On the marketing side, analysts had previously done models of promotion response, but they didn't get used. Someone always complained that the model lacked this piece or that; the perfect had become the enemy of the good. With the sales force sizing project, Kallukaran encouraged the marketing clients to "use what we have." He initially worked with one of the smaller brand teams first and showed why the new approach was better than the more intuitive decision approach they were using before. He contrasted that intuitive method with what data and analytics would tell them, but didn't try to impose the model-based approach on them. "Take it as just another input to your decision," he would say. The efforts to persuade different groups to use the model were aided by the consistent approach across the company. Merck's president at the time liked the idea of being able to compare different brand team needs so that he could more easily evaluate their requests for resources. Over time, almost all groups at Merck adopted the model. Kallukaran's analytics team also was getting requests to recompute the model whenever there was a vacancy in a particular territory, and territory managers had been given more autonomy and profit-and-loss responsibility. So the team, which included system developers, created an "analytical app" that tells a sales manager whether to fill a vacancy or not. It has been widely used and allows local decision making without putting heavy demands on Kallukaran's central group.

Final Thoughts on Analytical Thinking

By this point—effectively the end of the book unless you really enjoy perusing footnotes—we hope to have convinced you of a number of things. First, that analytical thinking and decisions based on data and analytics will play an increasingly important role in business and society. We'll need many managers and professionals who are comfortable with analytical thinking, and we want you to be one of those. Second, we hope you now realize that you can play in this game even if you are not a statistics or math whiz. If you understand the stages and steps of analytical thinking and the attributes of a good analytical decision process, you can engage with the best quants and help to improve the outcome. You'll also make yourself a better thinker and decision maker along the way.

Third, while most people typically think of "solving the problem" as the core of analytical thinking, it's only one of the steps that make for a successful analytical decision. If the problem is framed incorrectly or sub-optimally, the solution won't be very useful. And if the results aren't communicated in an effective way, it's unlikely that any decision will be made on the basis of them, or any actions taken. If you're working on an analytical problem and trying to think of how to allocate your time, start with an equal allocation across these three stages.

Fourth and finally, many people believe that the world of analytical thinking and decisions is almost exclusively about numbers, rigorous statistics, and left-brain thinking in general. But the right brain needs to be seriously engaged as well. We've tried to show—in chapter 5 especially—that creativity is important to analytical thinking, and in this chapter have argued (based on lots of experience and observation) that relationships are just as important—perhaps more so—to progress with analytics than sheer number-crunching ability.

If you have read this entire book and given the ideas and examples some thought, you are now prepared to join the ranks of analytical thinkers. Congratulations! It's an exciting time to be in this group. The amount and importance of data in organizations is only going to shoot upward over time, and you will be able to move upward with it. We expect that your newfound analytical focus will benefit both your career and the success of the organizations you work with.

Notes

Chapter 7

1. Personal communication with author.

2. "Surveying the Economic Horizon: A Conversation with Robert Shiller," *McKinsey Quarterly,* April 2009, http://www.mckinseyquarterly.com/Surveying_the_economic_horizon_A_conversation_with_Robert_Shiller_2345.

3. David Olive, "Getting Wise Before That 'One Big Mistake,'" *Toronto Star,* December 17, 2007.

4. Charles Duhigg, *The Power of Habit: Why We Do What We Do in Life and Business* (New York: Random House, 2012).

5. Gary Loveman, "Foreword," in Thomas H. Davenport and Jeanne G. Harris, *Competing on Analytics: The New Science of Winning* (Boston: Harvard Business School Press, 2007), x.

6. More context on the movie and the characters can be found at http://business-ethics.com/2011/11/23/0953-margin-call-a-small-movie-unveils-big-truths-about-wall-street/.

7. *Margin Call,* film with direction and screenplay by J. C. Chandor, 2011.

8. Liam Fahey, "Exploring 'Analytics' to Make Better Decisions: The Questions Executives Need to Ask," *Strategy and Leadership* 37, no. 5 (2009): 12–18.

9. Information for this example came from several interviews with Anne Robinson; and Blake Johnson, "Leveraging Enterprise Data and Advanced Analytics in Core Operational Processes: Demand Forecasting at Cisco," case study, Stanford University Management Science and Engineering Department.

10. Kevin Harrington, "Seeing the Future in Value Chain Management," *Analytics Magazine*, March/April 2010.

11. Ibid.